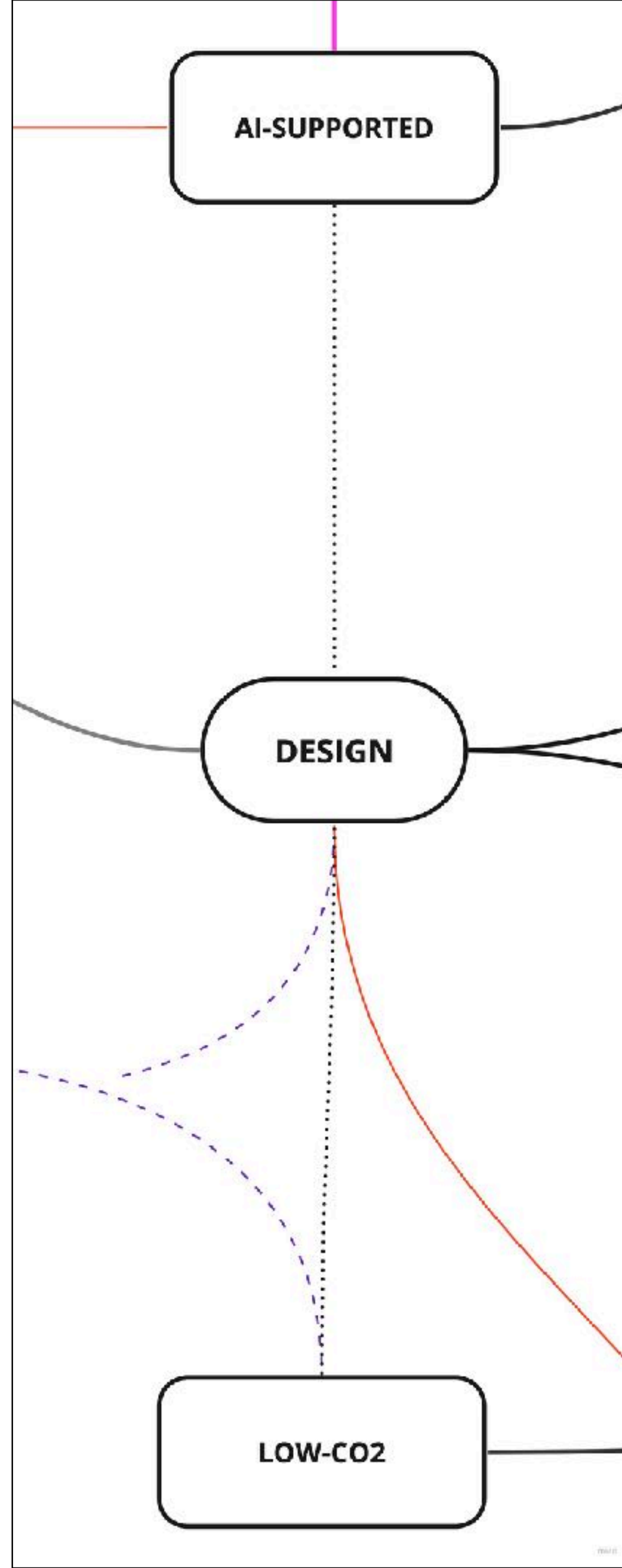
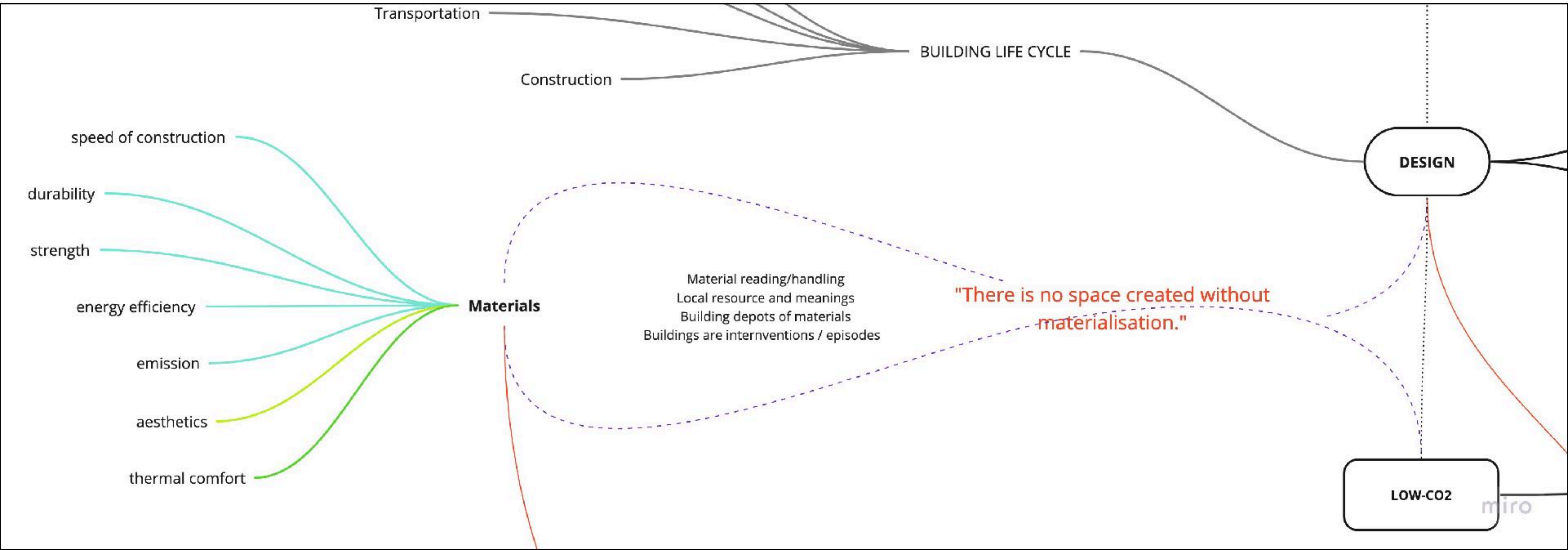


Ai-supported low CO2 circular design

Peng lee, 09.2023

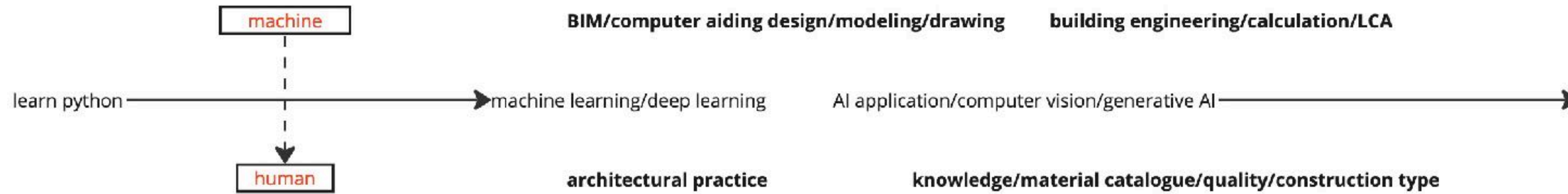






**INFORMAL / FORMAL
MATERIAL LITERACY / NETWORK?**

"while architecture field is relatively low tech...."
 What can machine do for human in architecture field?
 What can't machine do for human in architecture field?
 Narrow down to working with existing/renovation/demolition...?



learn from companies/firm:
 super-reuse
 Madaster
 Rotor(material bank)
 BC (excavated earth to building materials)



What are the available materials?
 how do you make materials available? make information available?
 how do we asses those materials?

 bridge the gap, what's missing in field?

Paper reviews

The Miro board is organized into several sections:

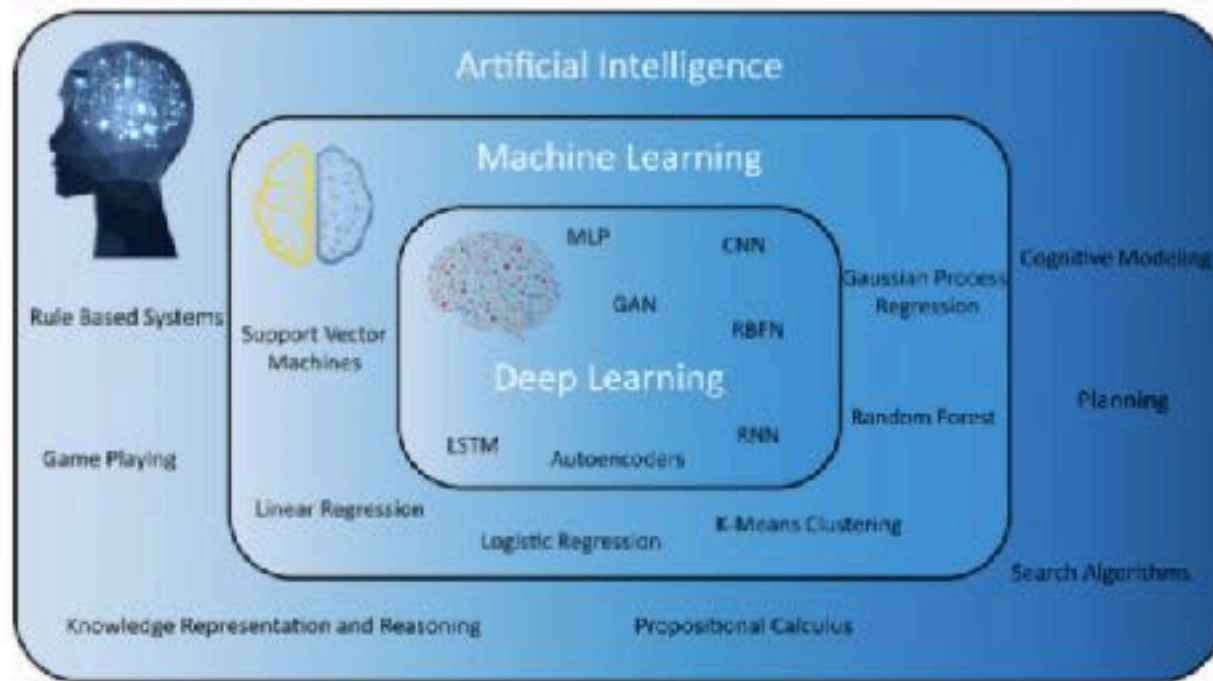
- Top Left:** A central note with a yellow sticky note icon and a small diagram.
- Top Row:** Four main sections: **GAN**, **Digital Surface Model**, **Point2Poly**, and **IFACADE**. Each section contains text, diagrams, and images.
- Middle Row:** A series of smaller notes and images, including a 3D model of a terrain.
- Bottom Row:** A series of notes and images, including a 3D model of a terrain.

The board also features a central note with a yellow sticky note icon and a small diagram.

