BUILDING ENERGY META MODELS

[9]

[2]

Predicting building energy performance at city scale.

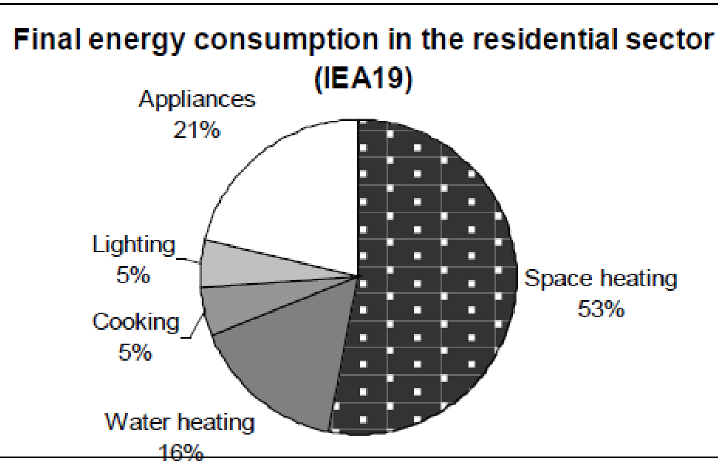
PRESENTED BY EMILY LENARDUZZI

MENTORED BY DR. CHARALAMPOS ANDRIOTIS AND DR. MARTÍN MOSTEIRO ROMERO AS PART OF THE SUSTAINABLE DESIGN GRADUATION STUDIO OF BUILDING TECHNOLOGY

2025

TU Delft Delft University of Technology

ENERGY DEMANDS

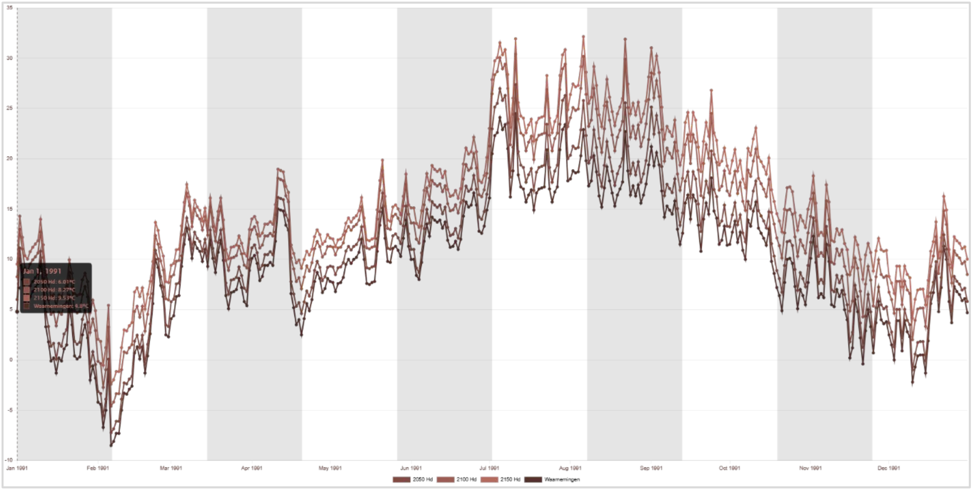


[1]

RESIDENTIAL BUILDINGS

[2]

CLIMATE CHANGE

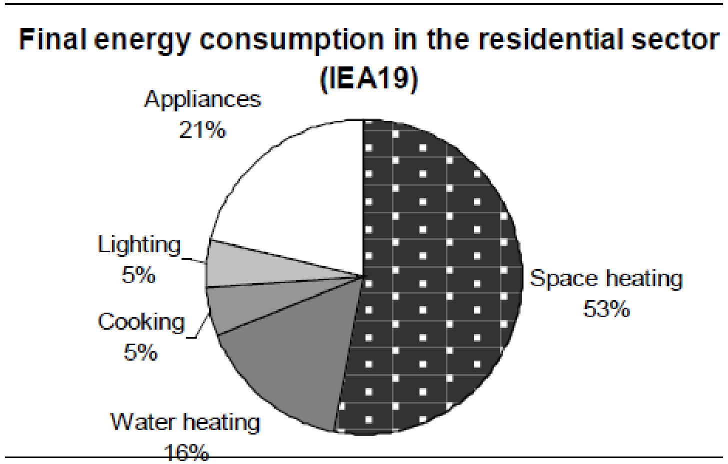


[3]

ENERGY DEMANDS

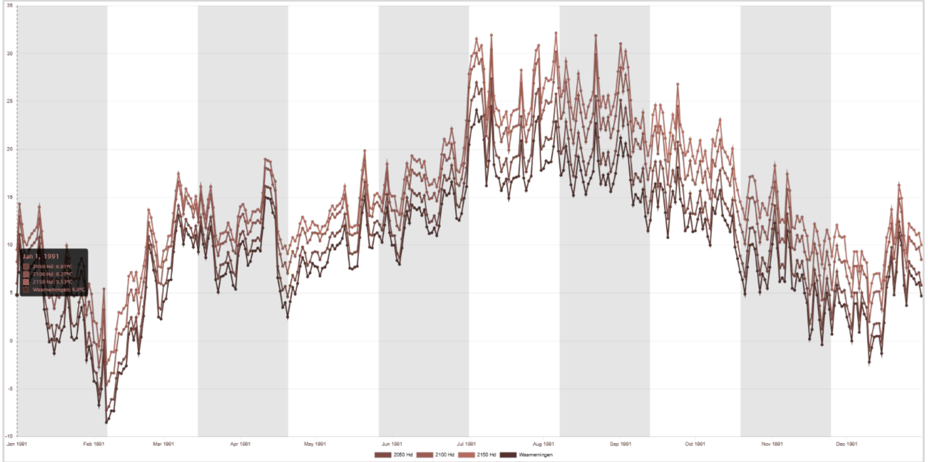
RESIDENTIAL BUILDINGS

CLIMATE CHANGE



[1]

[2]



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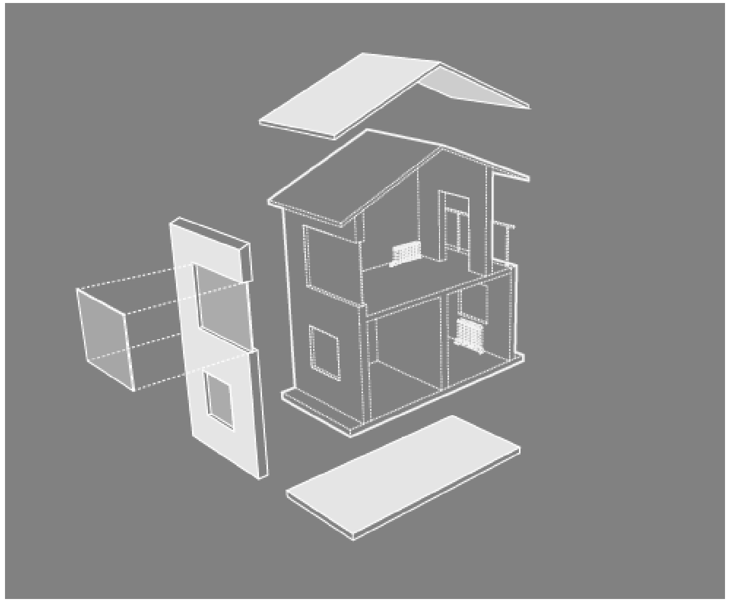
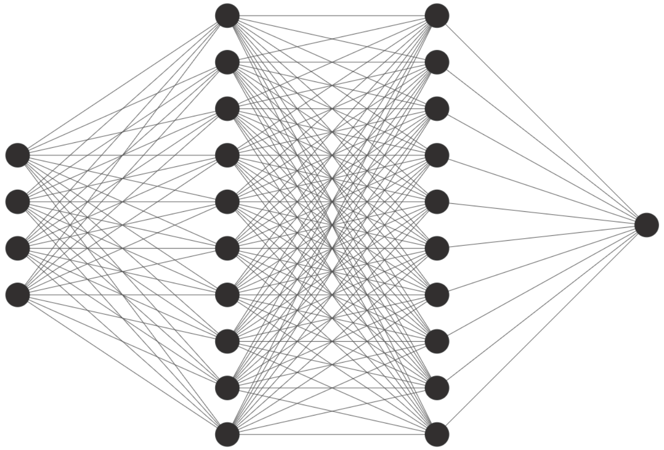


[4]

RETROFITS

[2]

CITY SCALE

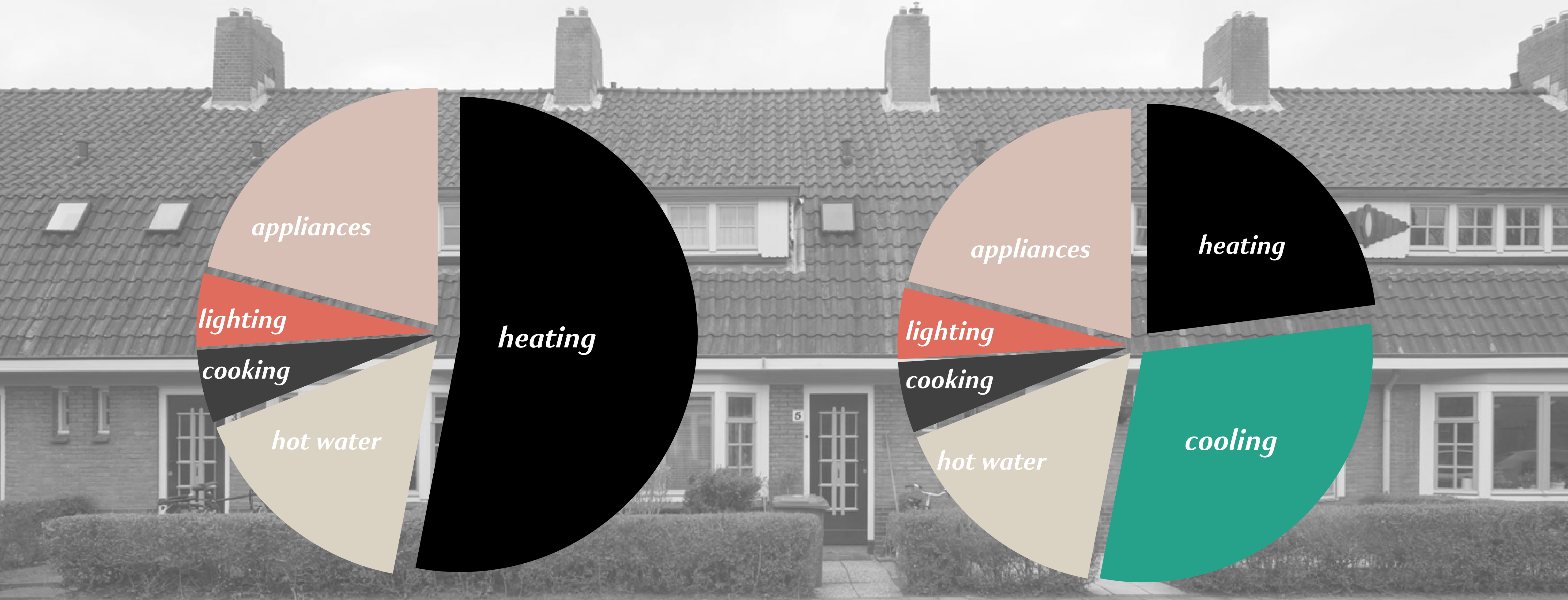


MACHINE LEARNING

large share of homes constructed before 1975 predate the introduction of thermal regulations, resulting in high thermal energy demands.

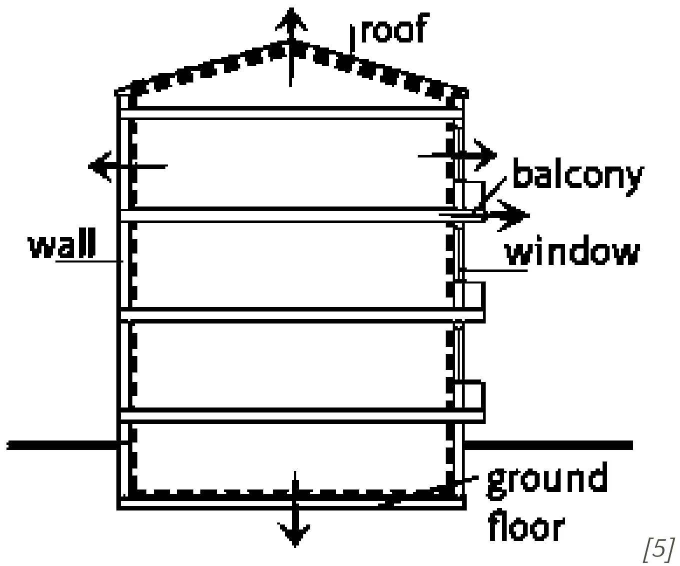
large share of homes constructed before 1975 predate the introduction of thermal regulations, resulting in high thermal energy demands.

climate change?



reducing energy demand

reduce energy losses via building envelope



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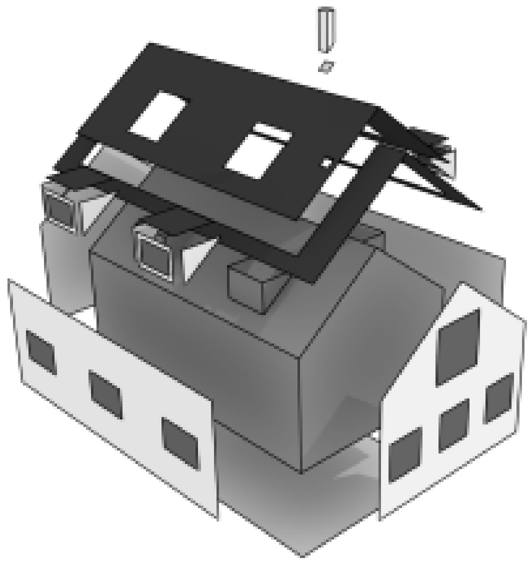

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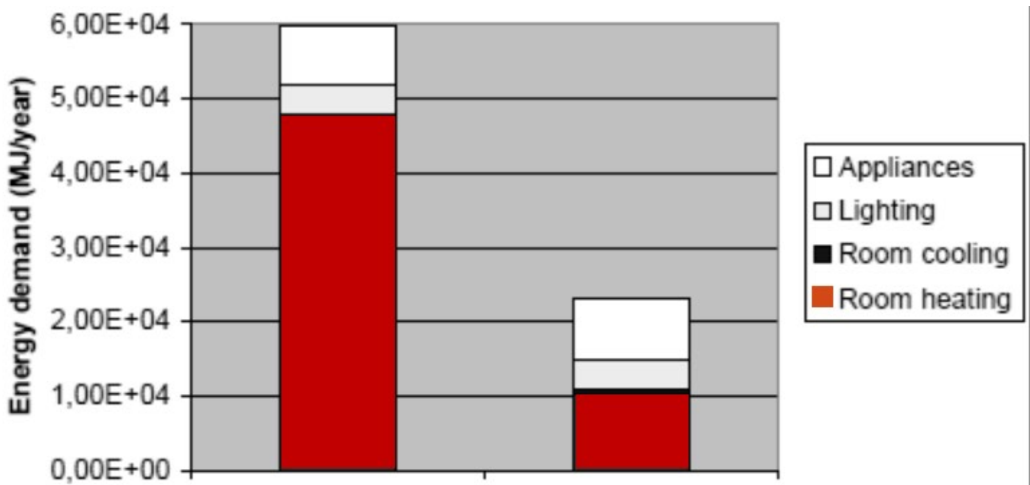
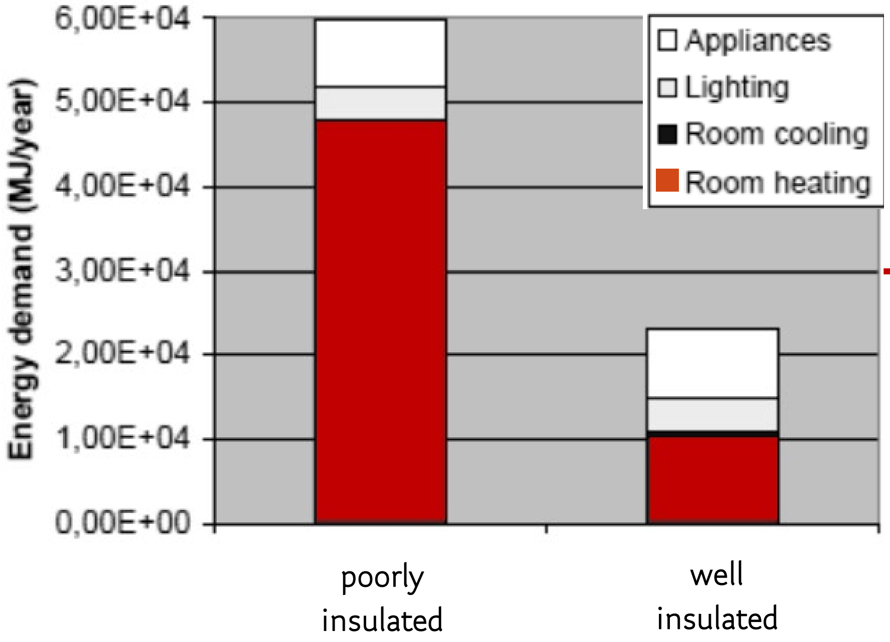


[1]

poorly insulated

well insulated

Netherlands targets a 49% reduction in greenhouse gas emissions by 2030 compared to 1990 levels.