Review
Artificial intelligence and smart vision for building and construction 4.0: Machine and deep learning methods and applications

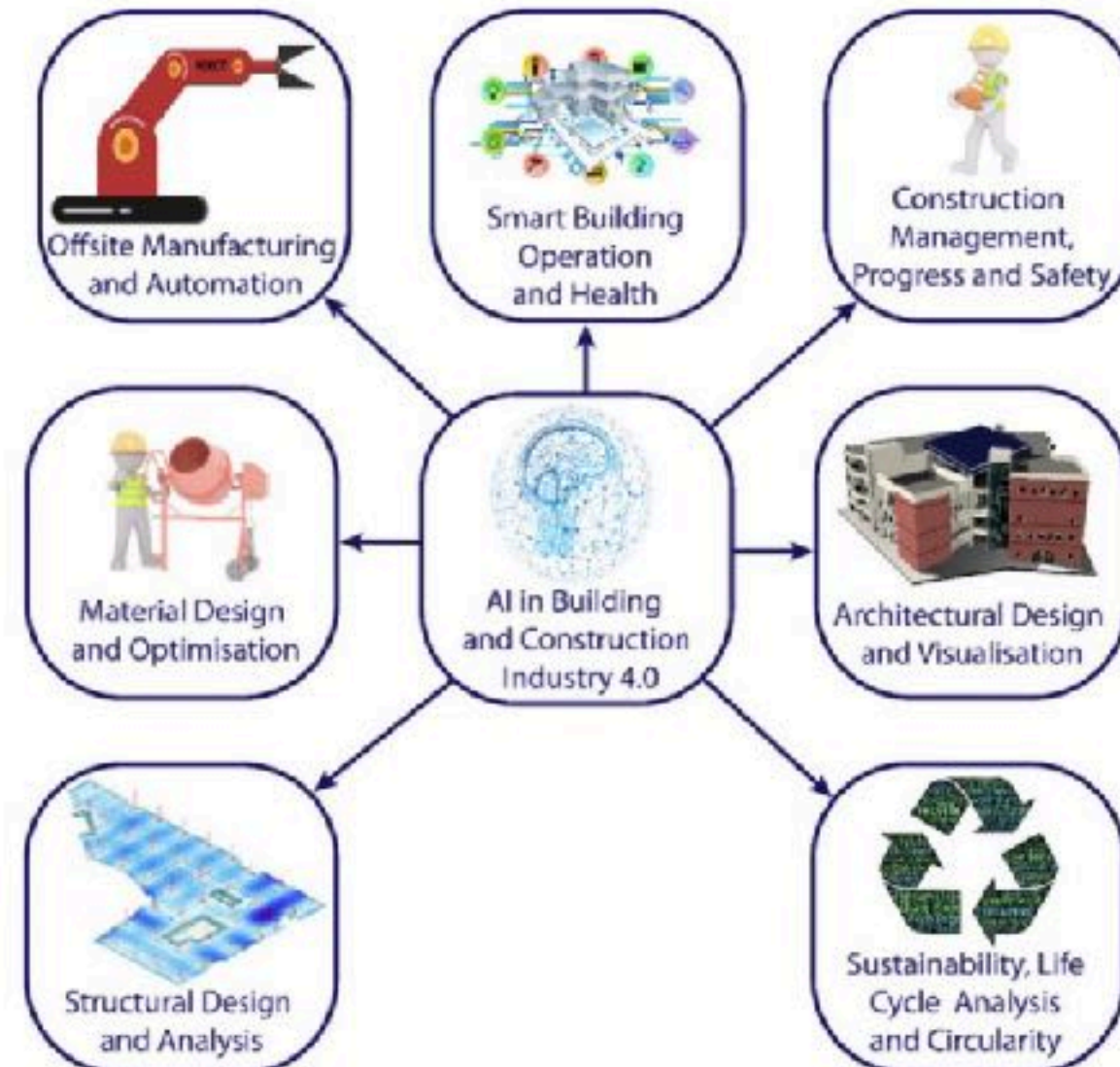
Shanaka Kristombu Baduge,^a Sadeep Thilakarathna,^a Jude Shalitha Perera,^a Mehrdad Arashpour,^b Pejman Sharafi,^c Bertrand Teodosio,^d Ankit Shringi,^b Priyan Mendis,^a

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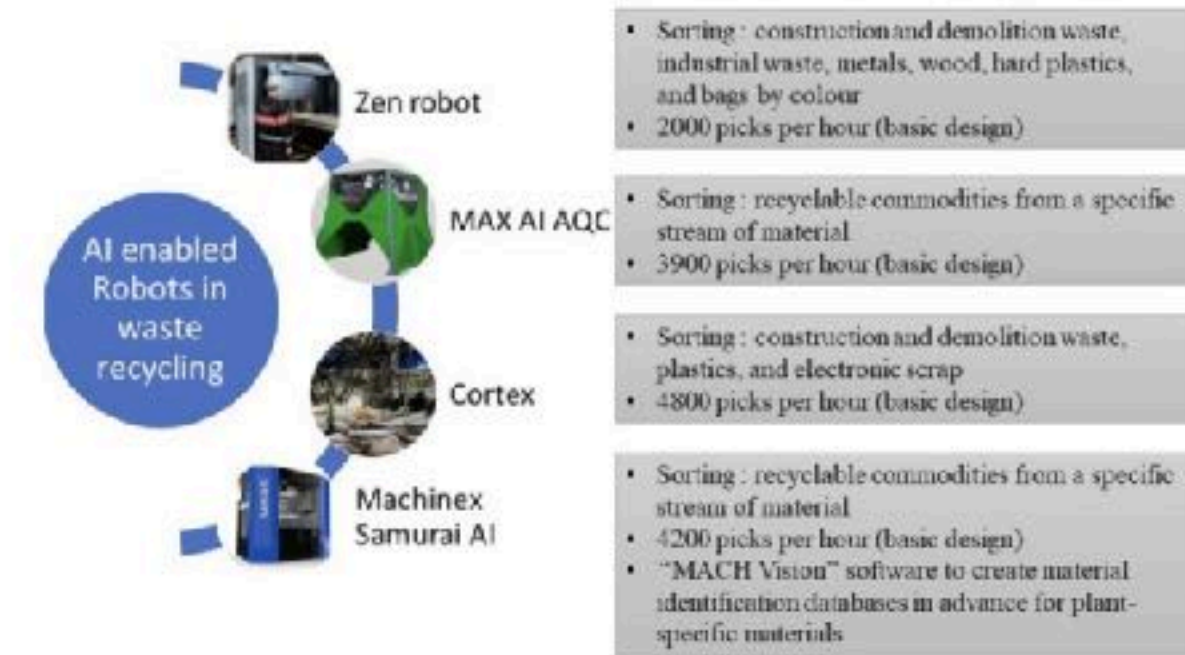
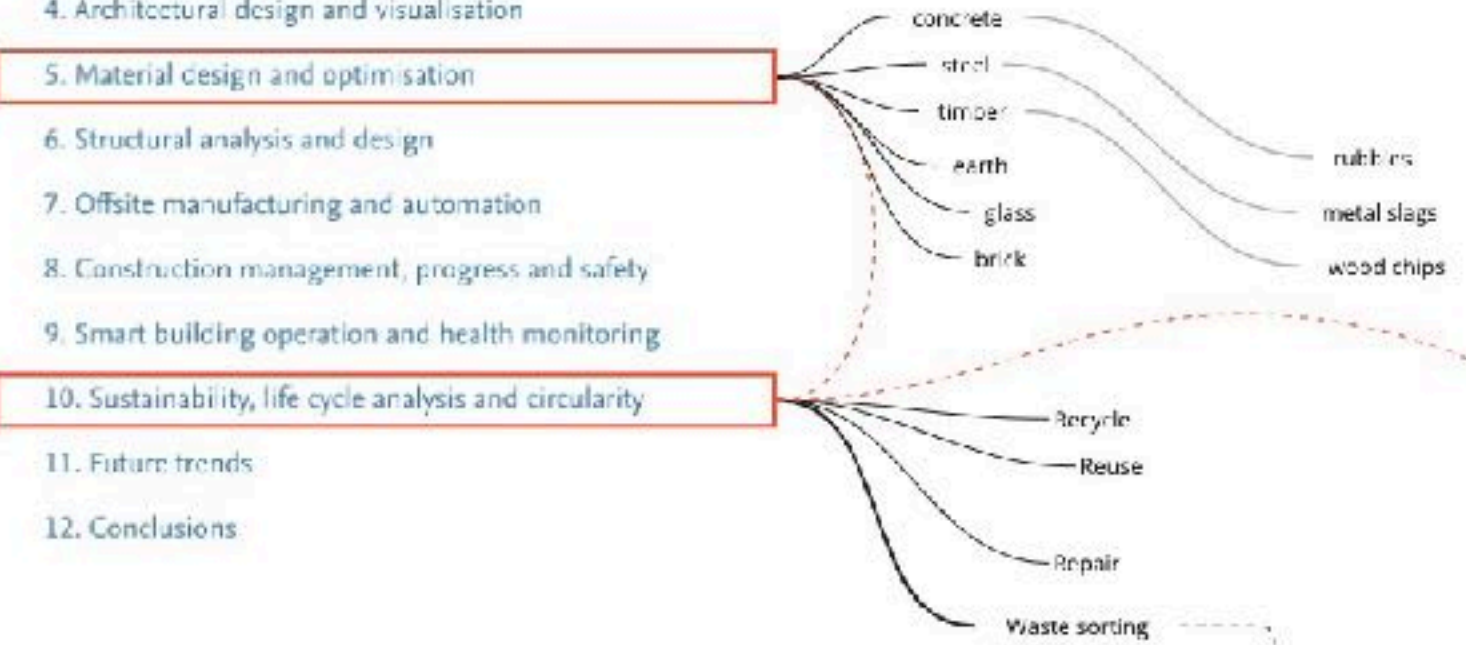
Fig. 1. Domains of AI, ML, DL, and widely used algorithms.



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Fig. 2. Application AREFAS of AI in building and construction industry 4.0.

1. Introduction
2. ML/DL algorithms and data acquisition
3. Methodology
4. Architectural design and visualisation
5. Material design and optimisation
6. Structural analysis and design
7. Offsite manufacturing and automation
8. Construction management, progress and safety
9. Smart building operation and health monitoring
10. Sustainability, life cycle analysis and circularity
11. Future trends
12. Conclusions



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Fig. 20. Commercial solutions for automated waste sorting.

GAN

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Building and Environment
Volume 222, September 2022, 109477

Generative Adversarial Networks in the built environment: A comprehensive review of the application of GANs across data types and scales

Abraham Nassir Wu,*, Rudi Steuffs, E. P. Biljocki

Abstract
Generative Adversarial Networks (GANs) are a type of deep neural network that have achieved many state-of-the-art results in generative tasks. GANs can be useful in the built environment, from processing large-scale urban mobility data and remote sensing images at the regional level, to performance analysis and design generation at the building level. We analyzed 100 articles to provide a comprehensive state-of-the-art review on how GANs are currently applied to solve challenging tasks in the built

Abstract

Generative Adversarial Networks (GANs) are a type of deep neural network that have achieved many state-of-the-art results in generative tasks. GANs can be useful in the built environment, from processing large-scale urban mobility data and remote sensing images at the regional level, to performance analysis and design generation at the building level. We analyzed 100 articles to provide a comprehensive state-of-the-art review on how GANs are currently applied to solve challenging tasks in the built

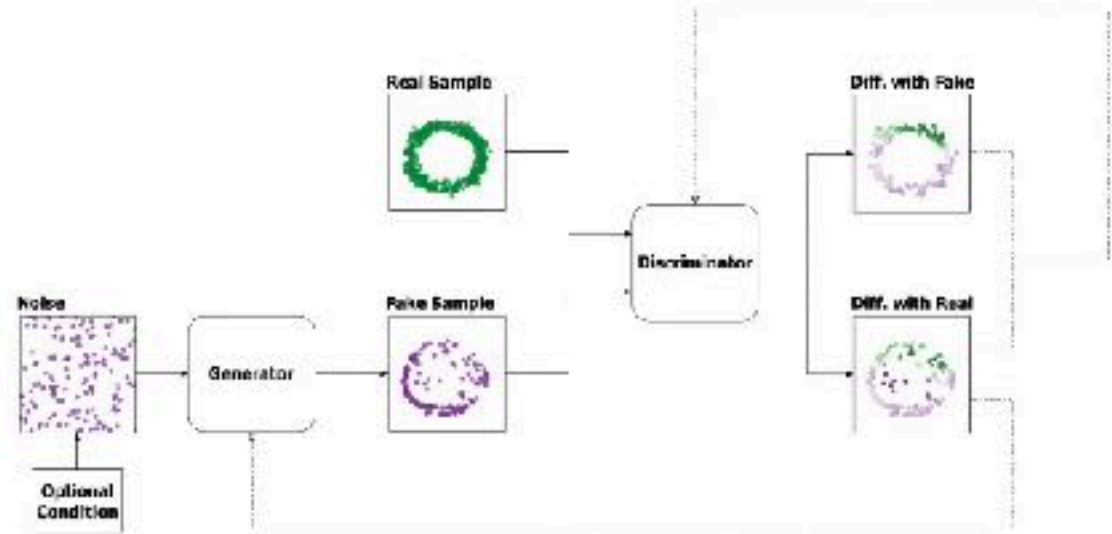


Figure 1: General architecture of a GAN. During forward propagation, random noise is passed into the generator to generate a fake sample (if a conditional vector is used, the GAN becomes a conditional GAN and the user can influence the outcome of the generator). The discriminator takes in both the real and fake samples to determine which is real. Then a loss gradient is calculated using a loss function, and the respective losses are back-propagated to the Generator and Discriminator. There is no restriction on the format of the real and fake samples, as long as the neural network architecture of the Generator and Discriminator adapts to the data formats.

tweaking the training data... how the user to input some additional information to... the intended dataset, of... fine more granular con...

Digital Surface Model

DSM BUILDING SHAPE REFINEMENT FROM COMBINED REMOTE SENSING IMAGES BASED ON WNET-CGANs

Krzysztof Bittner, Marco Koerner, Peter Keenan

Remote Sensing Technology Institute, German Aerospace Center (DLR), Wessling, Germany
Technical University of Munich, Munich, Germany

ABSTRACT

We describe the workflow of a digital surface model (DSM) refinement algorithm using a hybrid conditional generative adversarial network (CGAN) where the generative part consists of two parallel networks merged at the last stage forming a WNET and a net. The input is a so-called WNET-CGAN are stereo DSMs and pansharpened (AS2) half-meter resolution satellite images. Training data helps to propagate fine detailed information from a spectral image and complete the missing 3D knowledge from a stereo DSM about building shapes. Besides, it refines the building outlines and edges making them more rectangular and sharp.

Index Terms— Conditional generative adversarial networks, digital surface model, 3D scene reconstruction, 3D building shape, data fusion, satellite images

1. INTRODUCTION

A digital surface model (DSM) is an important and valuable data source for many remote sensing applications. Like building detection and recognition, autonomous analysis, urban planning, environmental investigation and disaster assessment tasks. The use of DSM for those remote sensing applications is motivated by the fact that it already provides geometric descriptions about the topography surface. With recent advances in sensor technologies, it became possible to generate DSMs with a ground sampling distance (GSD) smaller than 1 m not only from land surveying, aerial images, laser scanning data, or interferometric synthetic aperture

images or a fusion of noise removal filter are the ones commonly used for DSM quality improvements. Moreover, some methodologies propose to fuse DSMs estimated from different data sources to compensate the limitations and gaps which each of them has individually.

With recent developments devoted to deep learning, it became possible to achieve top success on many tasks including image processing. As a result, several works have already investigated their applicability for remote sensing applications, like lands use classification, building and road extraction, or traffic monitoring. Recently, a class of neural networks called generative adversarial networks (GANs) was applied to three-dimensional remote sensing data and proved to be suitable. Mostly, the generation of a realistic 3D surface models with reference building shape to the level of details (LoD) 2 from stereo satellite DSMs was studied using conditional generative adversarial networks (CGANs) [2, 3]. In this paper, we follow those areas and propose a hybrid CGAN architecture which couples half-meter resolution satellite pansharpened (AS2) images and DSMs to produce 3D surface models not only with refined 3D building shapes, but also with their complex structures, more accurate outlines and sharp edges.

2. METHODOLOGY

The hybrid CGAN-based domain adaptation neural networks introduced by Goodfellow et al. [4] yielded great achievements in generating realistic images. The idea behind the ad-

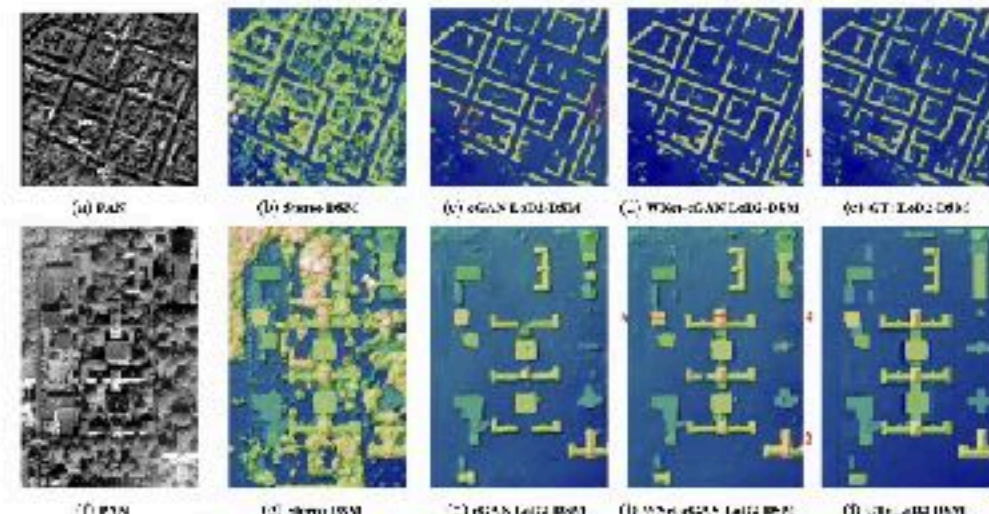


Fig. 2: Visual analysis of DSMs, generated by stereo CGAN and WNET-CGAN architectures, over selected urban areas. The DSM images are color-coded for better visualization.

Looking at Fig. 2a and Fig. 2f we can see that the edges and outlines can be seen very well in the PAN image. Refinement of 3D buildings only from PAN image though would be very difficult as it does not contain 3D information, which is very important. Therefore, the combination of these two types of information is a good compromise which leads to advantages: reconstruction even complicated buildings, which is difficult to reconstruct using a single source DSM information. To quantify the quality of the generated DSMs, we evaluated the metrics mean absolute error (MAE), root mean squared error (RMSE), normalized median absolute deviation (NMAD), and normalized standard deviation (NSD).

Point2Poly

ISPRS Journal of Photogrammetry and Remote Sensing
journal homepage: www.elsevier.com/locate/isprsjprs

Reconstructing compact building models from point clouds using deep implicit fields

Sheng Chen,*, Huijun Li, Xinyu Kang, Junghong Kim

ARTICLE INFO

Keywords: Deep learning, Point cloud, Building reconstruction, Implicit fields

ABSTRACT

With the development of deep learning, it has become possible to achieve top success on many tasks including image processing. As a result, several works have already investigated their applicability for remote sensing applications, like lands use classification, building and road extraction, or traffic monitoring. Recently, a class of neural networks called generative adversarial networks (GANs) was applied to three-dimensional remote sensing data and proved to be suitable. Mostly, the generation of a realistic 3D surface models with reference building shape to the level of details (LoD) 2 from stereo satellite DSMs was studied using conditional generative adversarial networks (CGANs) [2, 3]. In this paper, we follow those areas and propose a hybrid CGAN architecture which couples half-meter resolution satellite pansharpened (AS2) images and DSMs to produce 3D surface models not only with refined 3D building shapes, but also with their complex structures, more accurate outlines and sharp edges.



Figure 3: Building reconstruction results. The figure shows a grid of 3D building models reconstructed from point clouds. The models are shown in different colors and orientations to illustrate their compact and detailed structure.

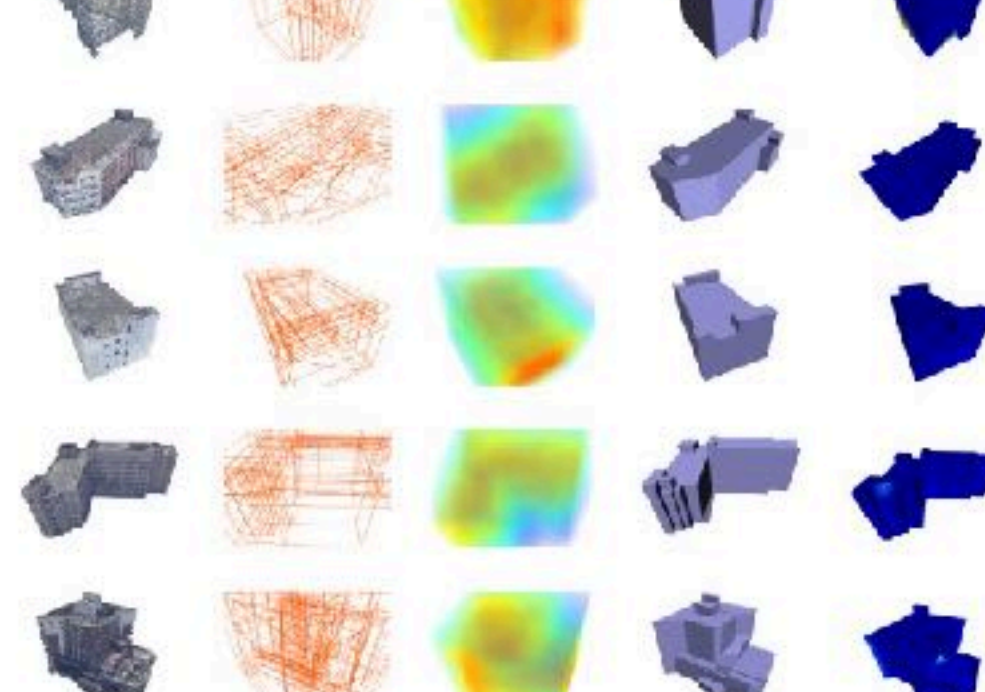


Figure 4: Visual analysis of DSMs, generated by stereo CGAN and WNET-CGAN architectures, over selected urban areas. The DSM images are color-coded for better visualization.

iFACADE

Facade Style Mixing Using Artificial Intelligence for Urban Infill

Ahmed Khairadeen Ali,*, and One Jae Lee

Architectural Engineering Department, College of Engineering, University of Duhok, Duhok 42001, Iraq
Haenglim Architecture and Engineering Company, Seoul 431810, Republic of Korea

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Received: 23 January 2023 / Revised: 26 March 2023 / Accepted: 9 May 2023 / Published: 11 May 2023

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Abstract

Artificial intelligence and machine learning, in particular, have made rapid advances in image processing. However, their incorporation into architectural design is still in its early stages compared to other disciplines. Therefore, this paper addresses the development of an integrated bottom-up digital design approach and describes a research framework for incorporating the deep convolutional generative adversarial network (GAN) for early stage design exploration and the generation of intricate and complex alternative facade designs for urban interiors. In this paper, a novel facade design is proposed using the architectural style, size, scale, and openings of two adjacent buildings as references to create a new building design in the same neighborhood for urban infill. This newly created building

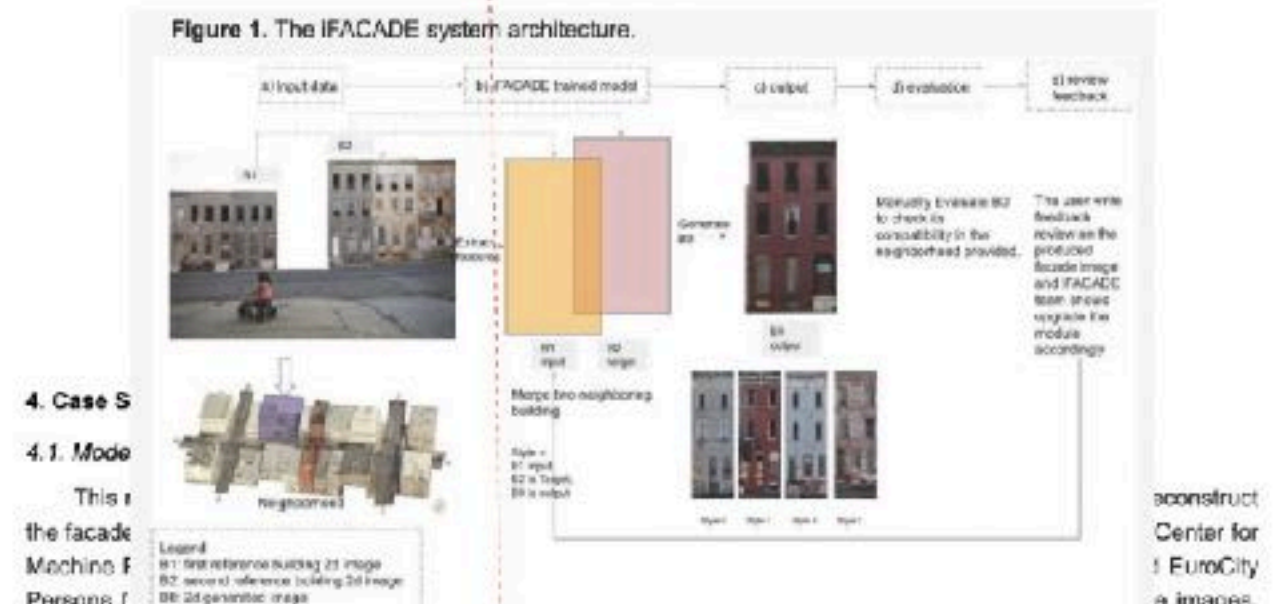


Figure 1: The iFACADE system architecture. The diagram shows a workflow from input data to facade style mixing, evaluation, and feedback. It includes a legend for building types and a case study showing the process of generating a facade design for a specific building.