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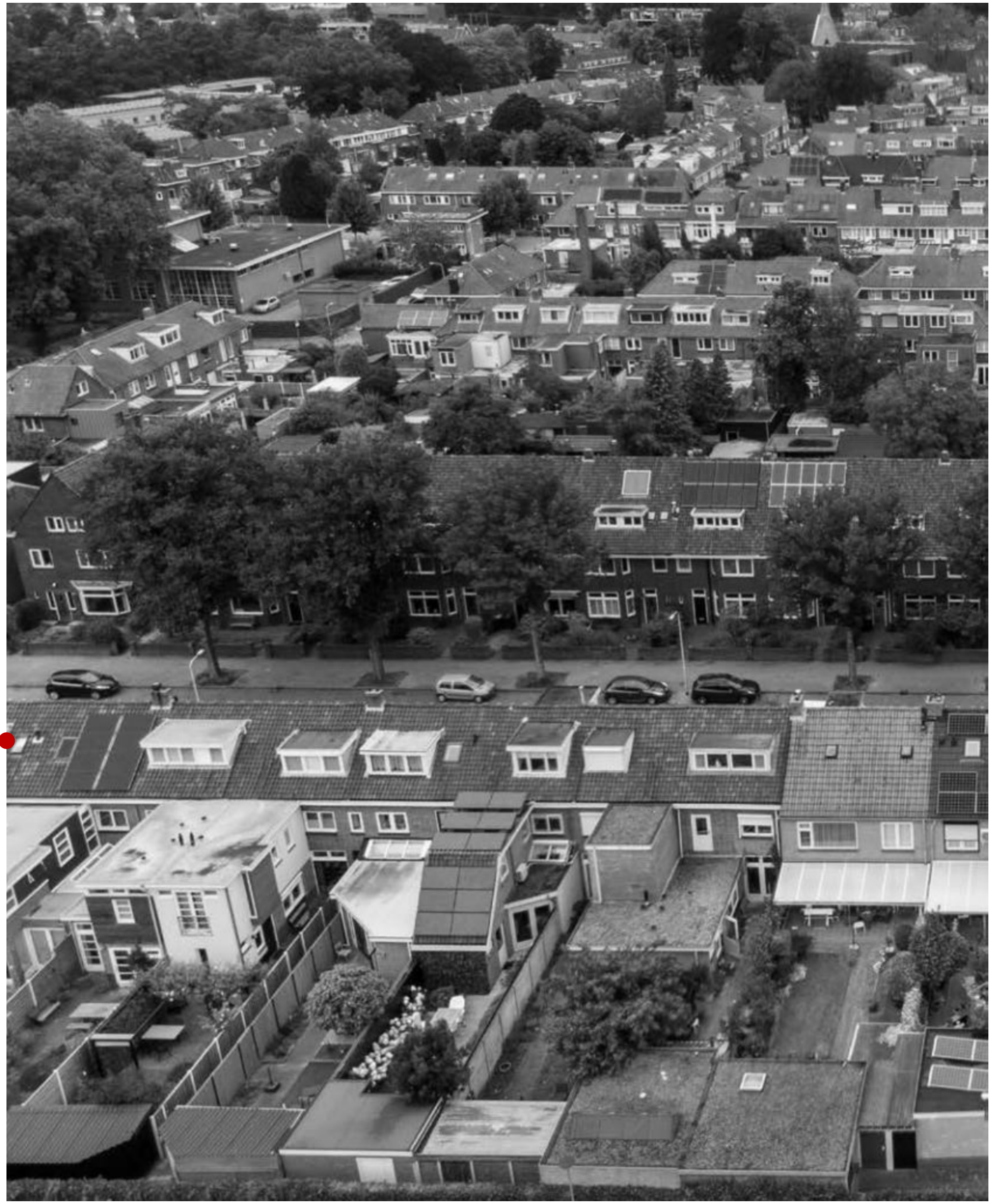
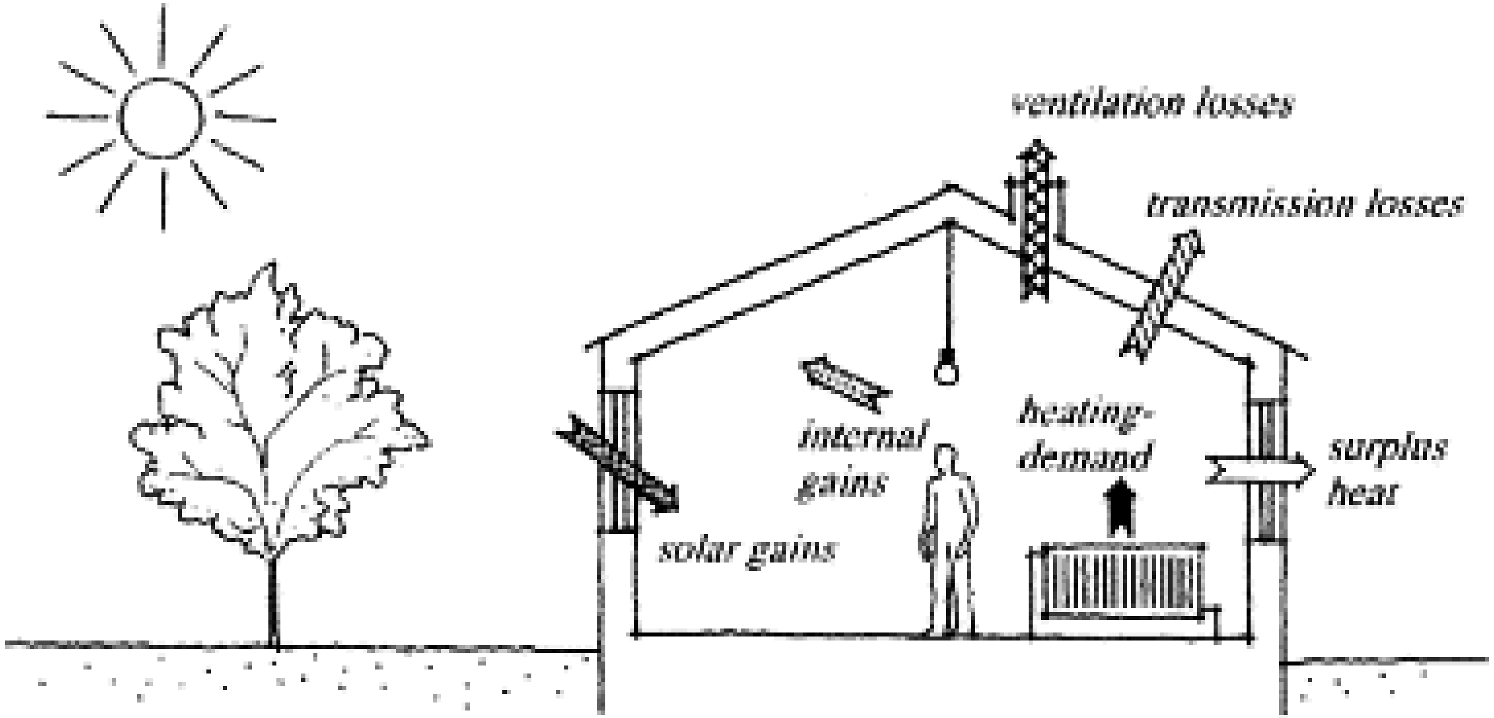


[2]

To understand strategies to reduce energy demand:

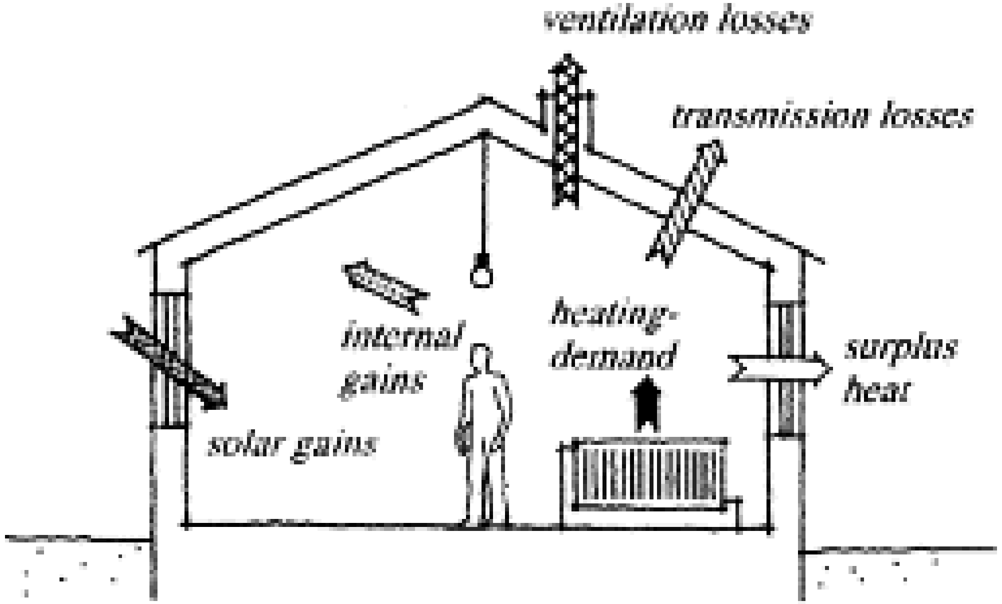
building energy modelling



[7]

energy demand = energy gains - losses

energy demand = transmission + infiltration + ventilation + solar + internal



[7]

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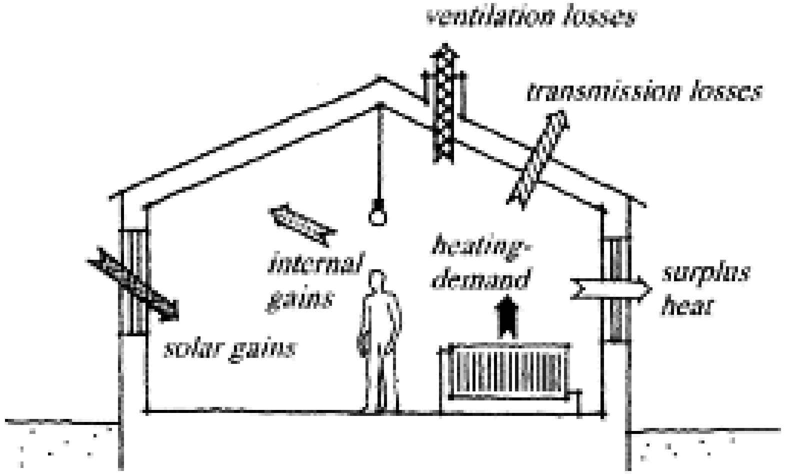


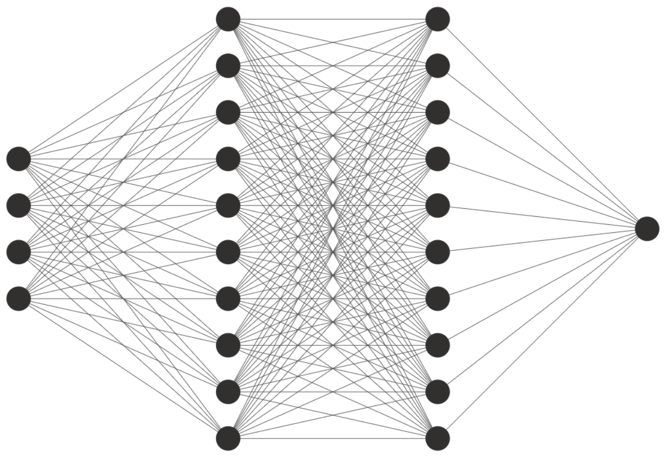
[7]

one building

[8] [7]

multiple buildings

PREDICTION MODEL



[8] [7]

BUILDING ENERGY MDOELLING

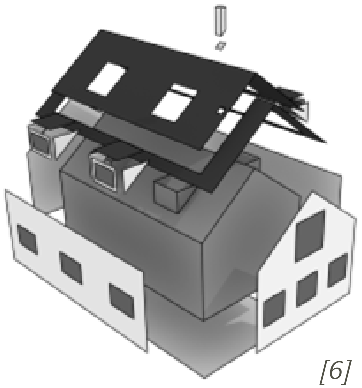
MAIN QUESTION:

How can machine learning be used to predict energy performance for residential buildings at city scale to reduce heating and cooling demands, considering future weather scenarios from climate change?

How can machine learning be used to predict energy performance for residential buildings at city scale to reduce heating and cooling demands, considering future weather scenarios from climate change?

RETROFITS:

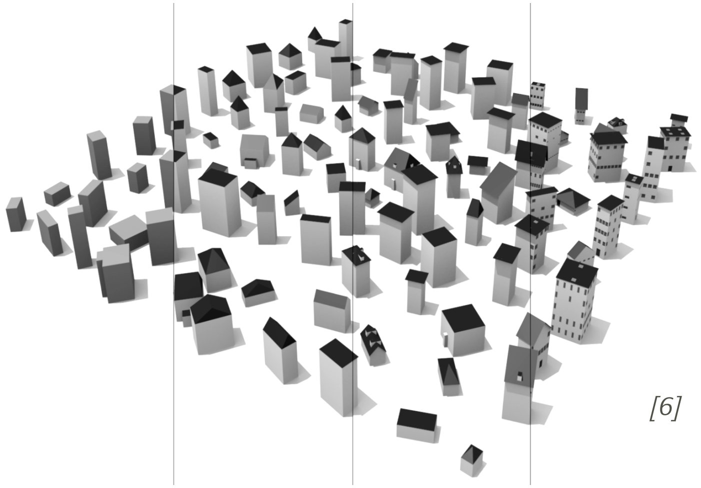
How can ML be used to assess the impact of retrofit strategies across different building typologies?



[6]

CITY SCALE:

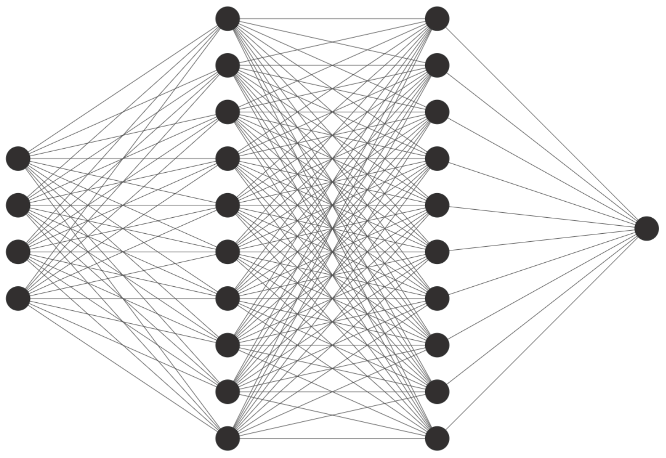
How can computational methods be leveraged for energy modelling at city-scale?



[6]

How can machine learning be used to predict energy performance for residential buildings at city scale to reduce heating and cooling demands, considering future weather scenarios from climate change?

MACHINE LEARNING:



How can ML models improve the efficiency of building energy modelling?

What is an effective ML model (in terms of time efficiency, useability) for predicting building energy performance?

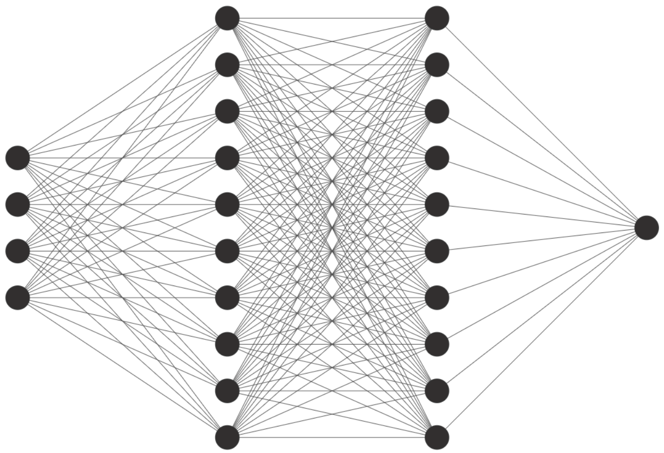
What are the limitations of ML models compared to traditional energy modelling?