4. Case S
4.1. Mode
This i
the facade
Machine f
Persons {
The image
detailed
architectural
style differences
that are neglected
in this paper. We
processed the
images manually
and chose the
best 420 images
and erased the
rest. The additional
images were
collected from
the eTRIMS
database, which
contained 60
facade images,
and the Ecole
Centrale Paris
facade database.
The facade
images collected
were processed
to 128 × 128
pixels with 3
channels, and
divided to 80
percent training,
15 percent test
and 5 percent
validation. The
facade images
constraints are
the following 12
classes: facade,
molding, cornice,
pillar, window,
door, sill, blind,
balcony, step,
decoration, and
background.
To increase the
training speed,
the images
resolution were
decreased to
128 × 128
pixels with three
channels; they
are not suitable
for high-resolution
image generation.
This research
normalizes the
image color
values to [-1, 1]
before feeding
the image into
the model.
4.2. iFACADE Model Training
This research
used Tensorflow
to implement
the model
training. We
also started to
generate
resolutions
from 8 × 8.
The models
were optimized
by stochastic
gradient
descent. For
all experiments,
the learning
rate was fixed
at 0.002,
which updates
the generator
once for each
discriminator
update.
We
implemented
the proposed
architecture in
Tensorflow
using a
workstation
with a
NVIDIA
2080 Ti
GPU. Our
model uses
StyleGAN [6]
with the
ADAM
optimizer
(b1 = 0.5,
b2 = 0.999)
and was
trained for
11 days and
6 h. The
learning rates
of the
generator
and
discriminator
were both
0.0001. The
stack size
was 4. We
set the
number of
filters to 1
and used
leaky ReLU
(α = 0.1)
for all
operations,
except the
last one in
the generator,
where the
ReLU
activation
was used.



The Routledge Companion to Artificial Intelligence in Architecture

Edited By *Imdat As, Prithwish Basu*

Book

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 Imprint: Routledge
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 Pages: 486
 eBook ISBN: 9780367824259
 Subjects: Built Environment, Computer Science

ABSTRACT

Providing the most comprehensive source available, this book surveys the state of the art in artificial intelligence (AI) as it relates to architecture. This book is organized in four parts: theoretical foundations, tools and techniques, AI in research, and AI in architectural practice. It provides a framework for the issues surrounding AI and offers a variety of perspectives. It contains 24 consistently illustrated contributions examining seminal work on AI from around the world, including the United States, Europe, and Asia. It articulates current theoretical and practical methods, offers critical views on tools and techniques, and suggests future directions for meaningful uses of AI technology. Architects and educators who are concerned with the advent of AI and its ramifications for the design industry will find this book an essential reference.

TABLE OF CONTENTS

Part 1 | 90 pages
 Background, history, and theory of AI

17

Image analytics for strategic planning

Aldo Solazzo

The construction industry is a historically complex sector. In the late 20th century, the increasing difficulty to establish efficient processes became largely evident, indicating the need for a close management of the construction field.

A medial axis algorithm is applied to the original geometry. As a result, all three-dimensional elements are reduced to a set of splines from which curvature, torsion, and orientation are extrapolated and stored in a JavaScript Object Notation (JSON) format (Figure 17.7). The resulting data frame composed of all JSON files is the key component connecting design and manufacturing operations for timber construction and lamination. Storing information on wood curvature directly connected to individual material resources can potentially improve all processes of wood bending. Through robotic fabrication, laminated timber strips are produced optimizing material consumption, thanks to custom sawing paths executed by the robot. This process allows to implement from each given curvature a specific material resource while introducing novel practice for forestry survey and material management (Figure 17.8).

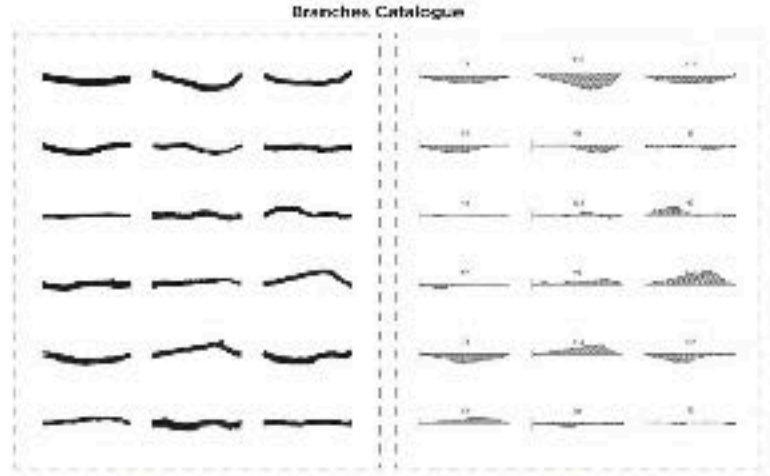


Figure 17.7 Database: storing information on wood curvature connected to individual material resources.



Figure 17.8 Database: storing information on wood curvature connected to individual material resources.

Automating forestry survey for timber construction

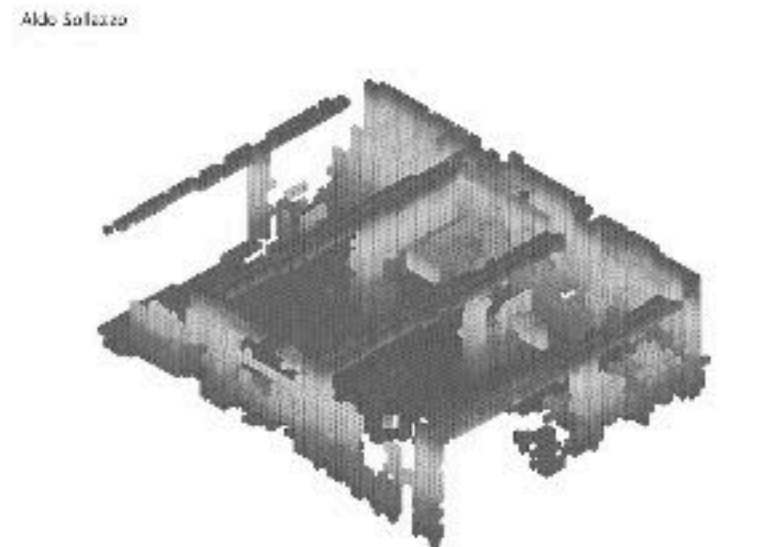


Figure 17.10 Point cloud depth map

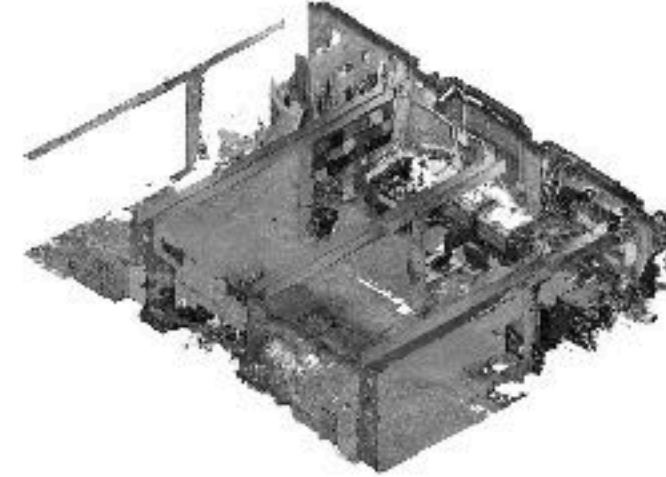


Figure 17.11 Point cloud reconstruction: OctoMap generation modeling arbitrary environments without prior assumptions.

This overall method allows to retrieve material properties from built environments, as well as building shapes and physical topologies, enabling a novel automated protocol blending machine perception, image analytics, and machine learning into data structures informing novel solutions for material and waste management (Figure 17.12).



Figure 17.12 Image processing: image subdivision to a suitable kernel size, performing heuristic evaluation for material classification.



Figure 17.13 Image processing: image subdivision to a suitable kernel size, performing heuristic evaluation for material classification.

Digitizing material collation from demolition sites

image into sets of pixels, also known as image objects, is performed through Markov Random Field (MRF) algorithms, a conceptually simple, flexible, and general framework for object instance recognition (He et al., 2017) (Figure 17.14).



Figure 17.14 Point cloud segmentation: color clustering over point cloud geometries for rust detection.

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Image analytics for strategic planning

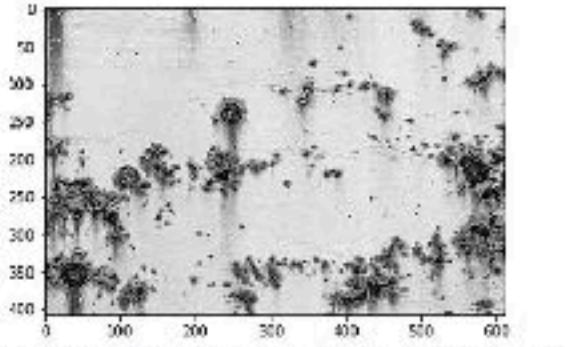


Figure 17.15 Image processing: edge detection segmentation to define area of rust through global thresholding.

The image dataset for this research is split into 6/31 raw images for training and 15/31 images for testing. The convolutional neural network is trained over 1,000 epochs, resulting in a de-

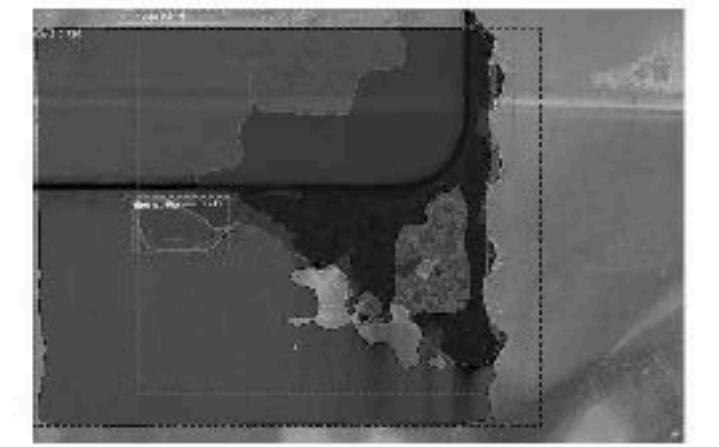


Figure 17.16 Semantic segmentation: applying Mask R-CNN semantic segmentation and rust detection.

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Conclusions
 In the increasingly complex AEC industry, data-driven workflows become fundamental to informed decision-making processes. Therefore, sensing emerges as a crucial variable to understand, evaluate, and project operations in our built environments by decoding physical components. In this context, the determination of digital methods can serve as a key to improve the

Autonomous inspection system for building maintenance

References

Barbot, F., Warren, J., Munkittrick, J., R. S. Venkatesh, M. J., S. Riffkin, M., Farnon, M., ... & Brown, S. (2012). Recovering construction through a productivity revolution. *McKinsey Global Institute*.
 Das, S. A. I., L. L. Eversole, M. J., Jones, J. A., C., & Bredahl, A. A. (2007). Navigation: From decisions using image processing via Matlab. In *TANCON 2007-2007 IEEE Sigpos. 40 Conference* (pp. 1327-1331). IEEE.

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Image analytics for strategic planning

Franc, T. M. (2010). The impact of emerging information technology on project management for construction. *Automation in Construction*, 19(5), 530-558.
 He, K., Glasziou, G., Dollin, P., & Girdhadi, R. (2007). *Mask e-con*. In *Proceedings of the IEEE International Conference on Computer Vision* (pp. 2961-2969).
 Jedjajko, B., & Tancig, M. (2012). Comparison of Aerial Imagery and Satellite Imagery for Autonomous Vehicle Path Planning. In *4th International DAAAM International Conference* (pp. 17-21).
 Kikawa, K., & Hiron, F. (2018). Automatic individual tree detection and canopy segmentation from three-dimensional point cloud images obtained from ground-based laser. *Forest of Intelligent Machinery*, 7(2), 199-115.
 Jones, K. (2018, April 11). How big data can transform the construction industry. *Concrete*.
 Kumarathin, S. S., Mohanraj, M. P., & Mathis, R. (2016). Barriers and impact of mechanization and automation in construction to achieve better quality practices. *Physics-Social and Behavioral Science*, 2(2), 111-128.
 Li, Y., & Liu, C. (2019). Application of multi-level drone technology in construction management. *International Journal of Construction Management*, 19(5), 401-412.
 Poon, C. S., Ann, T. W., & Ng, J. H. (2010). On-site sorting of construction and demolition waste in Hong Kong. *Resources, Conservation and Recycling*, 54(2), 157-172.
 Rakha, T., & Gerasimov, A. (2018). Review of Unmanned Aerial Systems (UAS) applications in the built environment: Towards automated building inspection procedures using drones. *Automation in Construction*, 92, 252-264.
 Schmittig, J., Nair, N., Barr, C., & Pevsley, R. (2017). Green assets—Quantifying and mapping urban trees with street-level imagery and computer vision. *Landscape and Urban Planning*, 165, 93-101.
 Soto-Parada, E., Correa-Echeverri, S., & Pineda-Pineda, M. J. (2017). Thermal analysis of urban environments in Medellín, Colombia, using an Unmanned Aerial Vehicle (UAV). *Journal of Urban and Environmental Engineering*, 11(2), 142-149.
 The Impact and Opportunities of Automation in Construction. (2019, December). *Global Infrastructure Insights*.

Combining AI and BIM in the design and construction of a Mars habitat

Naveen K. Muthumanickam, José P. Duarte, Shadi Nazarian, Ali Memari, and Sven G. Bilén

Naveen K. Muthumanickam et al.

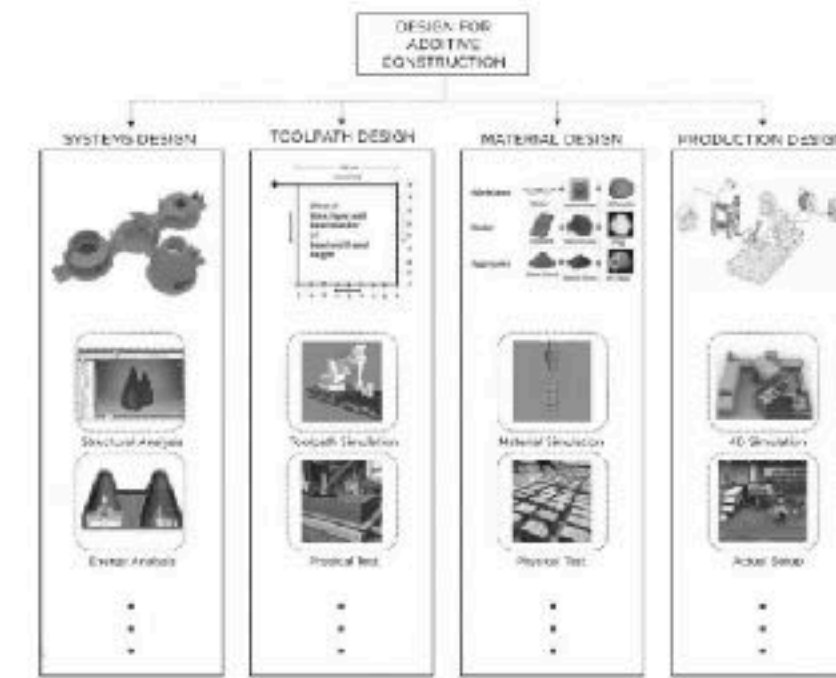


Figure 13.13 Multidisciplinary nature of design for additive construction (DIAC) involving a range of computational analyses and physical testing.

To address such technological gaps and streamline the additive construction design process, an end-to-end BIM framework was developed and used to design a Mars habitat from the conceptual design space to additively constructing it using industrial robots in the final

C

Generating new architectural designs using topological AI

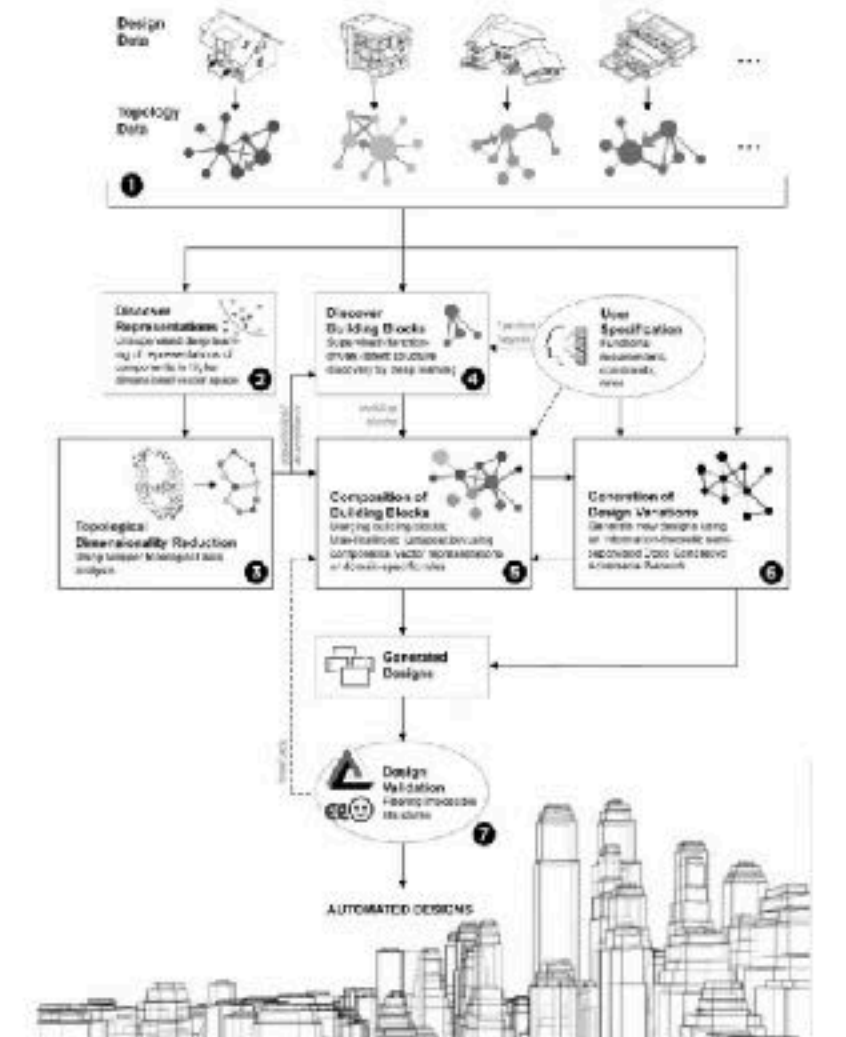
Prithwish Basu, Imdat As, and Elizabeth Munch

Architectural designs using topological AI

Methodology

Our topological-AI based framework comprises of the following key steps (see Figure 9.2):

1. Translate readily available three-dimensional building information modeling (BIM) models from a vast database of architectural projects on Archbase; they are translated into topological datasets to succinctly represent the designs.



ROTUNDORO. A web-based decision support tool for building refurbishment.

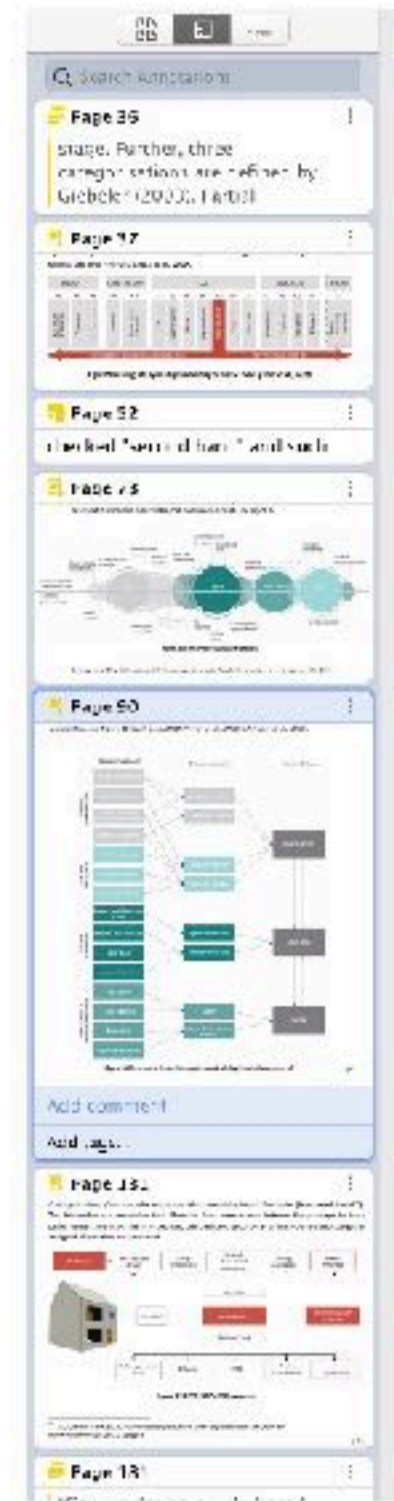
Julia Katharina Kaltenegger, Master Thesis, October 2021, email: jk.kaltenegger@gmail.com

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Abstract

When refurbishing residential buildings, insulation materials play a crucial role in improving housing quality and energy efficiency. Materials however differ in a wide set of criteria. It reaches beyond the thermal properties and addresses environmental, economic, health and safety characteristics. In collective decision-making, it remains difficult to find trade-offs between these criteria. This thesis introduces a web-based tool ROTUNDORO (Latin: circular) that offers an algorithm to assess refurbishing insulation materials, considering engineering evaluation methods and consumer preferences. The tool employs and expands on Building Information Modelling (BIM) practice on the one side and behavioural economic research on the other side. First, the Linked Building Data (LBD) method is used to link material performance to building components and to evaluate them with Life Cycle Assessment (LCA) and cost analysis. Applied to a Dutch terrace house (Tijuwoning) as a use case, the tool shows that bio-based materials perform best in environmental concerns, low embodied carbon, high noise and humidity reduction. Fossil- and mineral-based materials are yet market-leading, due to low price and easier application techniques in existing constructions (quality injection). Following the hard data comparison, the tool simulates the probability of acceptance by the homeowners of