PROJECT APPROACH

SIMULATION

[8] [7]

PREDICTION



BUILDING ENERGY MODELLING

GEOMETRY

CONSTRUCTION

WEATHER

[8] [7]

SIMULATIONS

HEATING DEMAND

COOLING DEMAND

BUILDING HEIGHT

BUILDING ORIENTATION

BUILDING VOLUME

NUMBER OF FLOORS

FLOOR AREA

WALL AREA

ROOF AREA

WINDOW AREA

INSULATIONS FLOOR

INSULATIONS ROOF

INSULAITIONS WALLS

U-VALUE WINDOWS

SOLAR

OUTDOOR TEMPERATURE

SOLAR RADIATION

WIND

HUMIDITY

BUILDING ENERGY MODELLING

[8] [7]

SIMULATIONS

HEATING DEMAND

COOLING DEMAND

PREDICTION MODEL

BUILDING HEIGHT

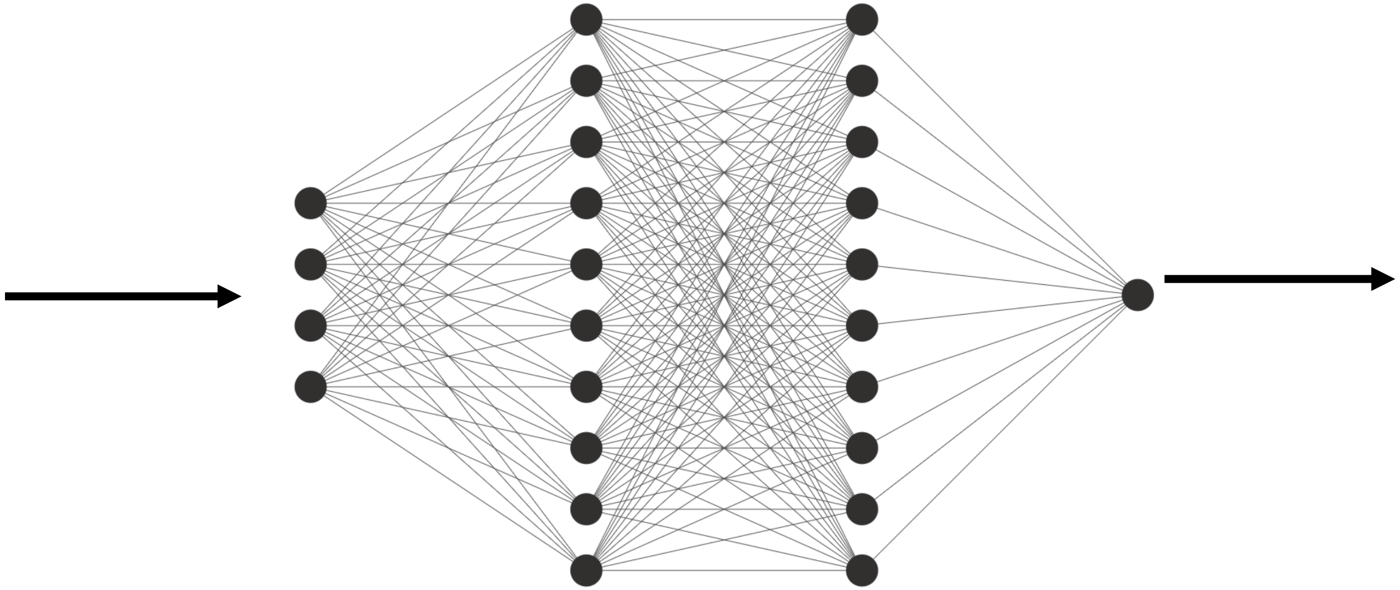
NUMBER OF FLOORS

FLOOR AREA

WALL AREA

INSULATIONS

OUTDOOR TEMPERATURE



HEATING DEAMND

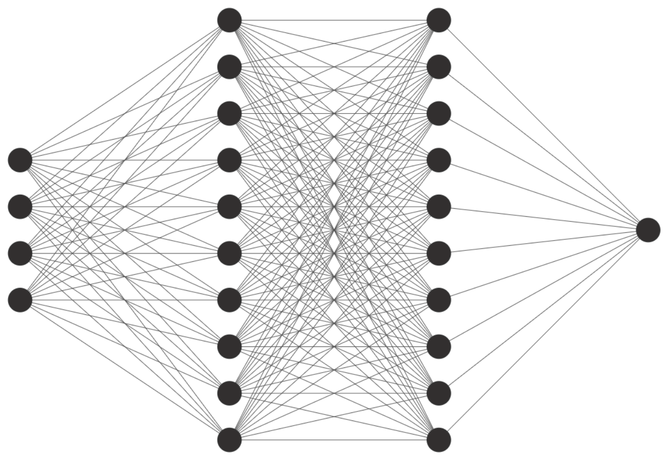
COOLING DEMAND

MACHINE LEARNING

SIMULATIONS

[8] [7]

PREDICTION



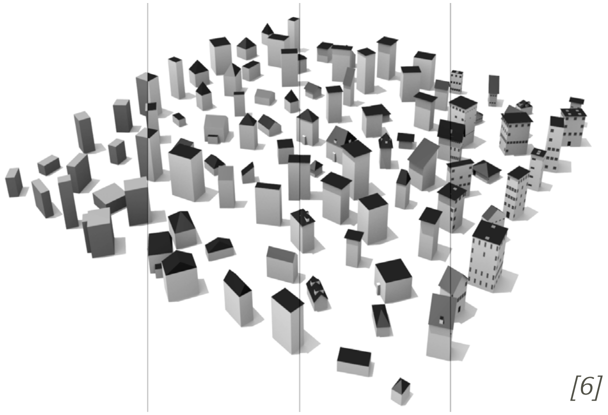
COLLECT BUILDING + ENVIRONMENTAL DATA → GENERATE BUILDING ENERGY MODELS → ANALYZE ENERGY DEMANDS → PROCESS INPUT DATA FOR MACHINE LEARNING → TRAIN MODEL → EVALUATE PERFORMANCE

BUILDING ENERGY MODELLING

MACHINE LEARNING

COLLECT BUILDING + ENVIRONMENTAL DATA

GEOMETRY



[6]

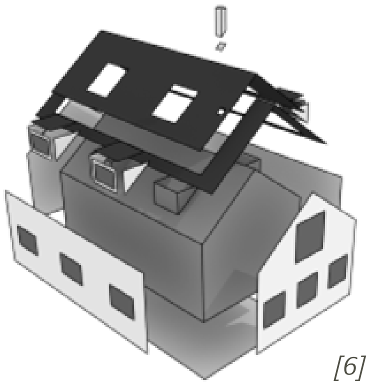
BUILDING HEIGHT

NUMBER OF FLOORS

FLOOR AREA

WALL AREA

CONSTRUCTION

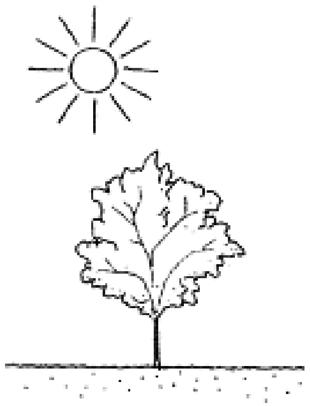


[6]

FLOOR / ROOF / FACADE INSULATING PROPERTIES

WINDOW THERMAL TRANSMITTANCE

WEATHER



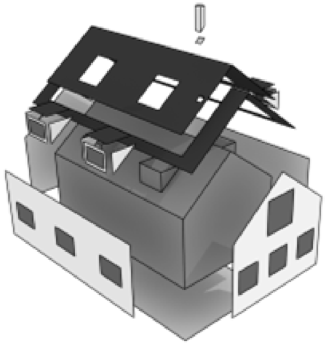
[7]

TEMPERATURES

SOLAR RADIATION

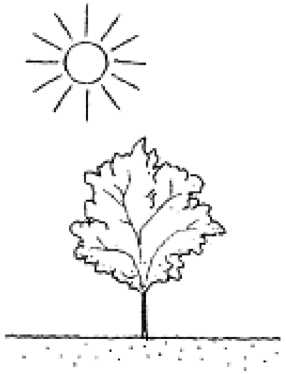
HUMIDITY

CONSTRUCTION

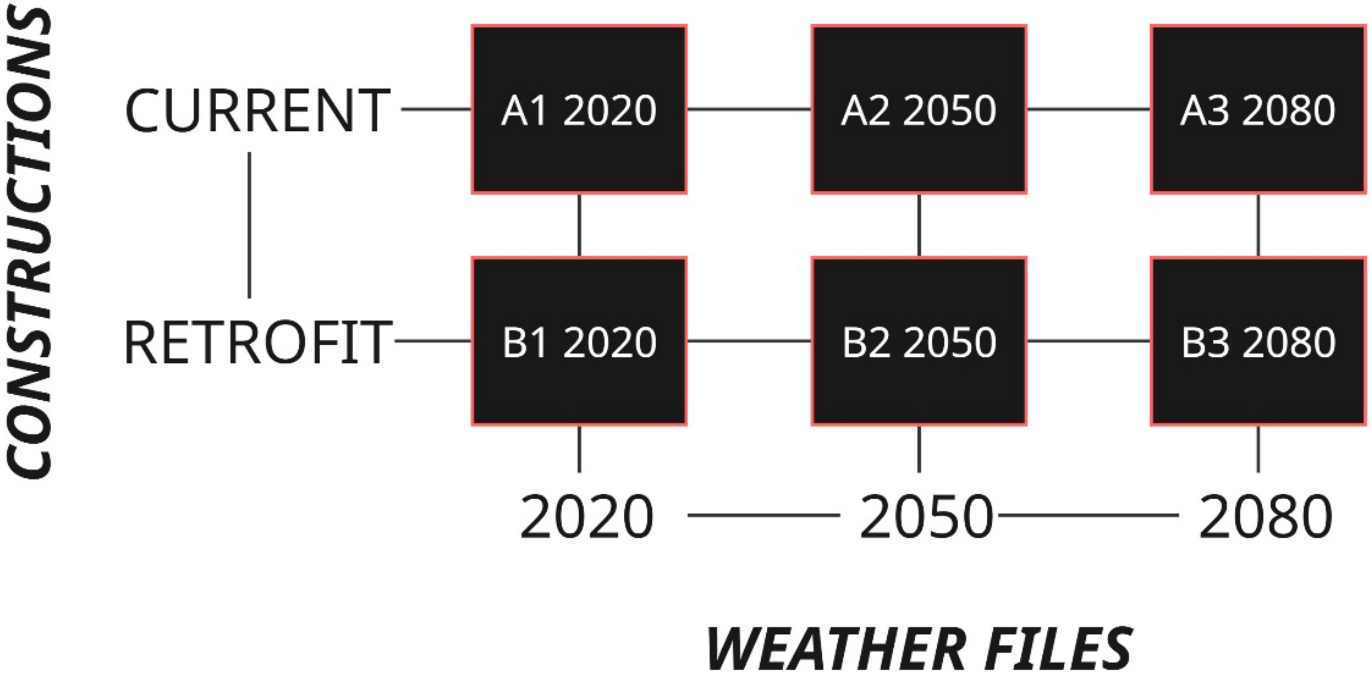


[6]

WEATHER

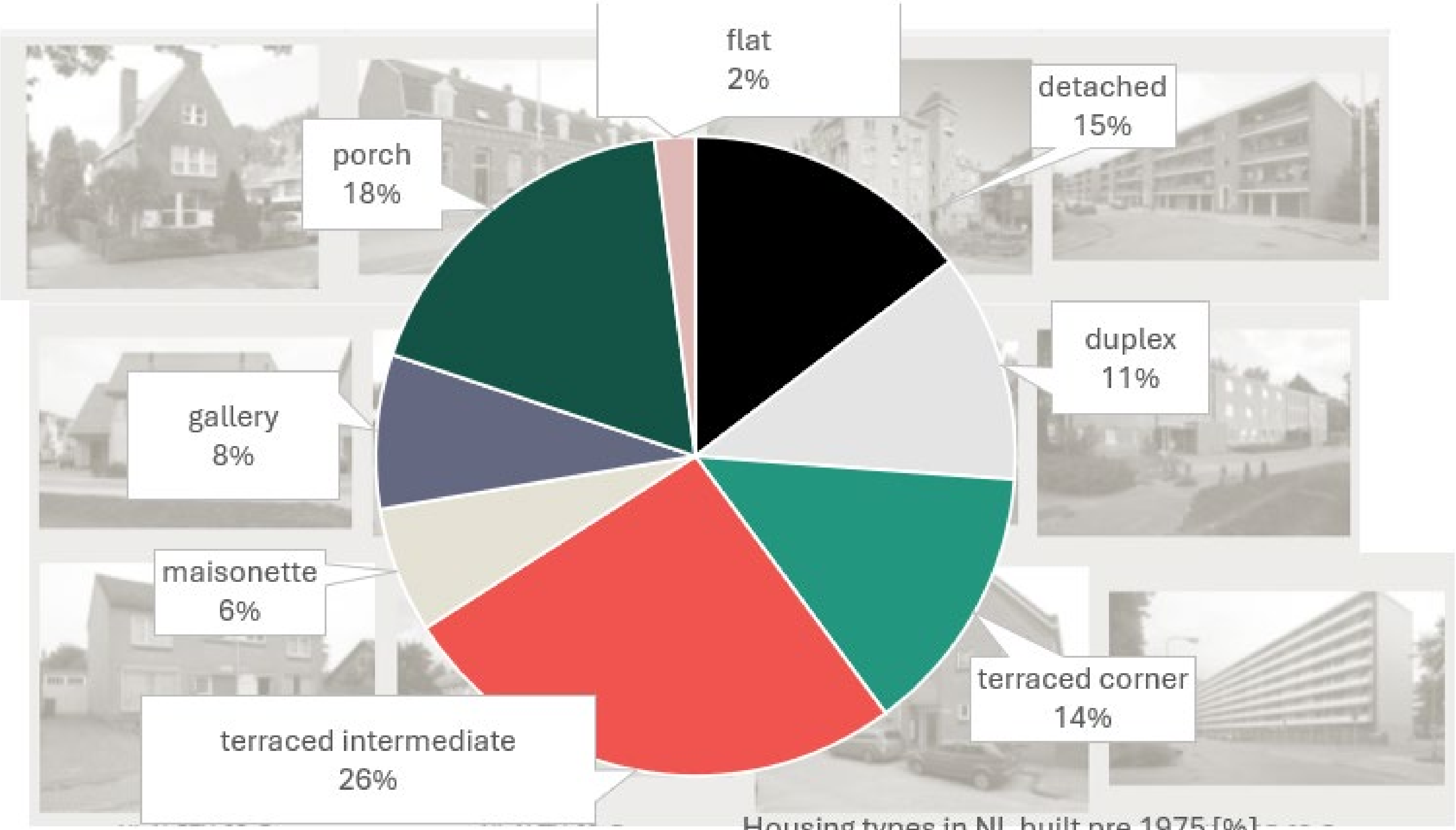


[7]



IDENTIFY BUILDINGS FOR STUDY

[2]



Housing types in NL built pre 1975 [%]

[2]


DETACHED

[10]


TERRACED CORNER

[2]


TERRACED INTERMEDIATE

[9]

MAP TO ARCHETYPE

DETACHED

[10]

TERRACED CORNER

[2]

TERRACED INTERMEDIATE

[9]

ARCHETYPE = [BUILDING TYPE] + [BUILDING PERIOD]

MAP TO ARCHETYPE

[10]

[2]

[9]

D
D. <1965
D.1965-1974
D.1975-1991
D.1992-2005
D.2006-2014
D.2015-2018

T.C
TC. < 1946
TC.1946-1964
TC.1965-1974
TC.1975-1991
TC.1992-2005
TC.2006-2014
TC.2015-2018

T.I
TI. < 1946
TI.1946-1964
TI.1965-1974
TI.1975-1991
TI.1992-2005
TI.2006-2014
TI.2015-2018

what parameters do we need?

CONSTRUCTION / THERMAL PARAMETERS

Detached house < 1965	current	package 1
ARCHITECTURAL		
ground floor	Rc 0.15	Rc 3.50
closed facade	Rc 0.35	Rc 1.70
sloping roof	Rc 2.50	Rc 3.50
flat roof	Rc 0.85	Rc 3.50
window	You 1.80	You 1.40
door	You 3.40	You 1.40
sealing (q;v10)	flat rate	0.7 dm3/s.m2

[2]

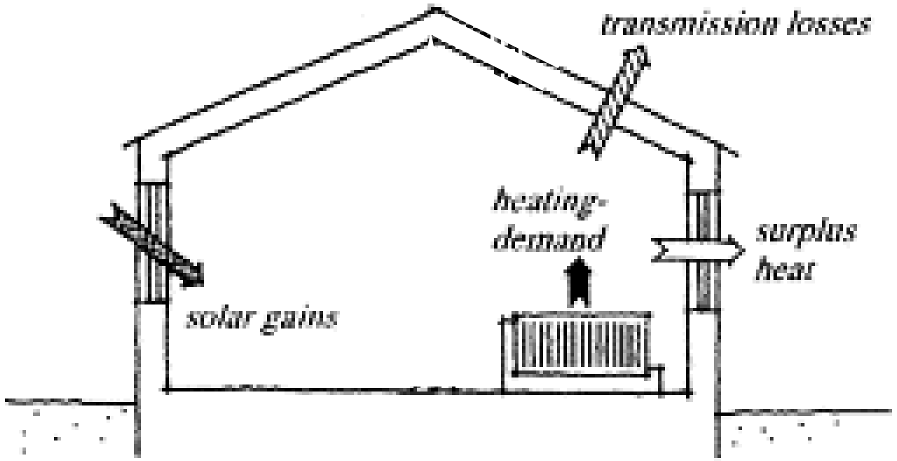
[11]

EXAMPLE HOMES GUIDE
[SAME ARCHETYPES AS USED FOR THIS STUDY]

NIEMAN
[BROADER TYPOLOGY CLASSIFICATION]

energy demand = energy gains - losses

energy demand = transmission + infiltration + ventilation + solar + internal



[7]

what parameters do we need?