Name	Lambda [W/mK]	Density [kg/m³]	Weight [kg/m²]	EE [MWh/m²]	EC [kgCO₂e/m²]	Costing [€/m²]	Lifetime [years]	Fire rating	Toxic Hazards [µg/m³]	dB drop [dB]	VDRF [m-value]
Mineral-based											
Glass Wool	0.034	18.4	1.06	51.50	1.60	6.80	75	A2	129.5	6.52	0.29
Rock Wool	0.035	45	2.58	48.91	2.90	7.40	75	A1	177	7.85	0.46
Fossil-based											
PIR	0.026	31	1.44	178.31	11.14	7.40	75	E	11.4	11.54	27.10 - 87.50
EPS	0.0323	23	1.21	117.50	8.70	5.85	75	E	27.6	2.16	15.19 - 58.09
XPS	0.027	35	1.51	178.20	24.80	8.11	75	E	27.6	2.81	15.39 - 100.91
Bio-based											
Flax wool	0.041	31	2.16	86.30	2.60	21.08	10	C	229.5	10.17	0.52 - 2.11
Wood Fibre	0.038	45	21.96	23.50	0.62	6.31	100	C-D	229.5	11.00	0.57 - 3.71
Cellulose 0.04	0.04	70	4.70	0.80	0.29	10.50	30	C	229.5	10.90	0.85 - 5.25
Sheep Wool	0.0413	25	1.75	21.5	-2.10	13.18	100	E	229.5	6.52	0.70 - 2.68
Hemp Linte	0.067	34.1	4.73	152.57	-4.59	22.97	100	B	179.1	15.48	1.19 - 6.10

Table 18 Material Comparative Analysis Itc 1.7 - 5.5

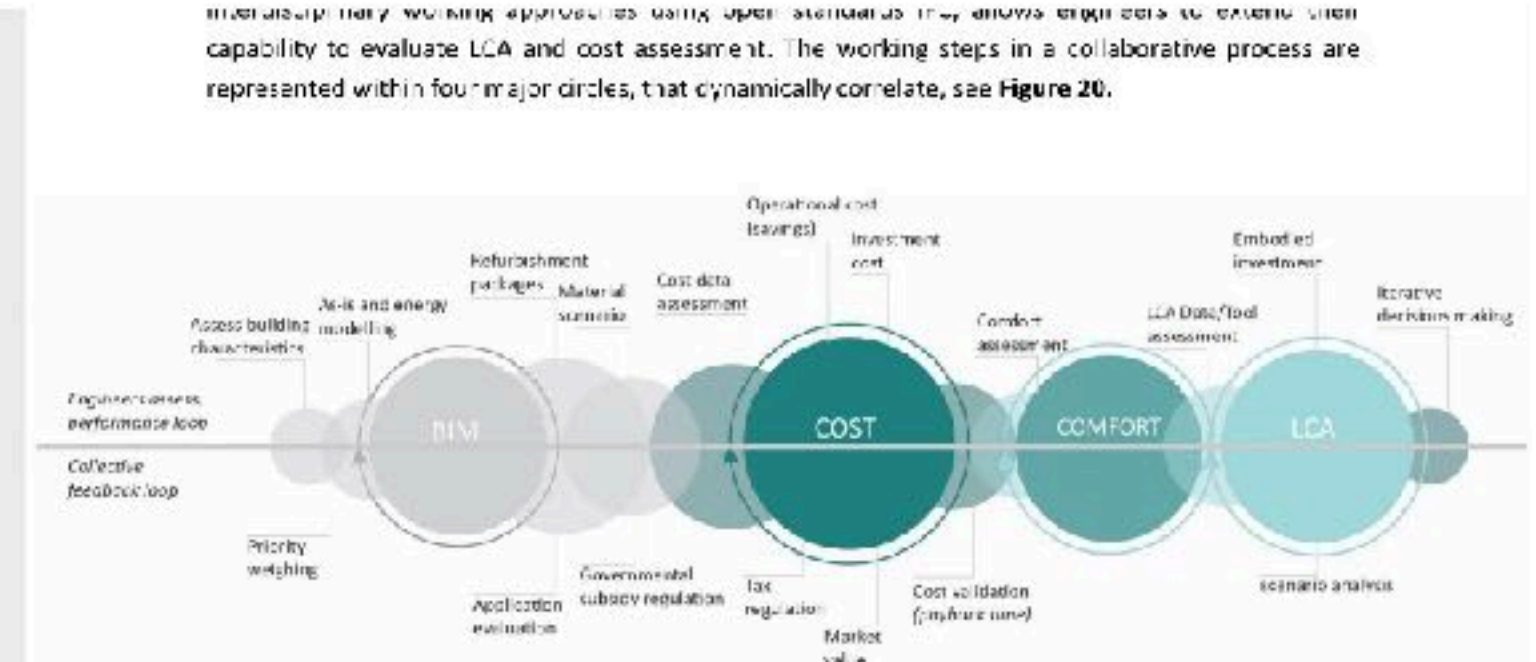


Figure 20 Sustainable evaluation process

Energy modelling is fundamental knowledge to create feasibility studies. It encompasses the BIM practice including parameters to perform operational energy simulations. Scenarios in materials' thermal properties and BIMs highlight energy reduction potential within a 3D model (visually and numerically). Examples of BIM-based software is Energy Plus inside Autodesk Revit, Design Builder for parametric performances and non-graphical evaluation using VALU LPA, based on the deterministic energy performance for buildings (NL national NTA 8800 (NEN 8800, 2020). The cost-savings potential

bio-based materials are underpinned by the commercial materials. Additionally, higher uncertainties and weights are required which leads to much higher market costs. Little knowledge is shared due to too little investment for research and development, and it causes a poor market reputation.

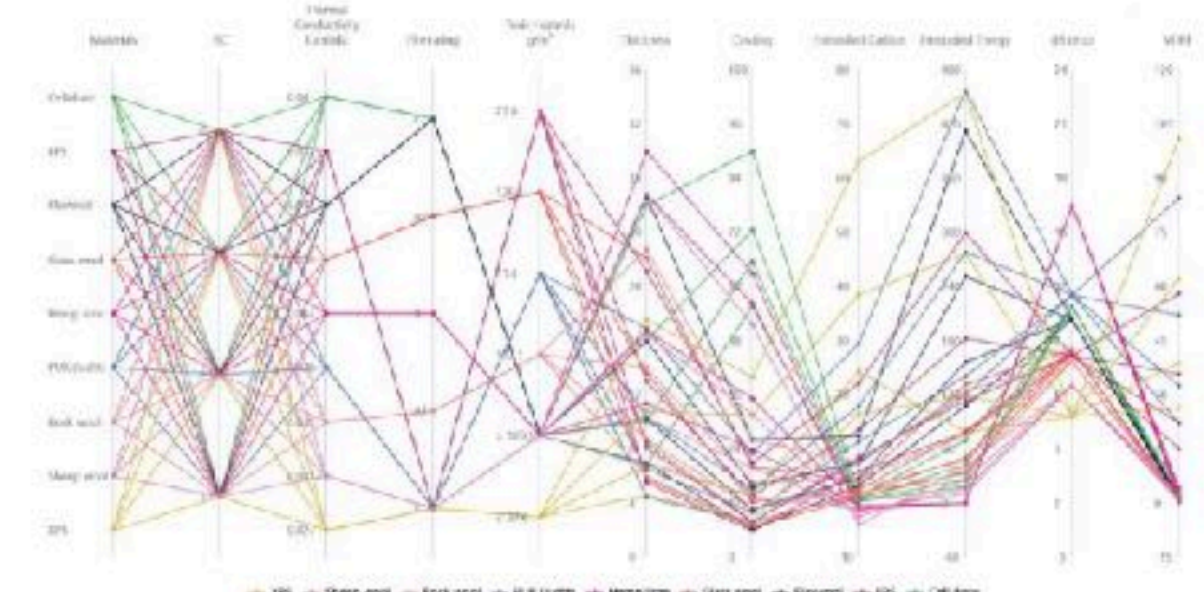


Figure 31 Material Comparative Analysis



Full Length Article

Salvaging building materials in a circular economy: A BIM-based whole-life performance estimator

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ABSTRACT

The aim of this study is to develop a BIM based Whole life Performance Estimator (BWPE) salvage performance of structural components of buildings right from the design stage. A literature was carried out to identify factors that influence salvage performance of steel buildings during their useful life. Thereafter, a mathematical modelling approach was adopted using the identified factors and principle/concept of Weibull reliability distribution for materials. The model was implemented in Building Information Modelling (BIM) environment and its study design. Accordingly, the whole-life salvage performance profiles of the case study built

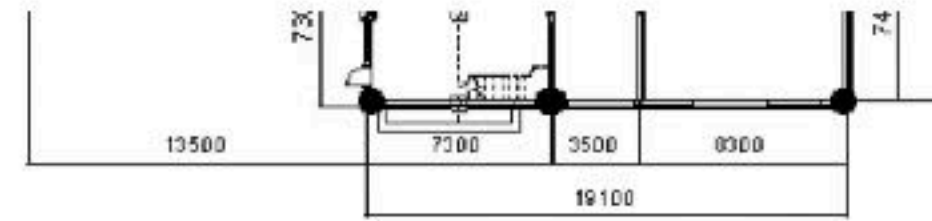


Table 2
 Characteristic Feature of the Case Study Building.

Feature	Value
Building type	Office
Number of floors	3
Ground floor area (GFA)	491.46 m ²
First floor GFA	351 m ²
Second floor GFA	351 m ²
Floor to ceiling height	2.8 m
Second floor roof area	402 m ²
Low level roof	168 m ²

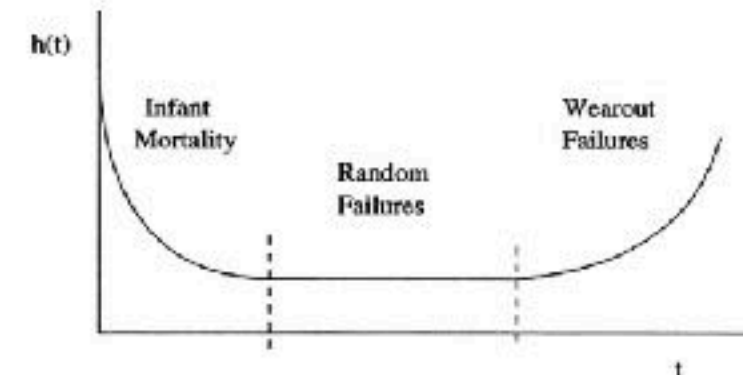


Fig. 4. Bathtub Curve – Hazard (Failure) function against time (Khanke et al., 2003).

Table 3
 BWPE Model Parameters Description.

Notation	Description
S	Set of design specification, $S = \{S_1, S_2, \dots, S_n\}$
D(t)	Deterioration function of the building, which is a function of time
t	Age of building in year
nfc	Number of demountable connections
nc	Total number of connections
d _c	Ratio of demountable connections to total connections
f _a	Ratio of prefabricated assemblies to total number of elements
nfb	number of prefabricated assemblies
nc	total number of possible building elements
v ₁	Ratio of volume of material without secondary finishes
v ₂	Volume of materials without secondary finishes
v ₃	Total volume of building materials
v ₄	Volume of material without hazardous content
v ₅	Ratio of volume of materials without toxic content to the total volume of materials
SP	Salvage Performance of building ($0 \leq SP \leq 1$)
SP _{re}	Reusable component of building
SP _{rc}	Recyclable component of building
r	Fraction of building materials that goes to landfill
α	Life expectancy of building

necessary as there is no single reliability distribution function that can be used to model the behaviour of building materials without modification. Table 3 shows the variables and parameters used in the modelling and their meaning.

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Table 5
 Design Specification of the Case Study building

Element	Building type	Material specification
Foundation system	Steel	Hy pile foundation
	Timber	Concrete ground beam
	Concrete	Concrete ground beam
Structural frame system	Steel	Prefabricated steel with bolted connections
	Timber	Hardwood timber post with nailed connections
Floor system	Concrete	Concrete with bolted connections
	Steel	Gypsum steel flooring with carpet
	Timber	Timber board with T-section timber frames with ceramic tiles
Wall system	Concrete	Concrete floor with carpet
	Steel	Curtain walls with bolted connections
Window and doors	Timber	Cladded timber cavity walls filled with nailed connections
	Concrete	Concrete wall with paint finishing
	Steel	Steel windows and doors with steel frame
Ceiling system	Timber	Timber windows and doors with timber frame
	Concrete	Double-glazed glass with aluminium frame
Roof system/floor	Steel	Aluminium strips on prefabricated steel frame
	Timber	Pressure-treated timber planks on timber trusses free of copper chromium acetate
	Concrete	Softie plaster and paint finishing
	Steel	Insulated steel plate flat roof on steel truss
	Timber	Insulated slate roofing sheet on timber truss
	Concrete	Concrete roof with sand and cement screed

BWPE is a BIM-based system that could be used by all the practitioners in the construction industry, leveraging on the capabilities of BIM such as parametric modelling, visualisation, material database, etc. to analyse and visualise the effects of design decisions and materials selection on salvage performance of buildings. BWPE is expected to be used by the practitioners in the construction industry to estimate the

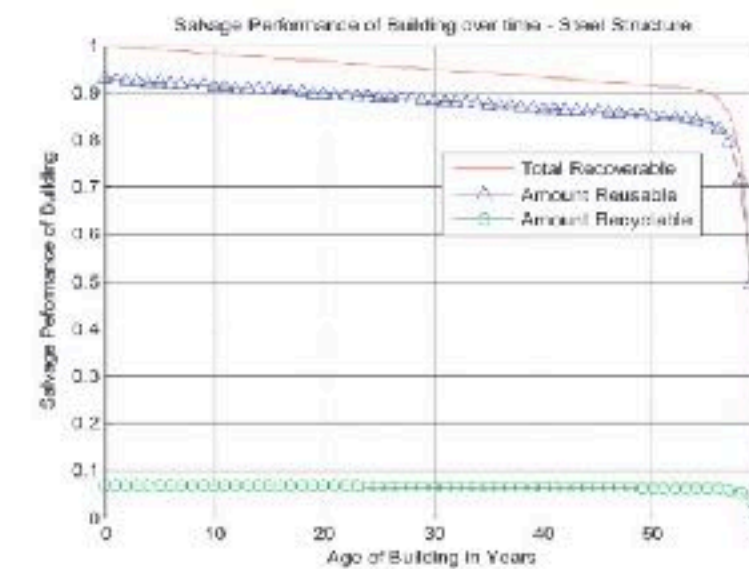
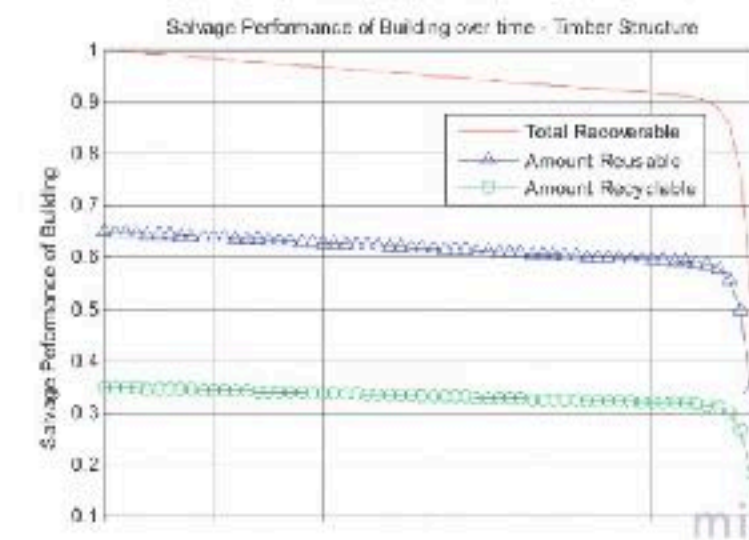


Fig. 9. Salvage Performance of Case Study Building – Steel Structure.



Definition

- Building adaptation, John Douglas

What is adaptation? 3

Table 1.1 Value of the building sector in the UK (Goodier and Gibb, 2004)

Sector	Value (£bn)	%
New build (excluding civil engineering)	53.3	54
Construction refurbishment and repair	45.0	46
Total UK construction	98.3	100

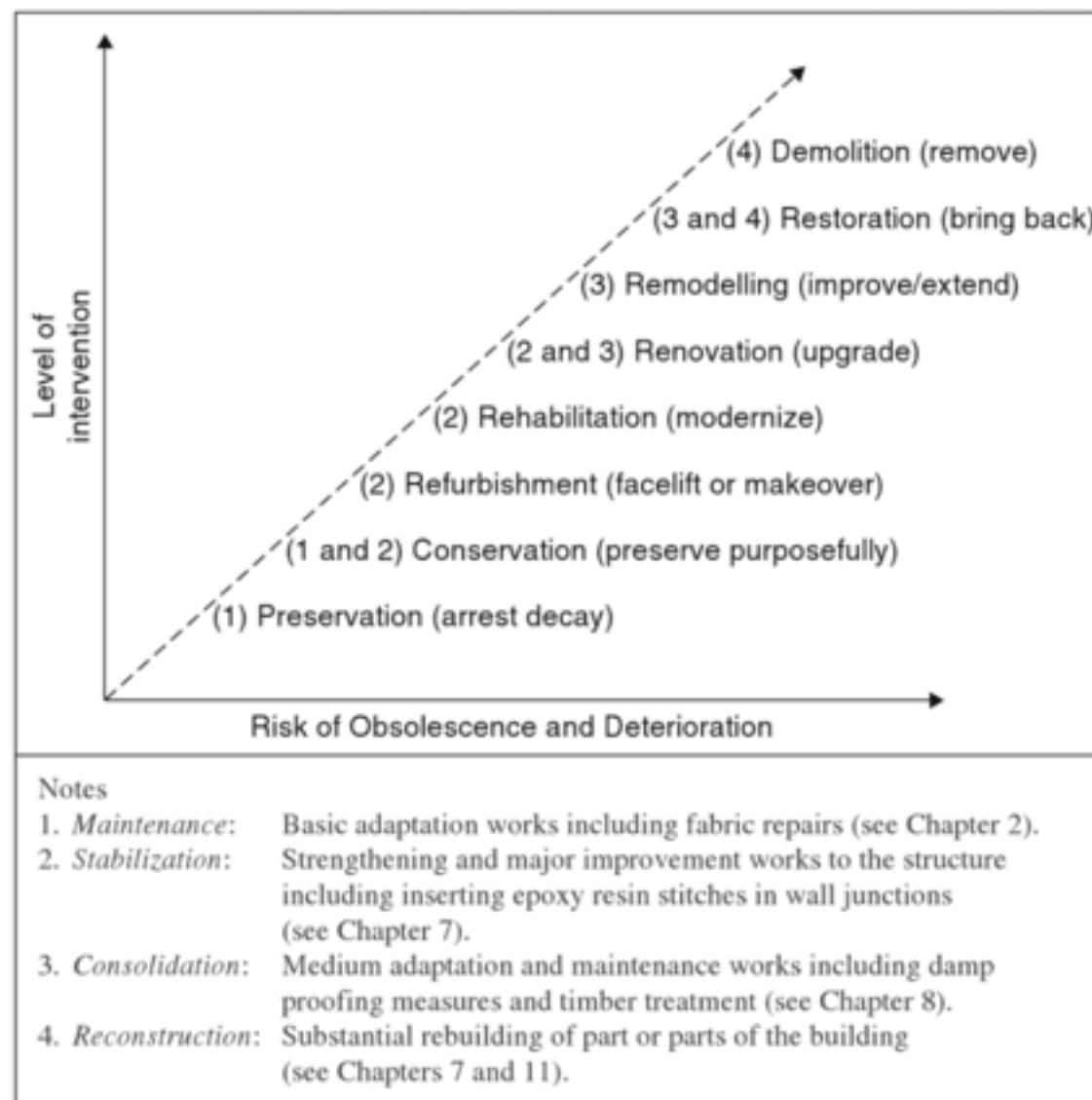


Figure 1.1 The range of interventions

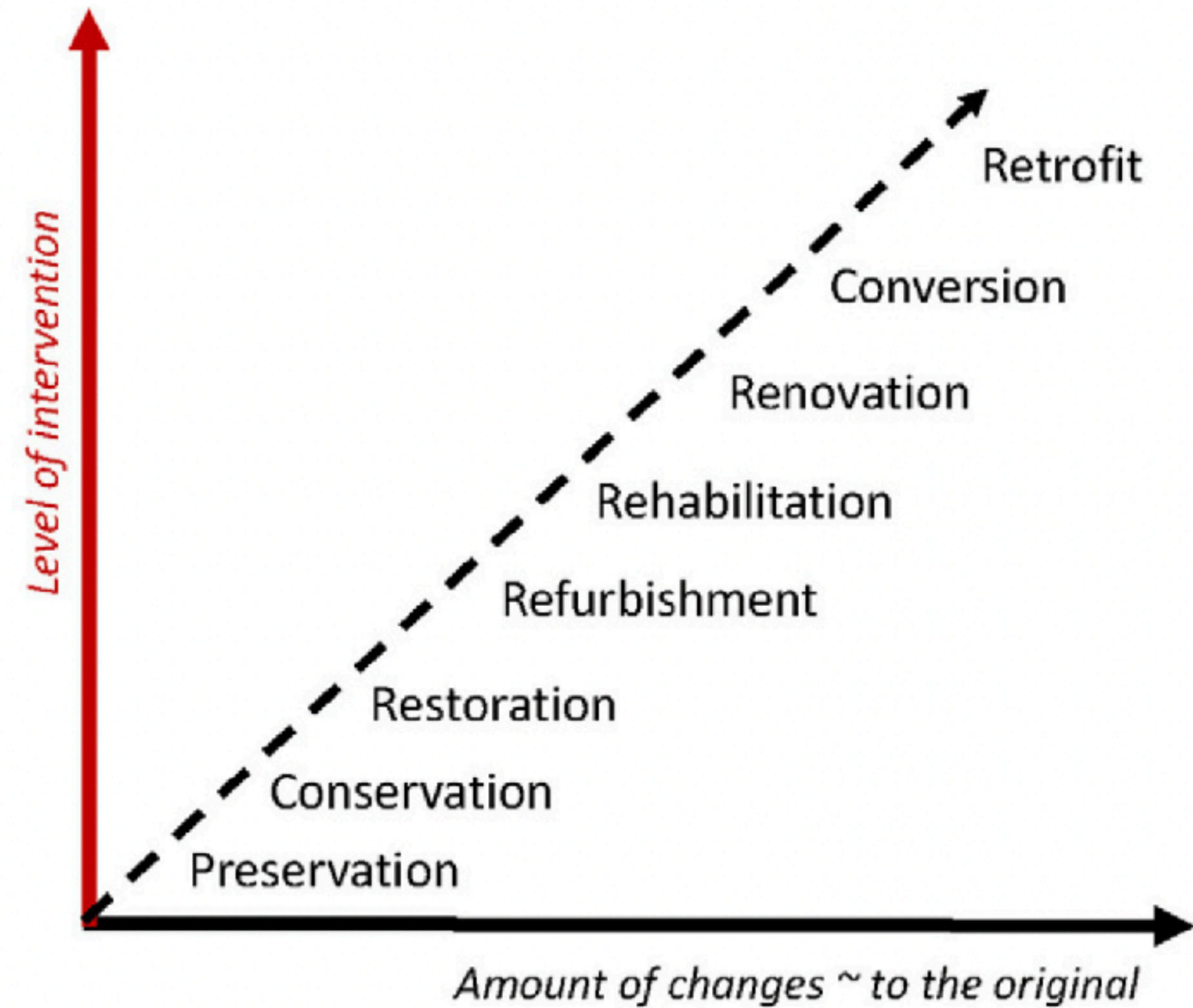


Fig. 1 Overview of building interventions in the spectrum of adaptive reuse.