INSULATIONS, THERMAL TRANSMITTANCE, INFILTRATIONS

Detached house < 1965	current	package 1
ARCHITECTURAL		
ground floor	Rc 0.15	Rc 3.50
closed facade	Rc 0.35	Rc 1.70
sloping roof	Rc 2.50	Rc 3.50
flat roof	Rc 0.85	Rc 3.50
window	You 1.80	You 1.40
door	You 3.40	You 1.40
sealing (q;v10)	flat rate	0.7 dm3/s.m2

[2]

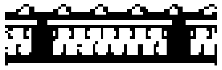
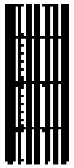
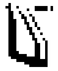
[11]

INSULATIONS / EXAMPLE HOMES GUIDE
[SAME ARCHETYPES AS USED FOR THIS STUDY]

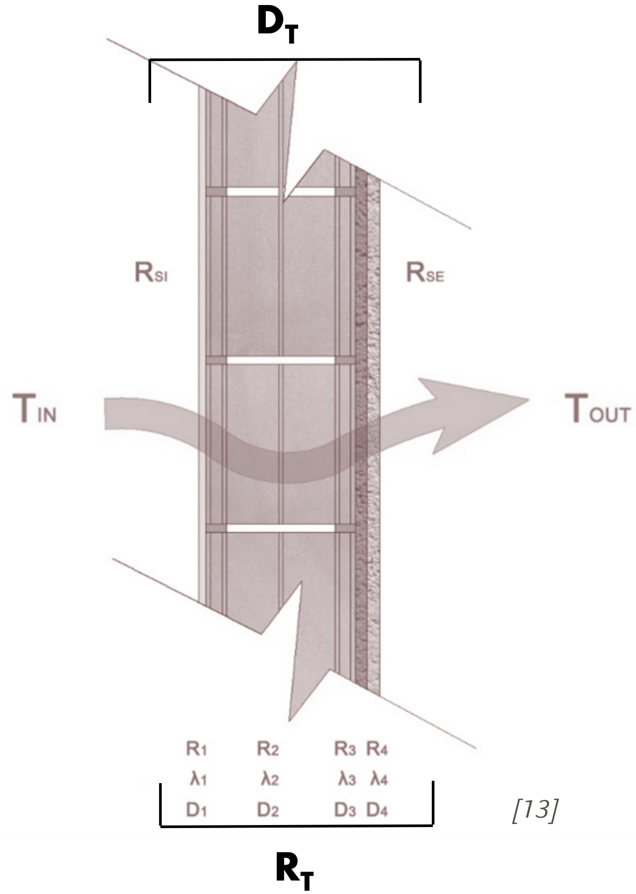
INFILTRATIONS / NIEMAN
[BROADER TYPOLOGY CLASSIFICATION]

IDF INPUTS

constructions vary per archetype.

Roof	Wall	Window	Floor
			
lightweight concrete/roof screed	solid clay-brick masonry	single / double-glazed unit	softwood/timber floor

[12]



[13]

Each archetype was assigned a simplified definition of envelope layers, using the overall assembly thickness, Dt, and overall insulation Rc, used to calculated the conductivity:

$$\lambda_T = \frac{Dt}{Rt}$$

constructions vary per archetype.

CURRENT CONDITION

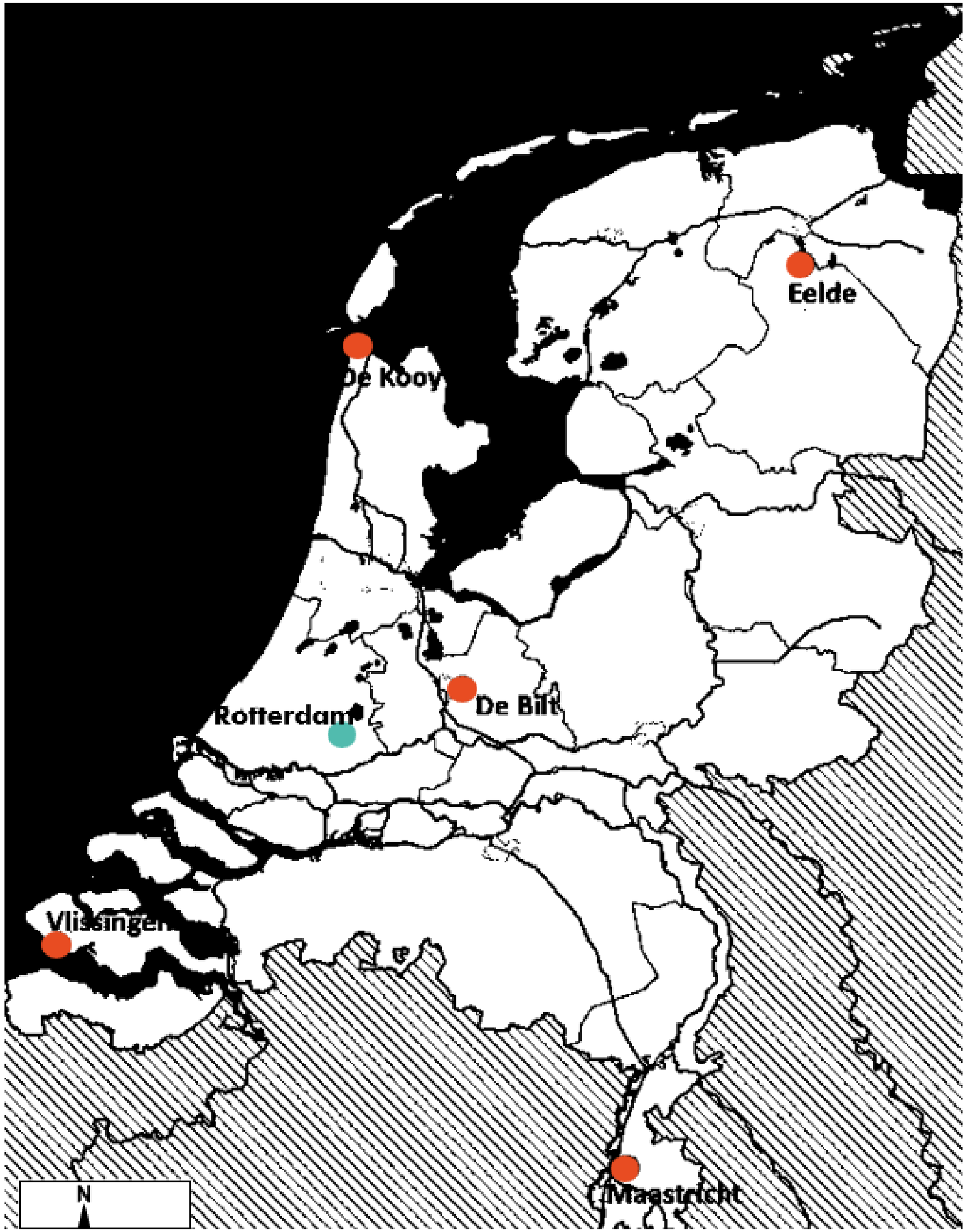
Archetype ID	Infiltration	Material ID	Insulation	Thickness	Conductivity	Window ID	U_Factor	SHGC	WWR
TI.1946	0.0030	G.TI.1946	0.15	0.15	1.00				
TI.1946		F.TI.1946	0.35	0.3	0.86				
TI.1946		R.TI.1946	2	0.2	0.10				
TI.1946						W.TI.1946	2.9	0.6	0.32
TI.1946-1964	0.0030	G.TI.1946-1964	0.15	0.15	1.00				
TI.1946-1964		F.TI.1946-1964	0.35	0.3	0.86				
TI.1946-1964		R.TI.1946-1964	0.72	0.2	0.28				
TI.1946-1964						W.TI.1946-1964	2.9	0.6	0.33
TI.1965-1974	0.0030	G.TI.1965-1974	0.17	0.15	0.88				
TI.1965-1974		F.TI.1965-1974	0.43	0.3	0.70				
TI.1965-1974		R.TI.1965-1974	0.86	0.2	0.23				
TI.1965-1974						W.TI.1965-1974	2.9	0.6	0.40
TI.1975-1991	0.0030	G.TI.1975-1991	0.52	0.15	0.29				
TI.1975-1991		F.TI.1975-1991	1.3	0.3	0.23				
TI.1975-1991		R.TI.1975-1991	1.3	0.2	0.15				
TI.1975-1991						W.TI.1975-1991	2.9	0.6	0.32
TI.1992-2005	0.0015	G.TI.1992-2005	2.5	0.15	0.06				
TI.1992-2005		F.TI.1992-2005	2.5	0.3	0.12				
TI.1992-2005		R.TI.1992-2005	2.5	0.2	0.08				
TI.1992-2005						W.TI.1992-2005	1.8	0.4	0.33

RETROFIT CONDITION

Archetype ID	Infiltration	Material ID	Insulation	Thickness	Conductivity	Window ID	U_Factor	SHGC	WWR
TI.1946	0.0030	G.TI.1946	3.5	0.15	0.04				
TI.1946		F.TI.1946	1.7	0.3	0.18				
TI.1946		R.TI.1946	3.5	0.2	0.06				
TI.1946						W.TI.1946	1.4	0.6	0.32
TI.1946-1964	0.0010	G.TI.1946-1964	3.5	0.15	0.04				
TI.1946-1964		F.TI.1946-1964	1.7	0.3	0.18				
TI.1946-1964		R.TI.1946-1964	3.5	0.2	0.06				
TI.1946-1964						W.TI.1946-1964	1.4	0.6	0.33
TI.1965-1974	0.0010	G.TI.1965-1974	3.5	0.15	0.04				
TI.1965-1974		F.TI.1965-1974	1.7	0.3	0.18				
TI.1965-1974		R.TI.1965-1974	3.5	0.2	0.06				
TI.1965-1974						W.TI.1965-1974	1.4	0.6	0.40
TI.1975-1991	0.0010	G.TI.1975-1991	3.5	0.15	0.04				
TI.1975-1991		F.TI.1975-1991	1.7	0.3	0.18				
TI.1975-1991		R.TI.1975-1991	3.5	0.2	0.06				
TI.1975-1991						W.TI.1975-1991	1.4	0.6	0.32
TI.1992-2005	0.0015	G.TI.1992-2005	3.5	0.15	0.04				
TI.1992-2005		F.TI.1992-2005	2.5	0.3	0.12				
TI.1992-2005		R.TI.1992-2005	3.5	0.2	0.06				
TI.1992-2005						W.TI.1992-2005	1.4	0.4	0.33

2020

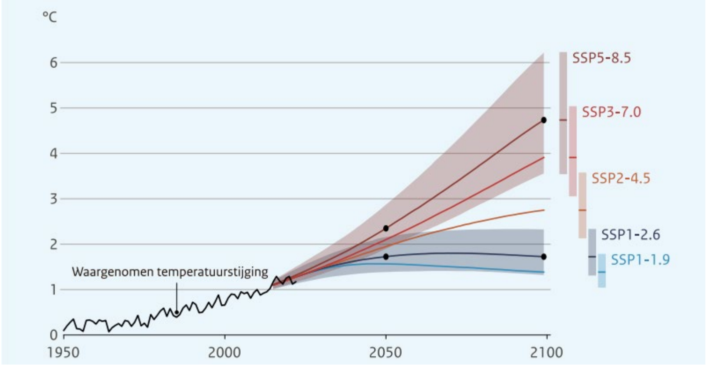
ROTTERDAM EPW WEATHER FILE



[14]

2050, 2080

DE BILT FUTURE WEATHER FILE



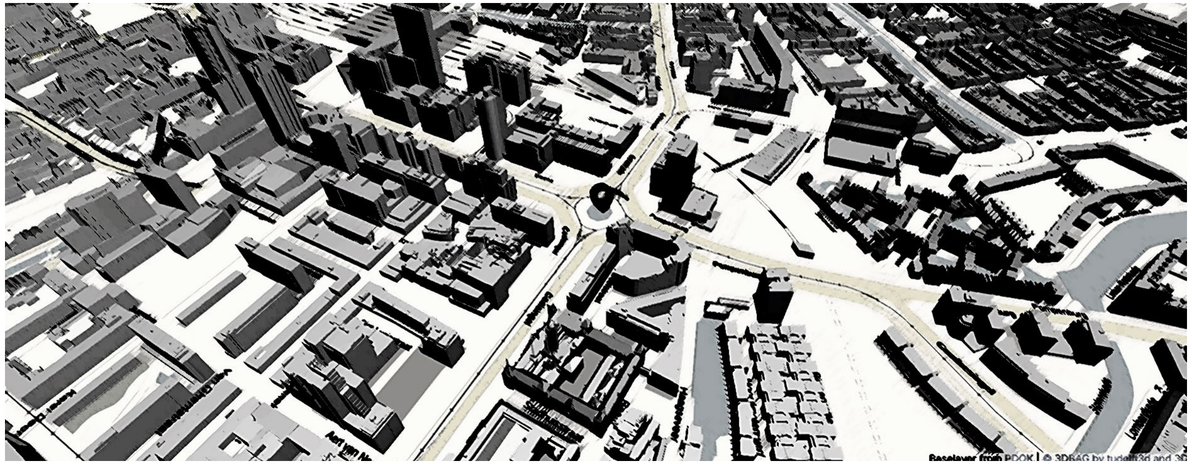
[3]

[10]

[2]

[9]

3D BAG



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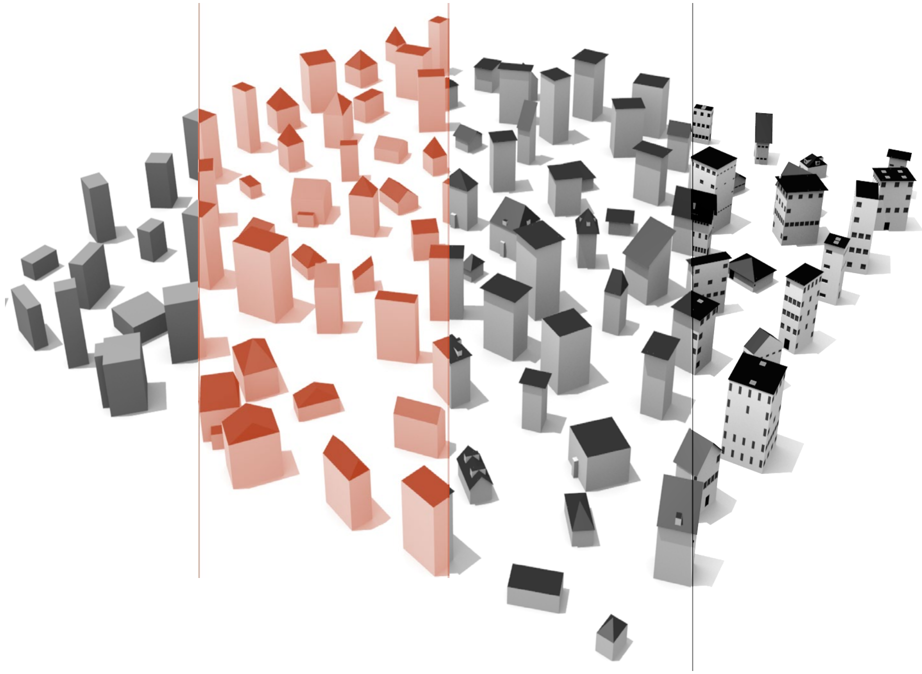

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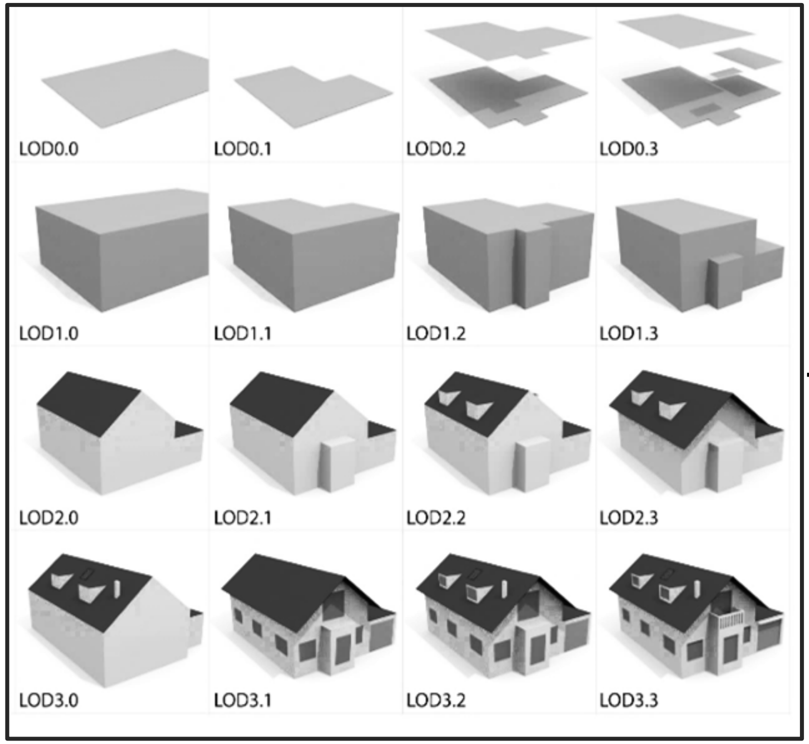