Drawing: Els De Vos

Definition

Refurbish manual, Georg Giebeler

	Planning work required for building (M) compared to new build ¹					Planning work required in comparison to M (building) ²			
	Prelim. design, design	Approval	Detailed drawings	Tenders	Award, site management, cost accounts	XL: Block/complex	S: Part of building/storey	XS: Dwelling/room	
Reconstruction/restoration	++	o	+	+	+	/	/	/	Costly, time-consuming planning because research is necessary
Demolition/deconstruction	n/a	n/a	n/a	-	-	-	+	n/a	Often carried out by specialised contractors
Renovation/maintenance	n/a	n/a	n/a	-	+	o	o	o	Costly, time-consuming organisation (When can work be carried out?) and accounting (many management services)
Repairs/maintenance	n/a	n/a	--	-	+	o	o	o	Costly, time-consuming organisation/accounts, often no planning services
Partial refurbishment	--	n/a	+	++	++	n/a	n/a	n/a	Costly, time-consuming organisation and accounting, frequently disputes with neighbours
Refurbishment	--	n/a	o	+	++	o	+	+	Great demands placed on site management because of many uncertainties
Total refurbishment	--	n/a	+	+	+	o	+	n/a	In total slightly higher costs/more works reqd. at new/existing interface
Conversion	+	o	++	++	++	o	++	++	High design costs due to adaptation to suit the existing; high construction costs
Gutting/rebuild with part retention	o	+	o	+	+	/	/	/	Extra costs for safety measures only
Extension	+	o	+	o	o	/	/	/	Measures in the existing account for only a small part of the total budget
Fitting-out	+	+	++	++	++	n/a	n/a	n/a	Many parts of existing bldg. continue to be used; partial fit-out; costly, costly, time-consuming organisation/accounts, often disputes w. neighbours
Change of use	n/a	+	n/a	n/a	n/a	o	o	o	Only an approval required, but can be very extensive

++ much more
+ more
o about the same
- less

-- much less
n/a hardly or never required

/ no comparison, cannot be evaluated (e.g. owing to major fluctuations)

¹ Provides a guide as to how much higher the conversion surcharge must be or where it can be ignored.

² Necessary increase in the conversion surcharge depending on the size of the project.

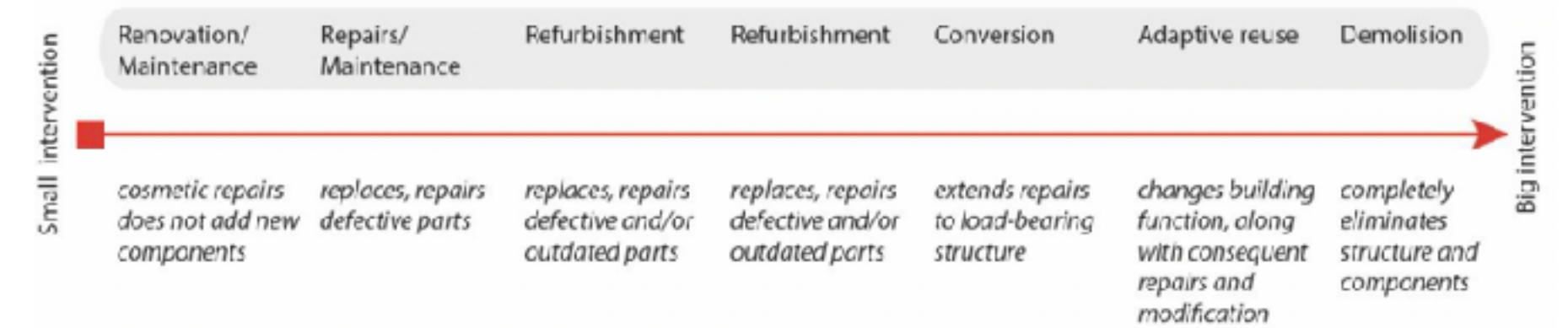
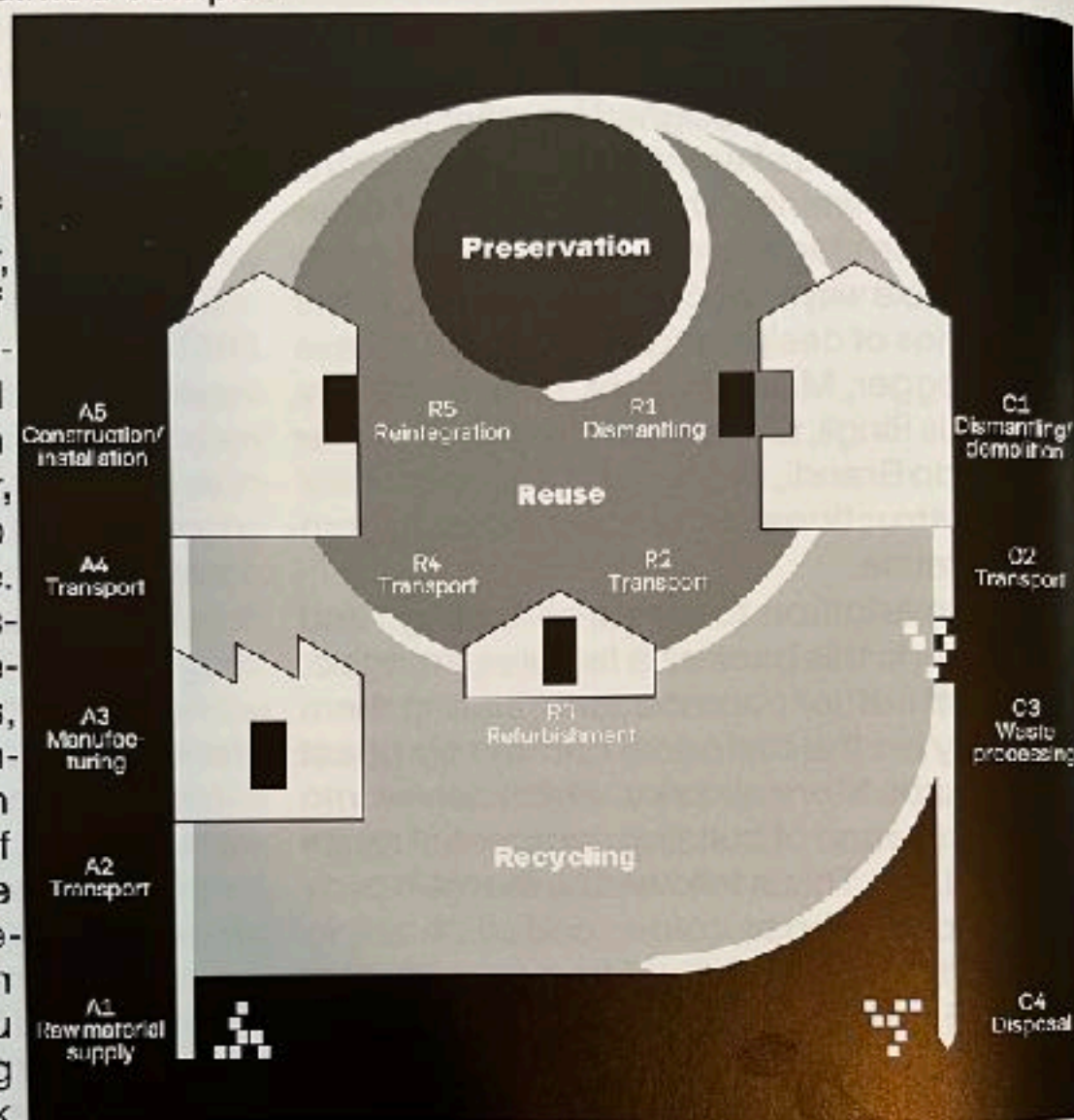


Figure 8 Level of interventions (Giebeler et al., 2009)

others intending to plan and involving reclaimed compo-

erent sections successively parallel with the construction of taken together, the breadth of building components architectural hasize that, in building sector, to be taken to tion of reuse. rsity of the is- perspectives re- various texts, often they con- back to each red margins of text, we have led cross red aspects in -so that you ular thinking ding this book.



Circular construction
Circular construction means giving new usage cycles to the fabric of buildings, thereby allowing their actual lifespan to be exploited to the full. In the model shown here, the smaller the cycle's volume, the lower the loss of environmental, economic, and cultural assets, and the more circularity and architecture become intertwined. Recycling building waste into new material, such as recycled concrete or steel, is primarily a question of processing that has only peripheral relevance to design and planning. By contrast, the reuse and reusability of entire building components, like the repair, repurposing, and extension of existing buildings and parts of buildings, are genuine architectural challenges in which every aspect of sustainability needs to be considered. In this book, we have used the umbrella terms 'preservation', 'reuse', and 'recycling' for those three cycles, though each of those terms can be differentiated depending on their different contexts (i.e. with regard to environmental impact, economics, cultural significance, etc.). The above diagram also shows how the various phases of reuse (R1, R2, R3, R4, R5) fit into this life cycle model, which is based on the EN EN 15804+A1/SIA 400, C52+A1 norms and underpins the environmental footprint assessment of Swiss buildings.



Handwritten notes at the top: *20190903 / LWA-20201302* and *31.11.2019 633*

Reuse
Old door fittings are reused on new doors. Intact bricks that have been removed from an old wall are reused to build a new wall. Multi-use systems, such as returnable deposit bottles with flip-top stoppers are generally reused repeatedly.

Repurposing / Adaptive Reuse
Intact old bricks are used as edging for planted areas. A disused ship's hull is turned upside down and used as the roof of a building. Beverage bottles are turned into plant containers.

Recycling / Reutilization
Recycled aggregate concrete (RAC) contains aggregates of crushed concrete or mixed demolition rubble. Disposable bottles are used as raw material to manufacture new bottles (recycled glass, PET plastic).

Reprocessing
Brick chips are turned into plant substrate and waste glass is used to make glass wool (thermal insulation).

Upcycling
Upcycling: Disposable glass bottles are transformed into drinking glasses or lampshades. Residual concrete waste is cast in moulds to create utilitarian objects. Disused freight containers are stacked together and fitted out to create a building. Downcycling: Old bricks are broken up and turned into fill material for roadbeds.

Wiederverwendung
Alte Türbeschläge kommen an neuen Türen wieder zum Einsatz. Ausgebaut intakte Mauerziegelsteine werden erneut zur Wand verbaut. Mehrwegsysteme im Allgemeinen werden wiederverwendet, wie z. B. die Pfandflasche mit Rückgeldeverschluss.

Weiterverwendung
Intakte Mauerziegelsteine werden als Randbegrenzung für Grünflächen verwendet. Ausgedientes Schiffsrumpf wird umgedreht zum Gebäudedach. Getränkeflaschen werden zu Pflanzenbehälter.

Wiederverwertung
Recycling von Beton erfolgt mit Anetzen an zertrümmerten Beton- oder Mischabbruchmaterial. Aus Einwegflaschen werden wieder Einwegflaschen (Recyclingglas, PET).

Weiterverwertung
Ziegelspalt wird zu Pflanzsubstrat oder Altglas zu Glaswolle (Wärmedämmstoff) weiterverwertet.

Upcycling
(Upcycling) Eine Einwegglasflasche wird zum Trink- oder Lampenglas verarbeitet. Restbetonabfälle erhärten in Gießformen zu neuen Gebrauchsgegenständen. Ausgeleitete Fruchtcontainer werden zu einem Gebäude gestapelt und ausgebaut.
(Downcycling) Alte Mauerziegel werden zertrümmert und zu Füllmaterial für Straßenböden.

architecture

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