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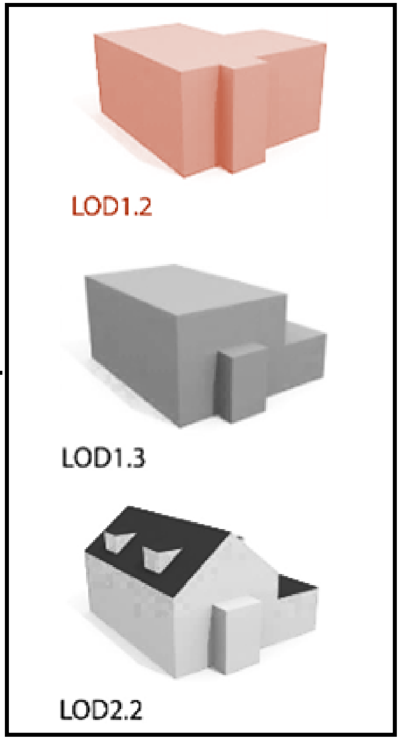


DEFINE LEVEL OF DETAIL FOR COLLECTION

LEVEL OF DETAILS FOR 3D BUILDING GEOMETRIES

AVAILABLE ON 3D BAG

COLLECT BUILDING GEOMETRIES FOR STUDY

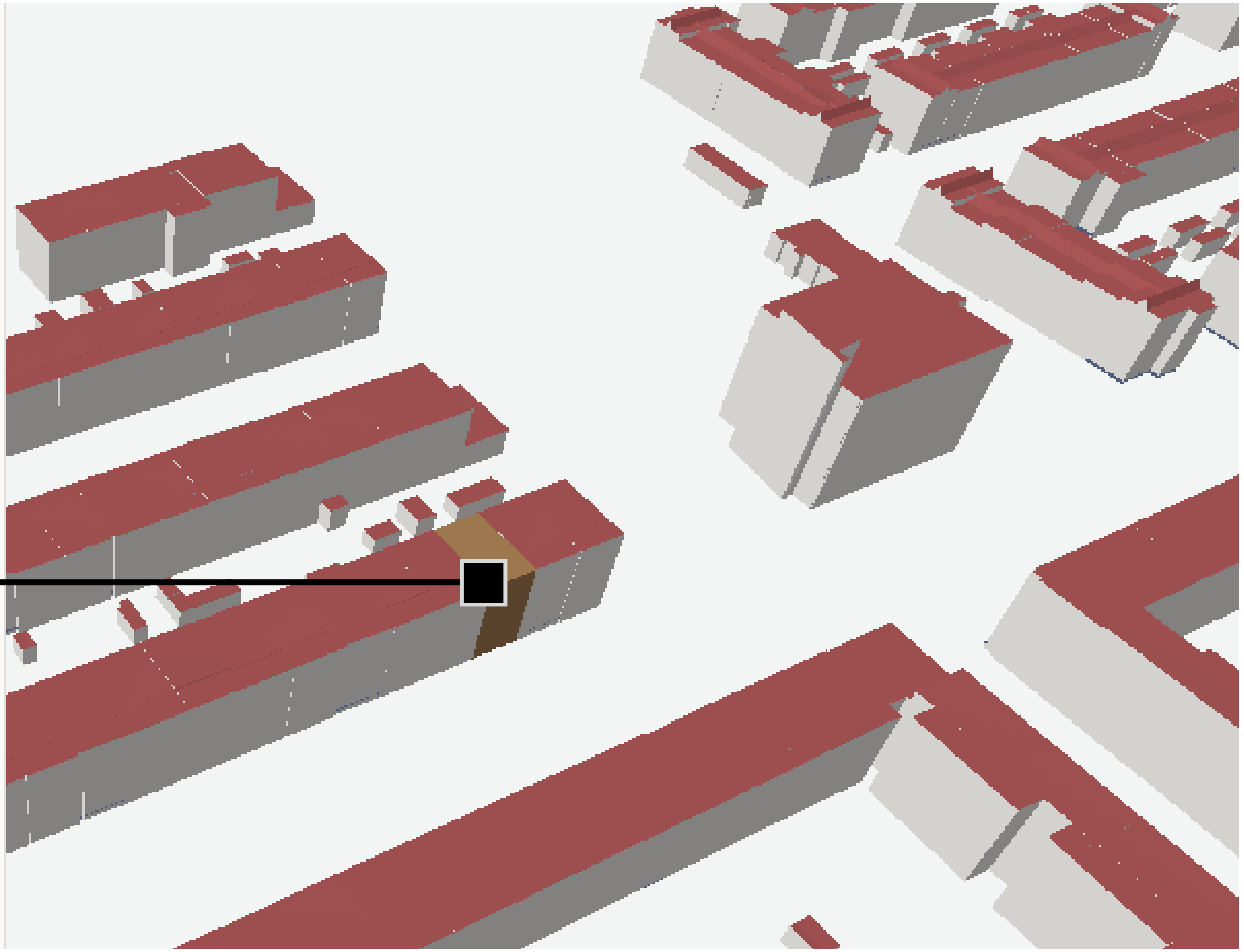
NL.IMBAG.Pand.0599100000013818-0

Parents:

68 Attributes 3 Geometries

Parent attributes

b3_bag_bag_overlap	0
b3_bouwlagen	4
b3_dak_type	slanted
b3_extrusie	0
b3_h_dak_50p	9.854999542236328
b3_h_dak_70p	9.868000030517578
b3_h_dak_max	10.034000396728516
b3_h_dak_min	4.03000020980835
b3_h_maaiveld	-0.8159999847412109



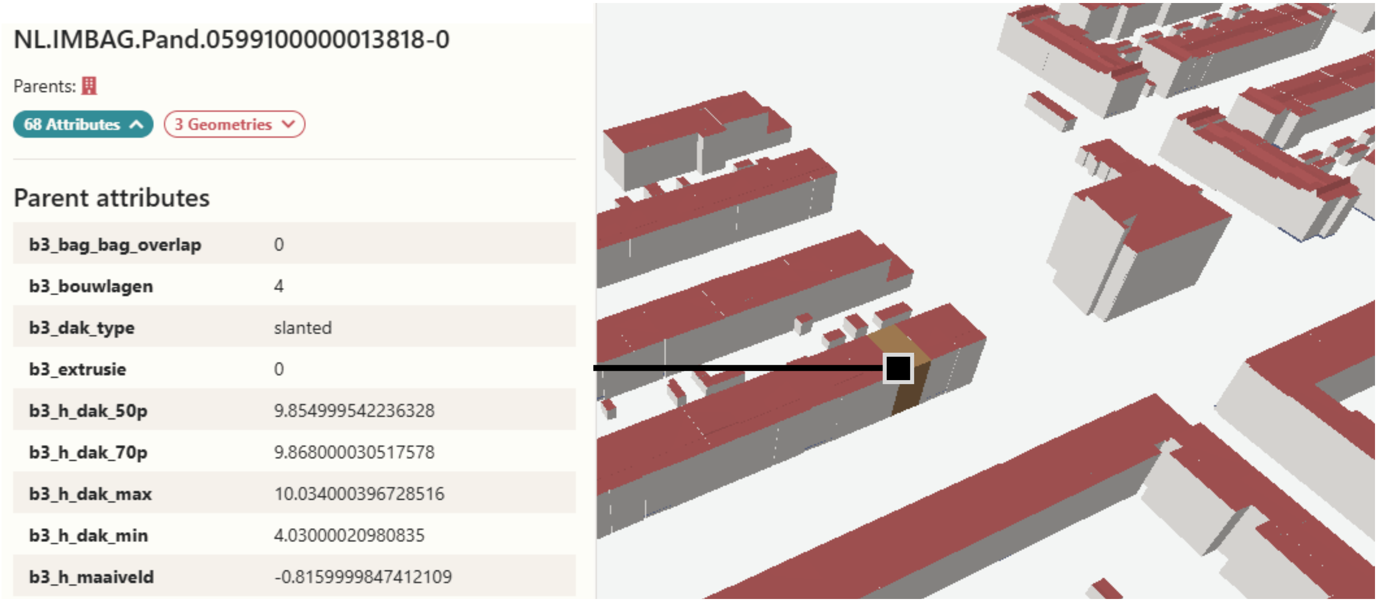
[15]

[10]

[2]

[9]

20,000 BUILDINGS / PAND IDS TO COLLECT



b3_bag_bag_overlap	0
b3_bouwlagen	4
b3_dak_type	slanted
b3_extrusie	0
b3_h_dak_50p	9.854999542236328
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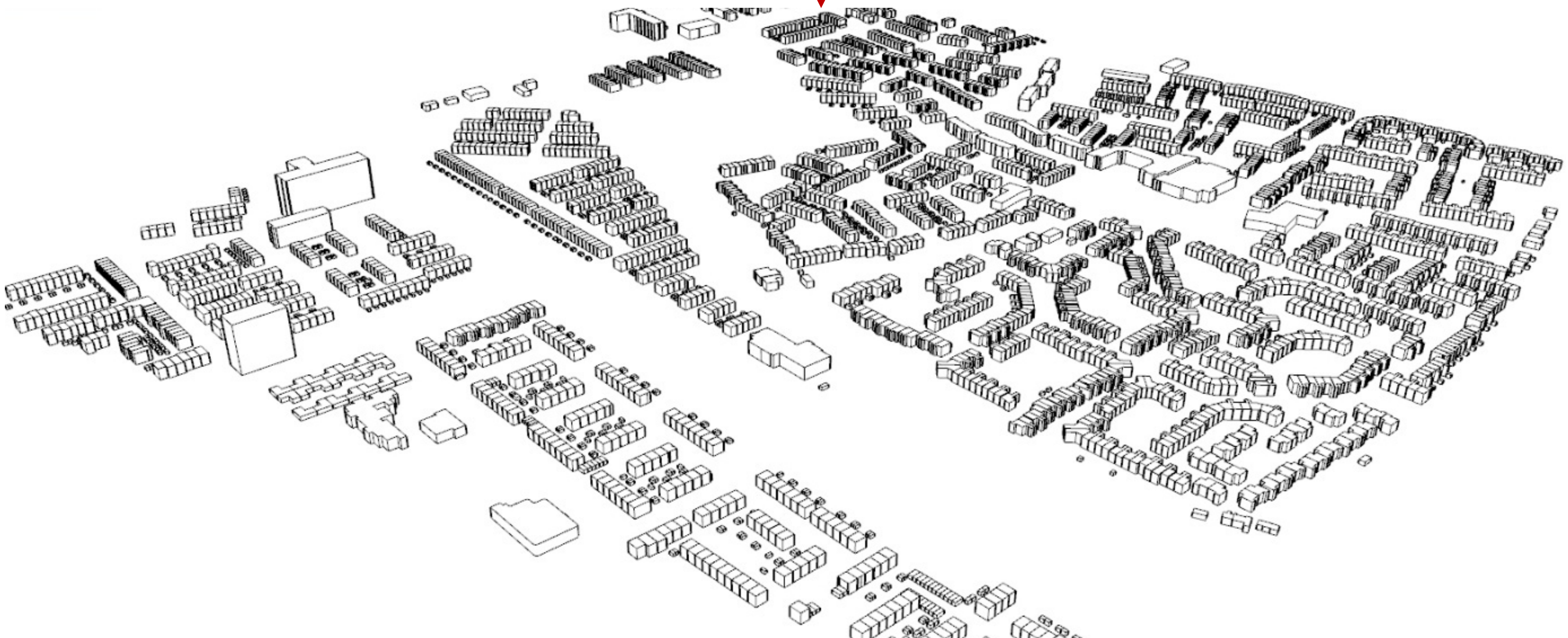
[15]

```
  Building      1
  Building      .
  Building      .
  Building      .
Building     20,000
```

QUERY 3D BAG API

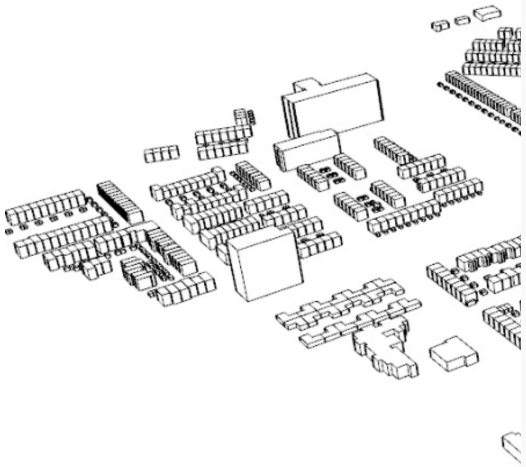
DOWNLOAD BUILDING PROPERTEIES FOR 20,000 BUILDINGS AT ONCE



Building 1
Building .
Building .
Building .
Building 20,000

QUERY 3D BAG API

DOWNLOAD BUILDING PROPERTEIES FOR 20,000 BUILDINGS AT ONCE



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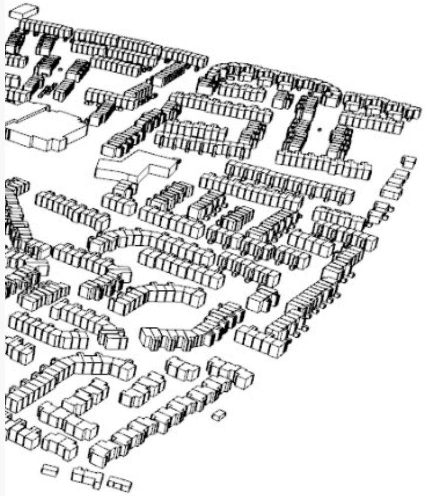
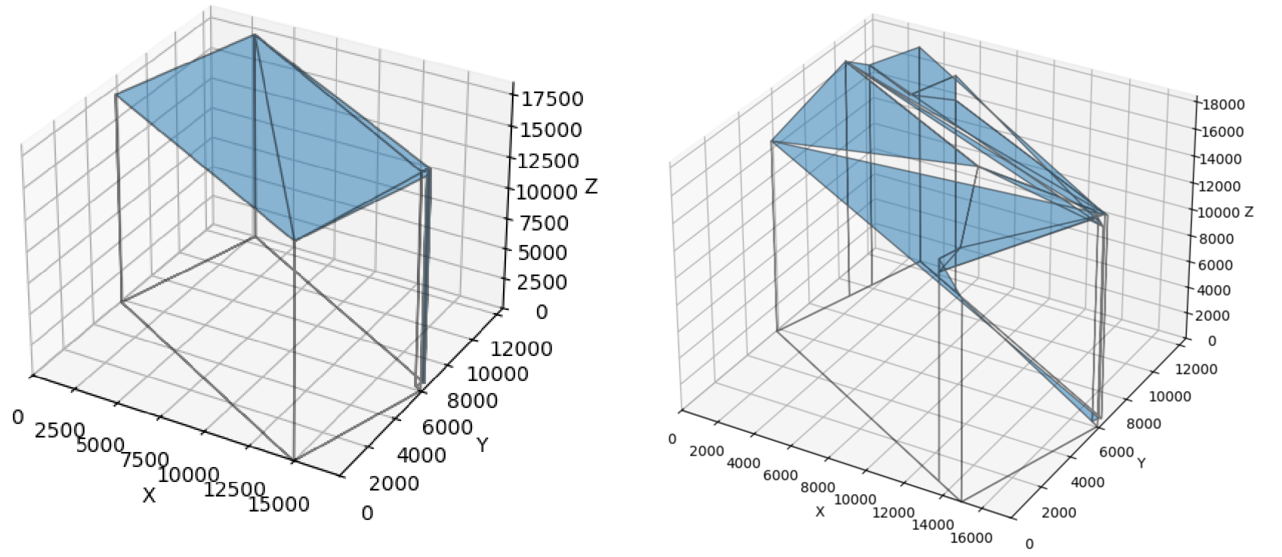
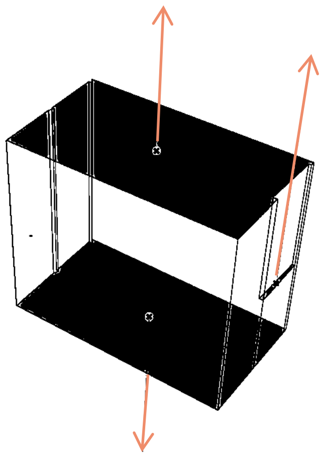




represented geometry from 3D BAG requires processing

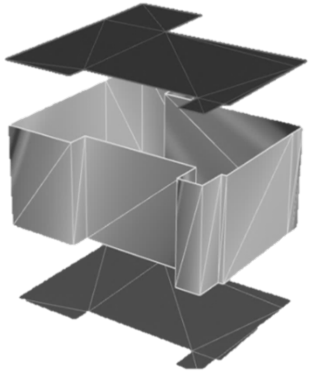
CHECKING SURFACE NORMALS, DEFINING SURFACE TYPES, ADDING SURFACE DATA TO FEATURES

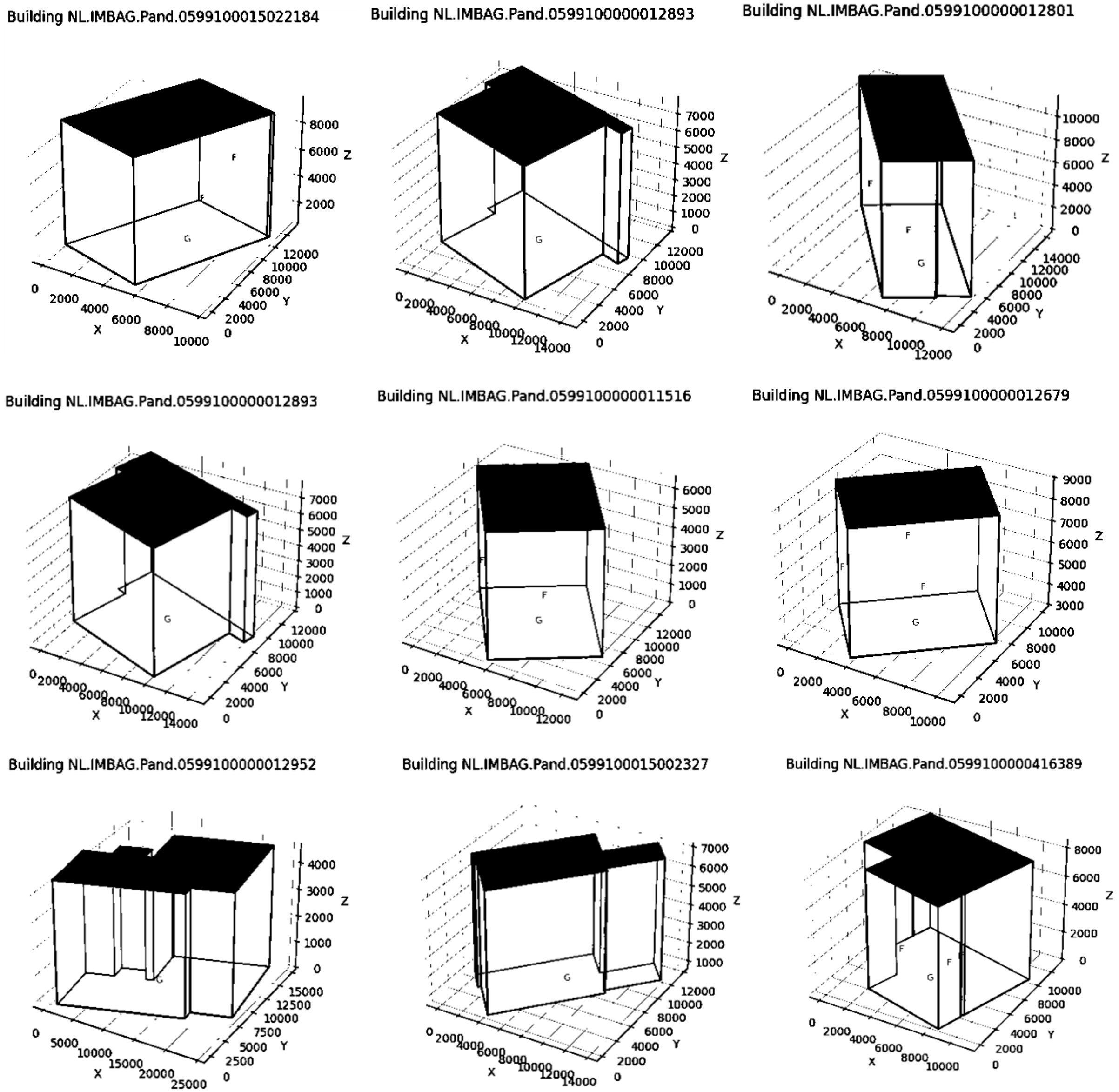


TYPE : R

TYPE : F

TYPE : G





MAKING DISTINCTION
BETWEEN BUILDING TYPES


DETACHED

[10]

0 shared walls


TERRACED CORNER

[2]

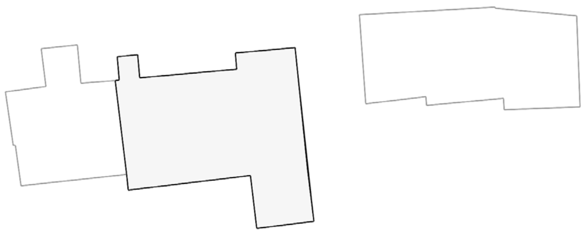
1 shared walls


TERRACED INTERMEDIATE

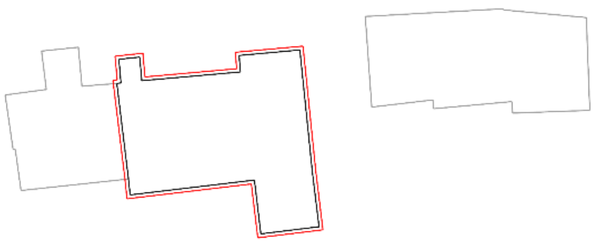
[9]

2 shared walls

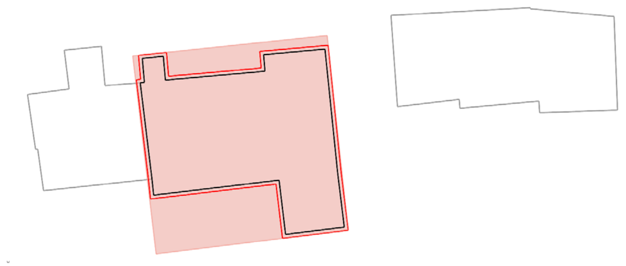
FIND NEIGHBOUR BUILDINGS + IDENTIFY SHARED SURFACES



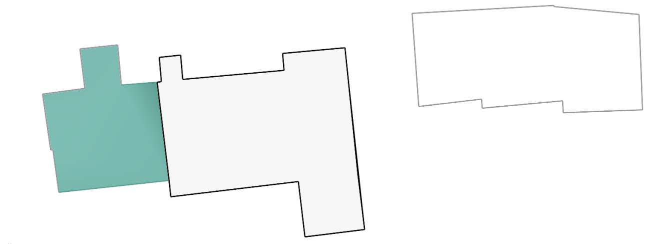
1. Extract the ground footprint



2. Apply a proximity buffer

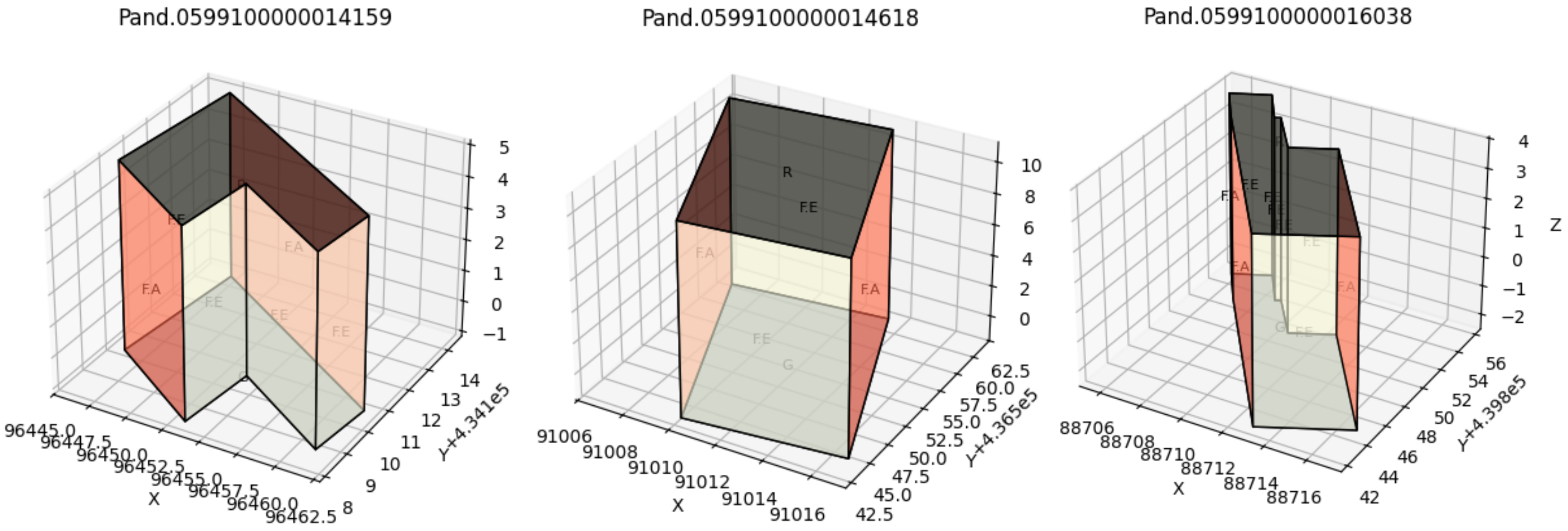


3. Query API for bounding box



4. Retrieve candidate neighbours

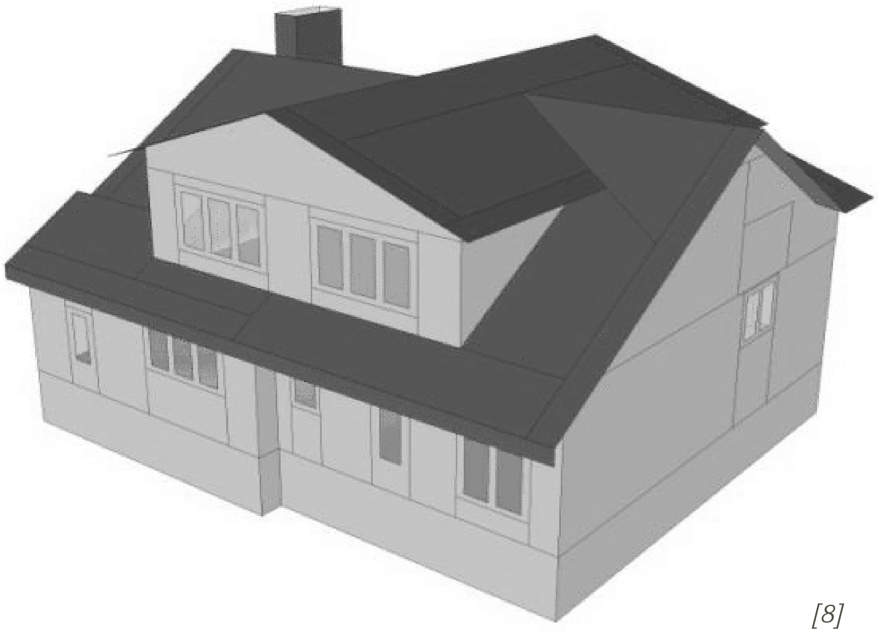
LABELLED SHARED WALL SURFACES FOR TERRACED HOUSES



i.e adiabatic surfaces where no heat transfer occurs.

COLLECT BUILDING + ENVIRONMENTAL DATA → GENERATE BUILDING ENERGY MODELS →

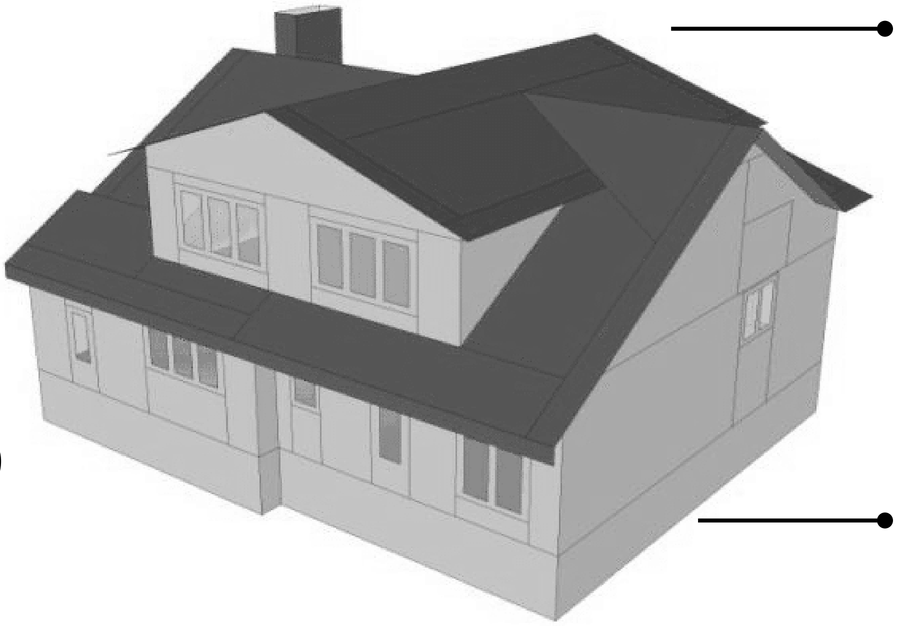
ENERGYPLUS



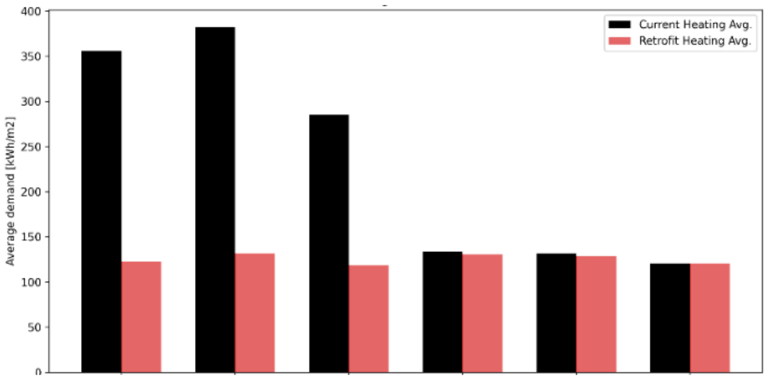
[8]

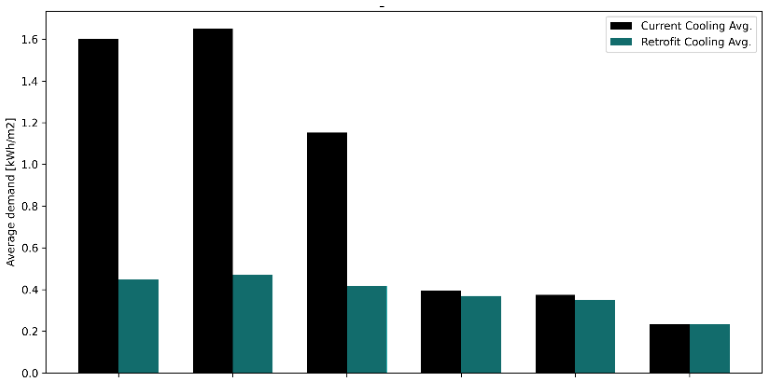
translate inputs to readable file to run energy plus simulations.

1. geometry
2. climate
3. construction
4. occupancy schedule
5. ventilation
6. infiltration
7. energy supply systems (gas boiler)



[8]

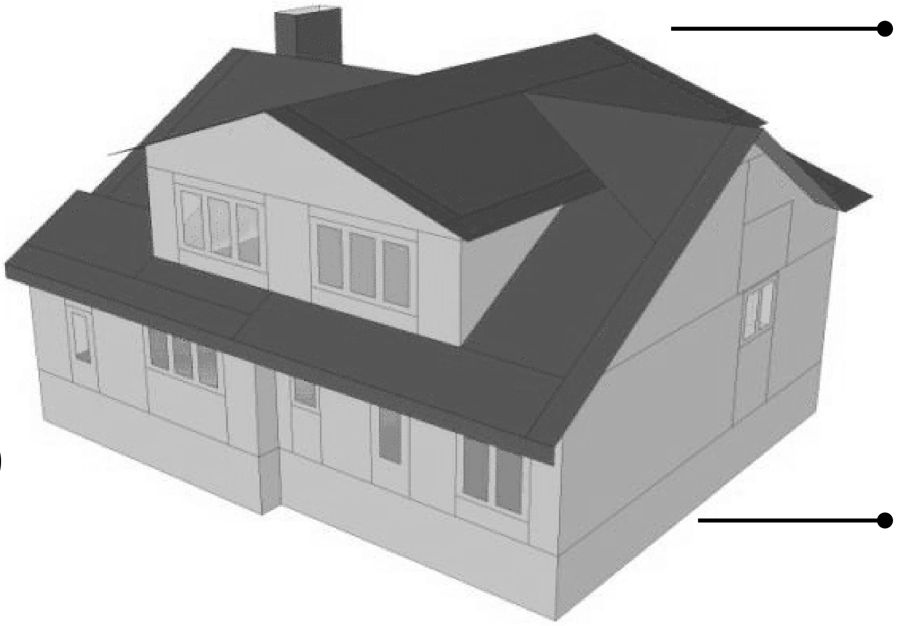




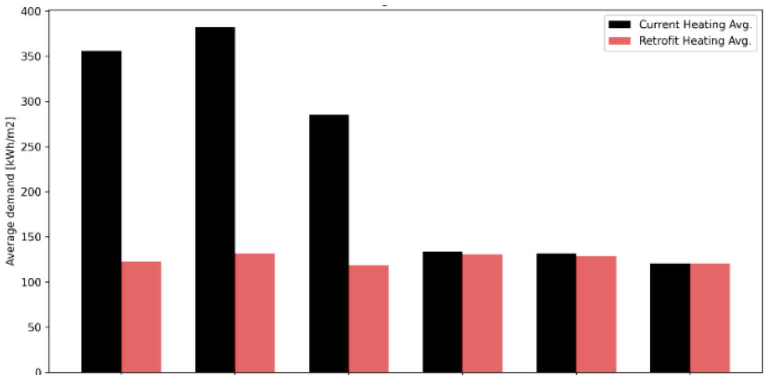
INPUT DATA FILE (IDF)

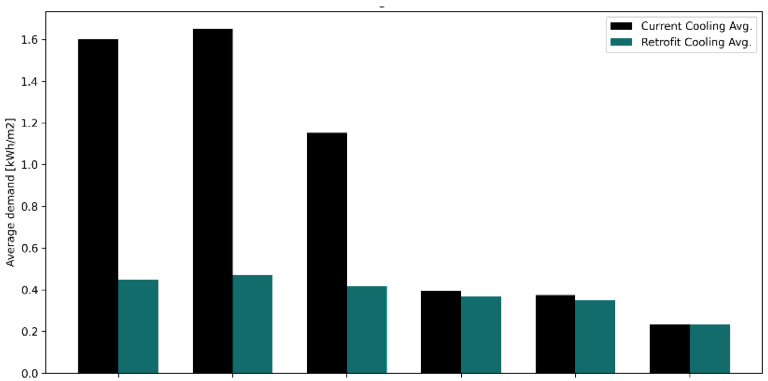
translate inputs to readable file to run energy plus simulations.

1. geometry
2. climate
3. construction
4. occupancy schedule
5. ventilation
6. infiltration
7. energy supply systems (gas boiler)



[8]





INPUT DATA FILE (IDF)

IDF INPUTS

SITE
SITE:GROUND TEMPERATURE

SYSTEMS
HVAC: IDEAL LOADS AIR SYSTEM

SCHEDULES
SCHEDULE : ALWAYS ON
THERMOSTATSETPOINT : DUALSETPOINT
ZONE CONTROL : THERMOSTAT

constant for each building

CONSTRUCTION
MATERIAL
CONSTRUCTION ASSEMBLY
WINDOW: SIMPLE GLAZING SYSTEM
ZONE INFILTRATION : DESIGN FLOWRATE

varies per archetype

GEOMETRY
BUILDING
ZONE
BUILDING SURFACE: DETAILED

varies per building

[8] [7]

DETACHED

[10]

TERRACED CORNER

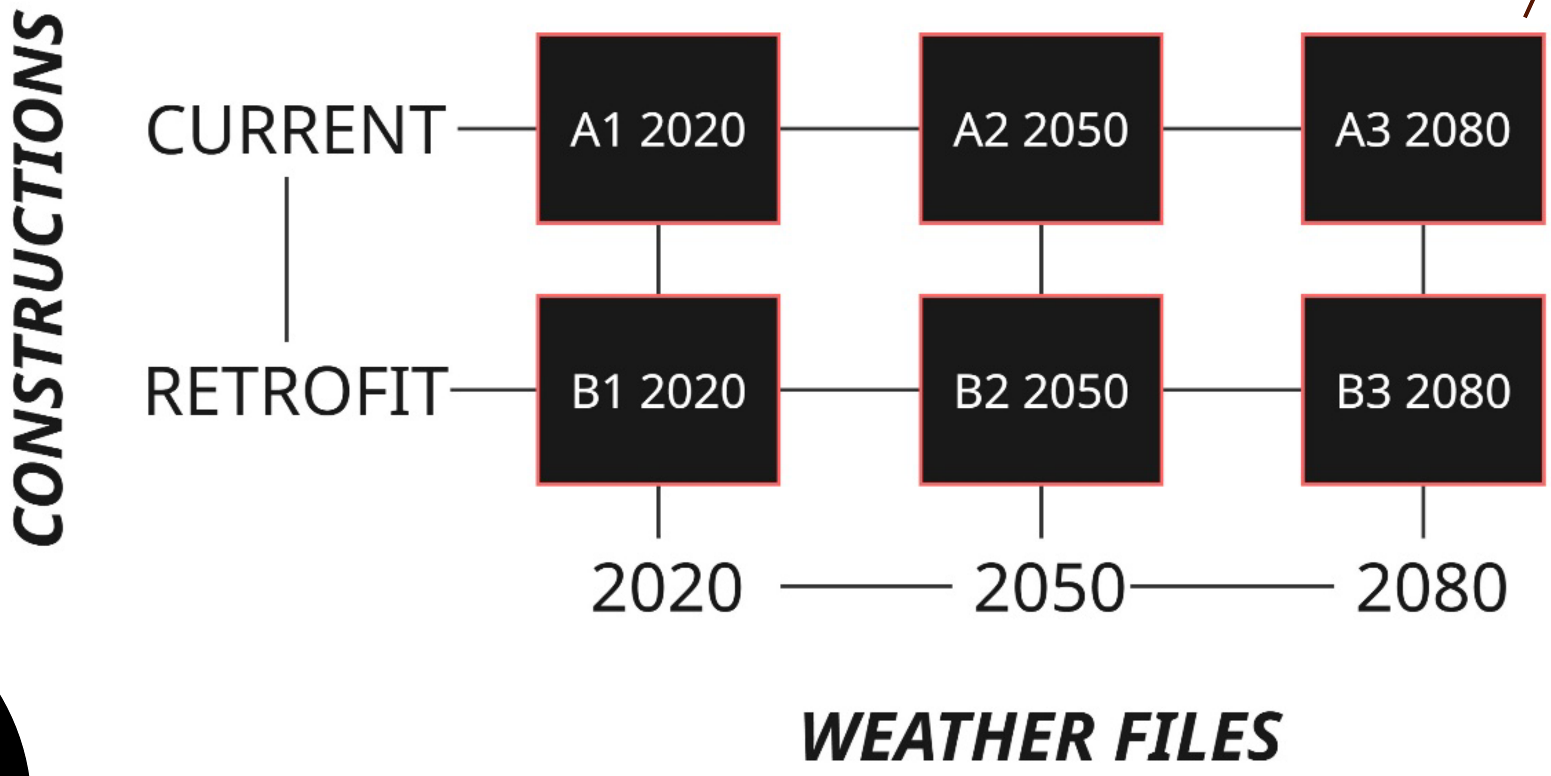
[2]

TERRACED INTERMEDIATE

[9]

SIMULATION MATRIX

20,000 buildings



120,000 IDF files

TYPICAL IDF EDITOR.

detailed manual inputs.

Class List

Simulation Parameters

[0001] Version
[0001] SimulationControl
[------] PerformancePrecisionTradeoffs
[------] Building
[------] ShadowCalculation
[------] SurfaceConvectionAlgorithm:Inside
[------] SurfaceConvectionAlgorithm:Outside
[------] HeatBalanceAlgorithm
[------] HeatBalanceSettings:ConductionFiniteDifference
[------] ZoneAirHeatBalanceAlgorithm
[------] ZoneAirContaminantBalance
[------] ZoneAirMassFlowConservation
[------] ZoneCapacitanceMultiplier:ResearchSpecial
[0001] Timestep
[------] ConvergenceLimits
[------] HVACSystemRootFindingAlgorithm

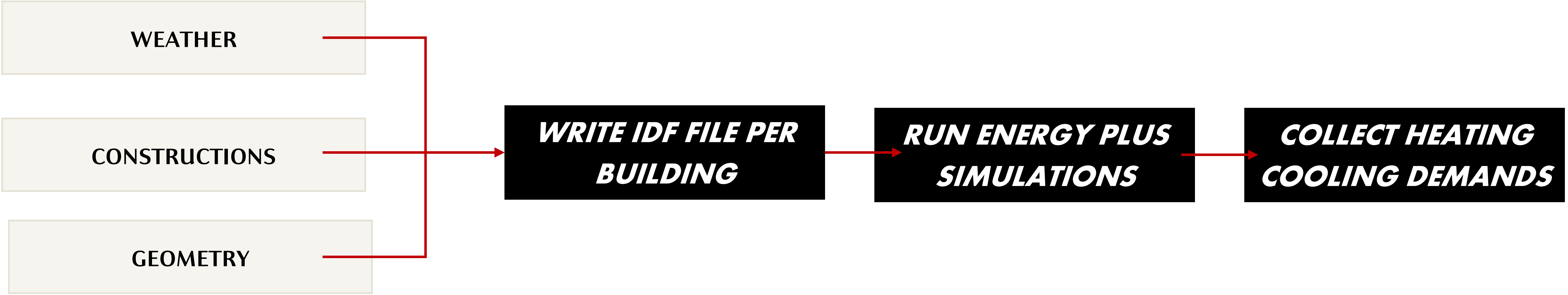
Compliance Objects

[------] Compliance:Building

Location and Climate

[0001] Site:Location
[------] Site:VariableLocation
[------] SizingPeriod:DesignDay
[------] SizingPeriod:WeatherFileDays
[------] SizingPeriod:WeatherFileConditionType
[0001] RunPeriod
[------] RunPeriodControl:SpecialDays
[0001] RunPeriodControl:DaylightSavingTime
[------] WeatherProperty:SkyTemperature
[------] Site:WeatherStation
[------] Site:HeightVariation
[------] Site:GroundTemperature:BuildingSurface
[------] Site:GroundTemperature:FCfactorMethod
[------] Site:GroundTemperature:Shallow
[------] Site:GroundTemperature:Deep
[------] Site:GroundTemperature:Undisturbed:FiniteDifference

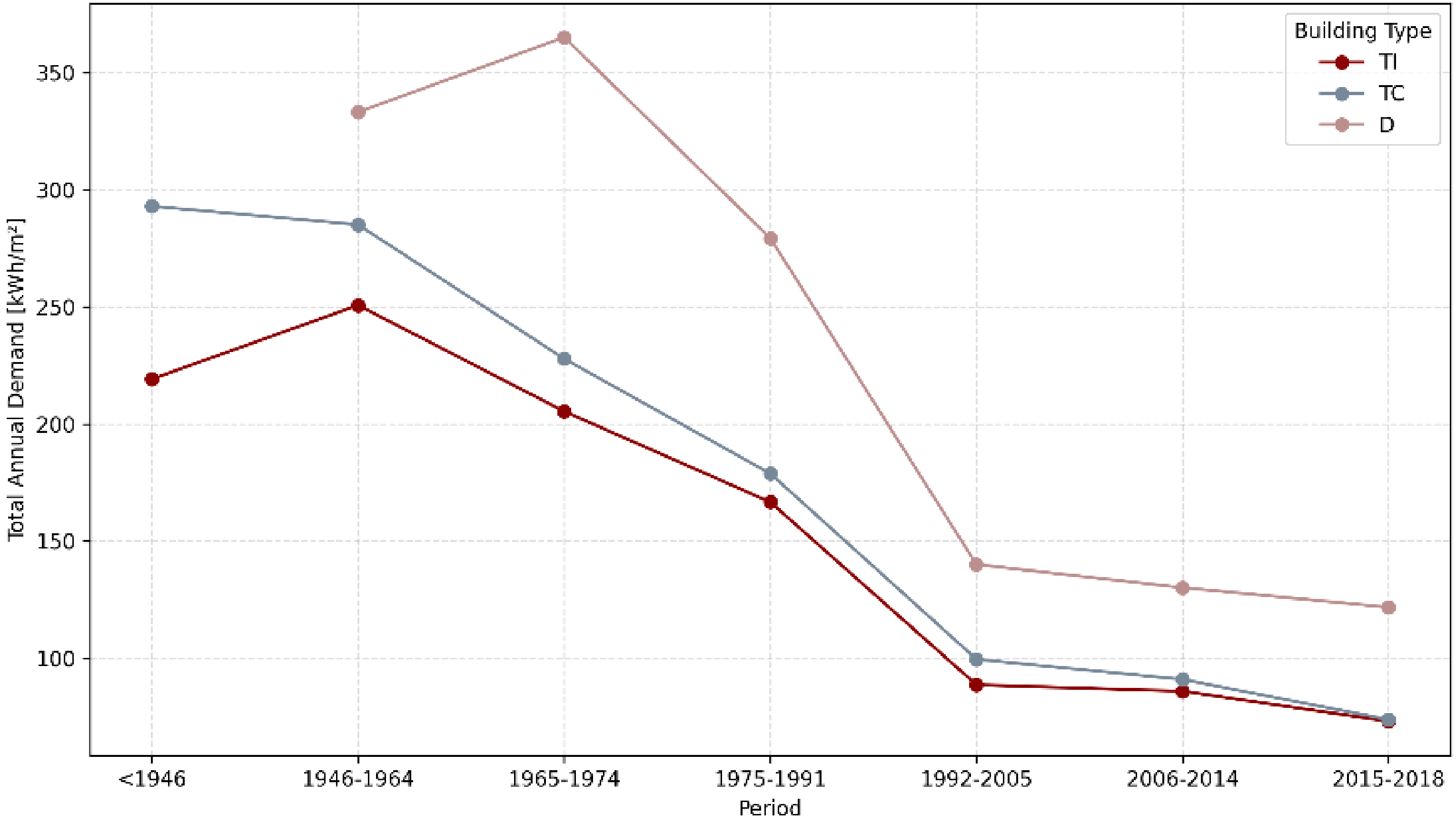
PYTHON SCRIPT TO AUTOMATE



what are the current energy demands for different archetypes?

total energy demand per archetype

detached home shows highest energy demands



detached home = more exposed building surfaces

DETACHED [D]

[10]

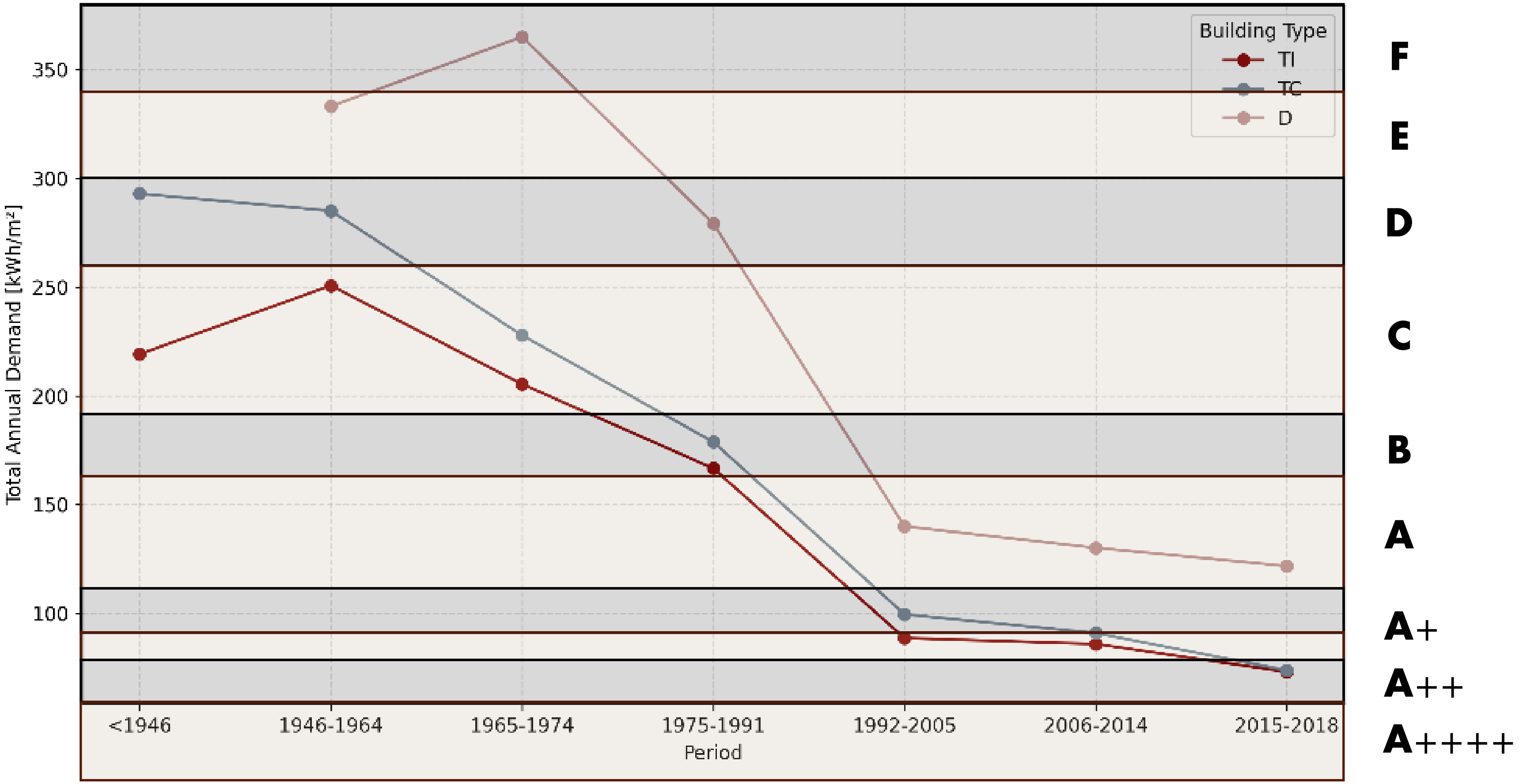
TERRACED CORNER [TC]

[2]

TERRACED INTERMEDIATE [TI]

[9]

energy labels per archetype *



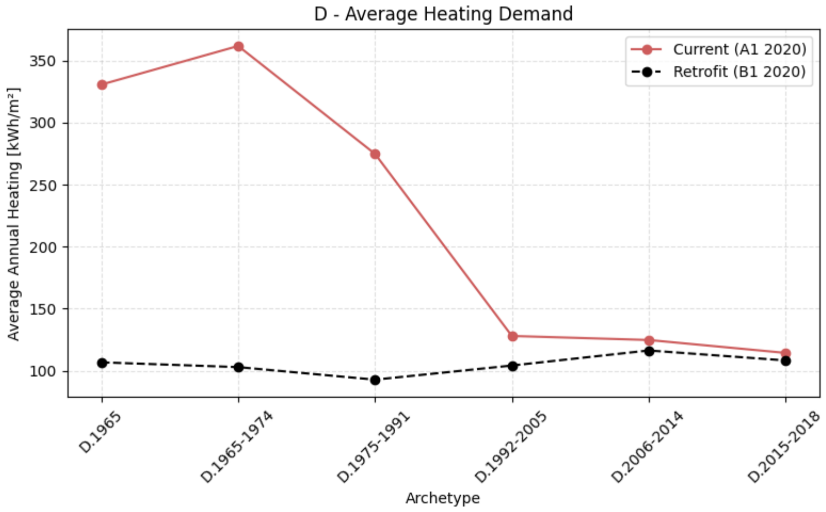
check results against energy label mapping.

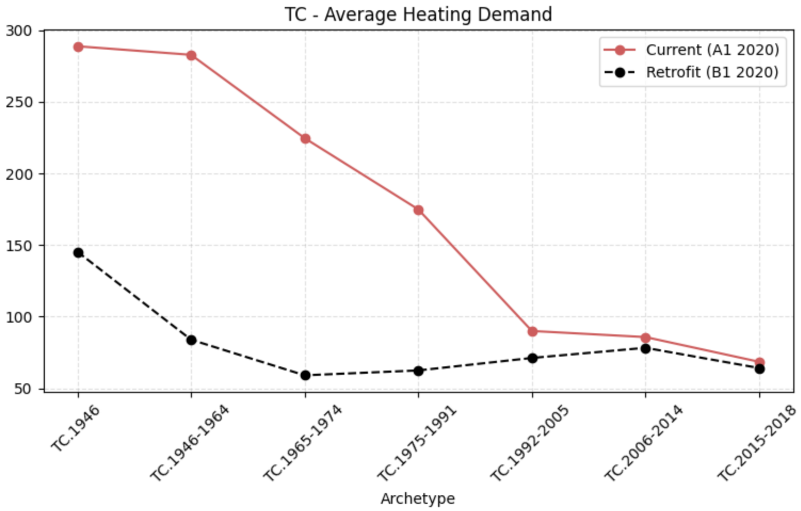
** energy label (NTA 8800) mapping to primary fossil energy consumption (including source energy conversion factors), not for total delivered energy.*

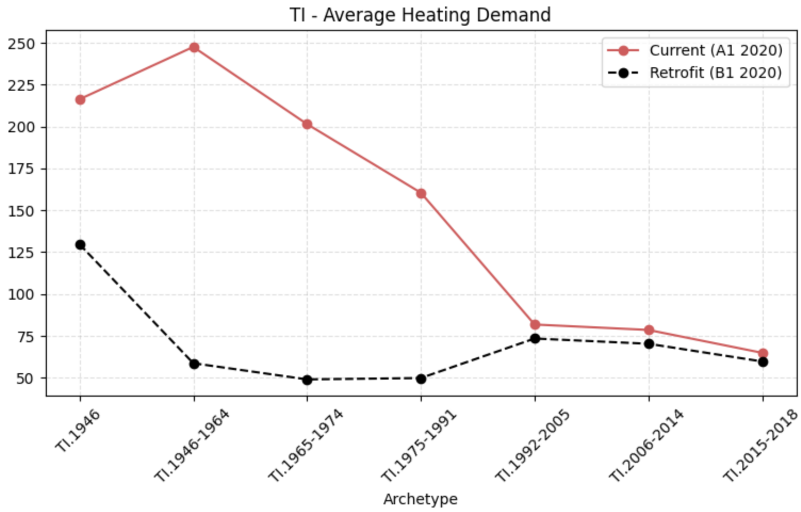
[10]

[2]

[9]





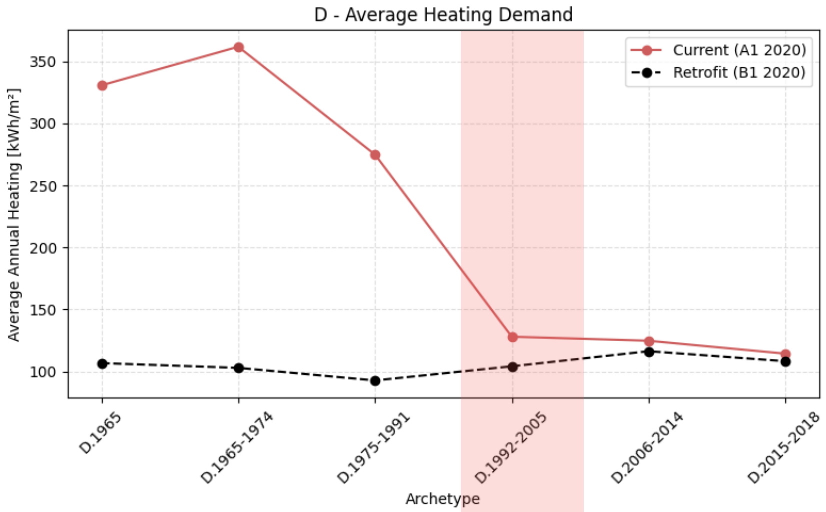


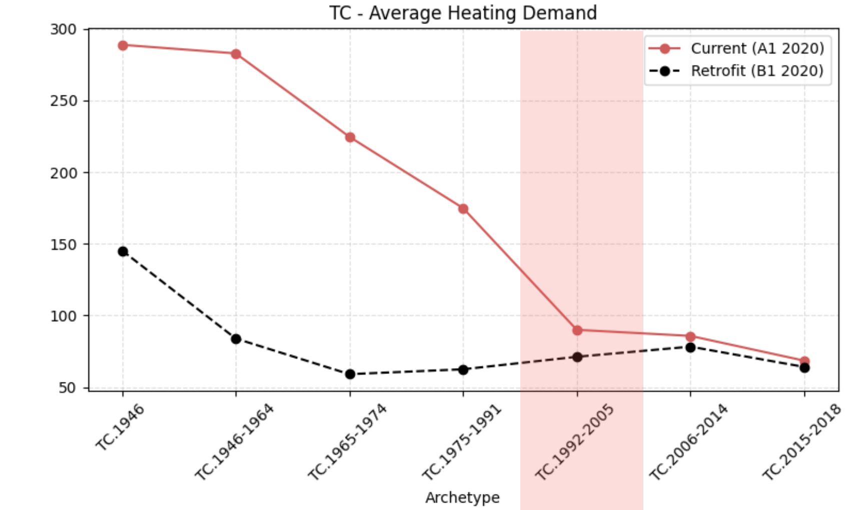
heating demand steeply declines in 1992-2005 for all archetypes.

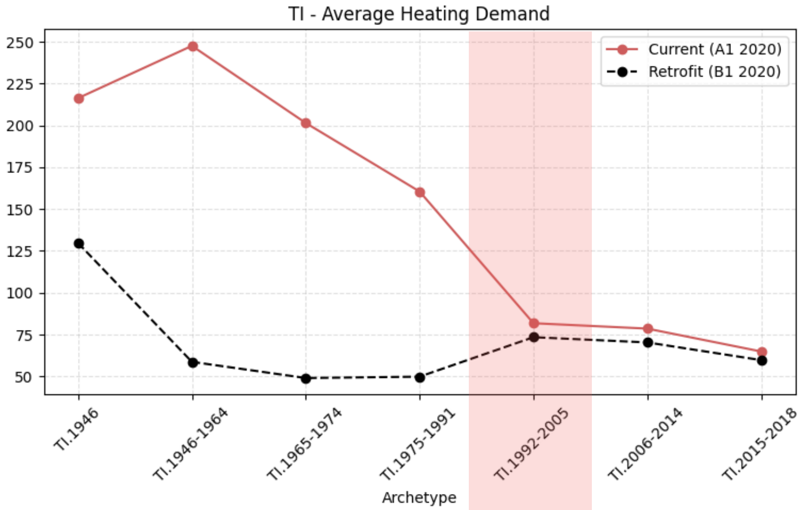
[10]

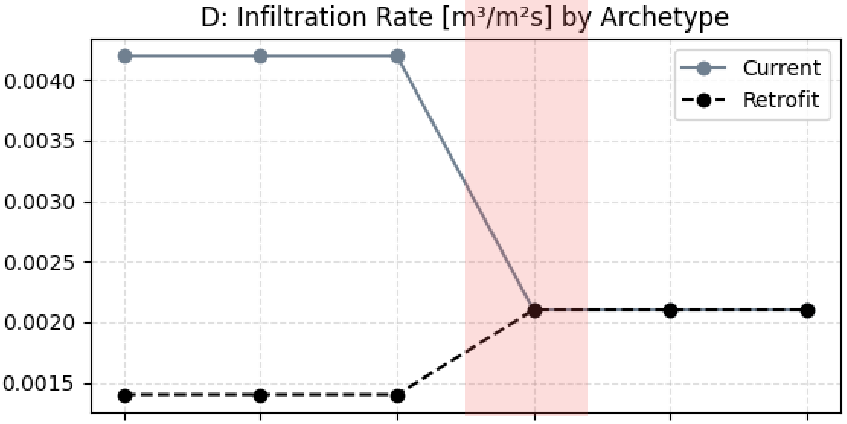
[2]

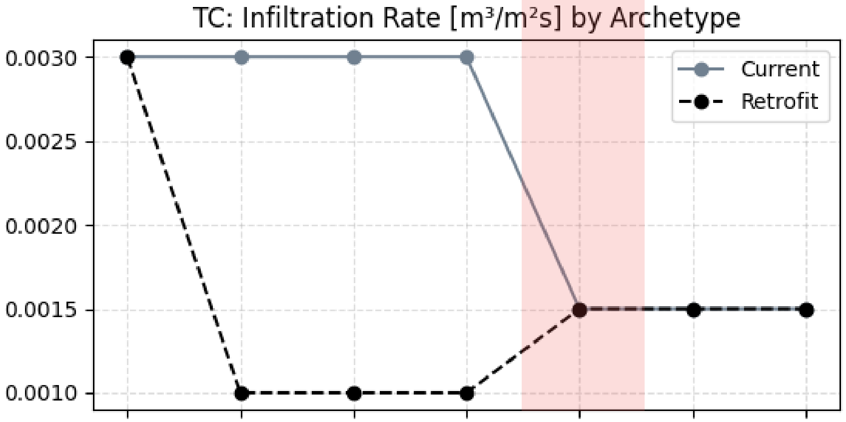
[9]

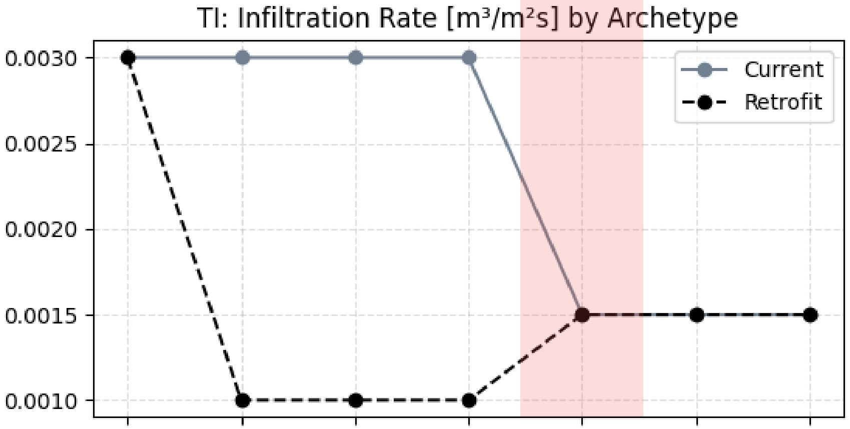










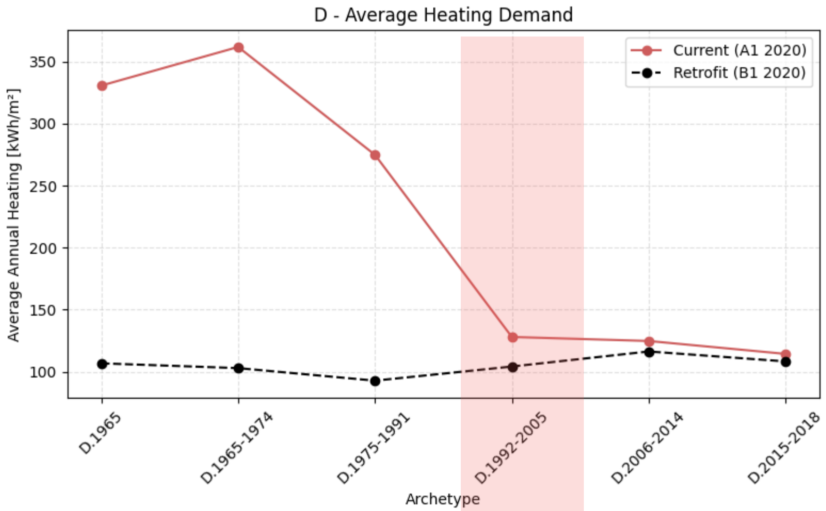


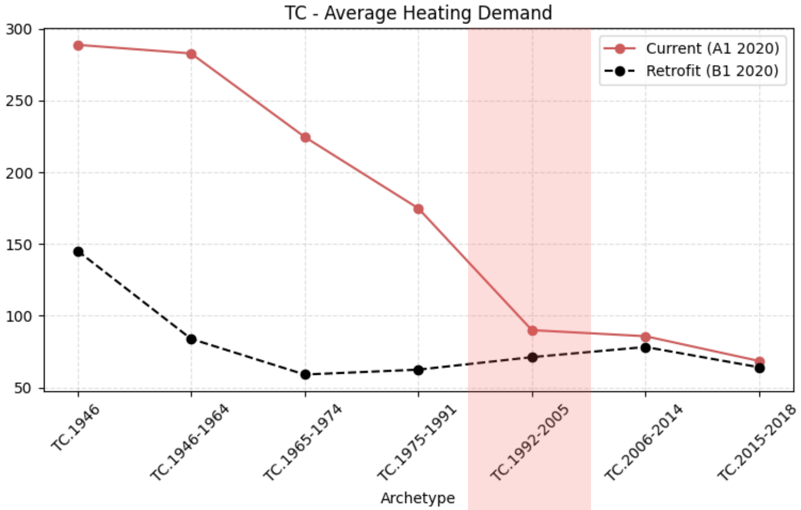
steep decline in heating demands driven by reduced infiltration

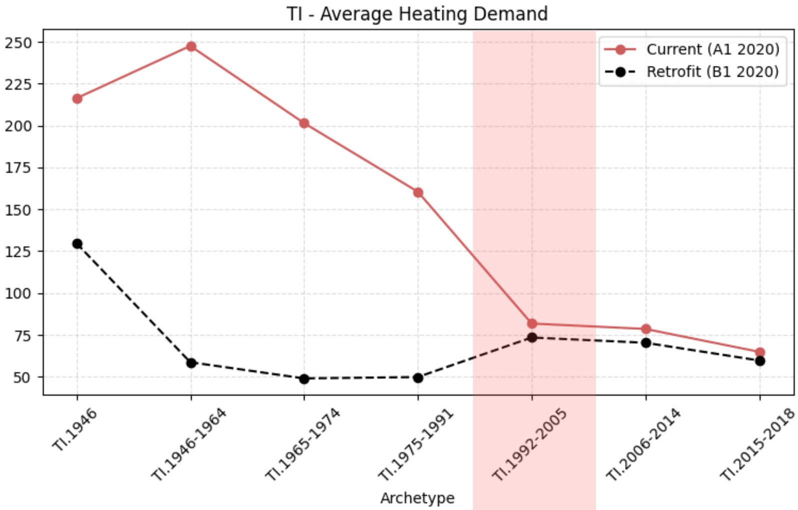
[10]

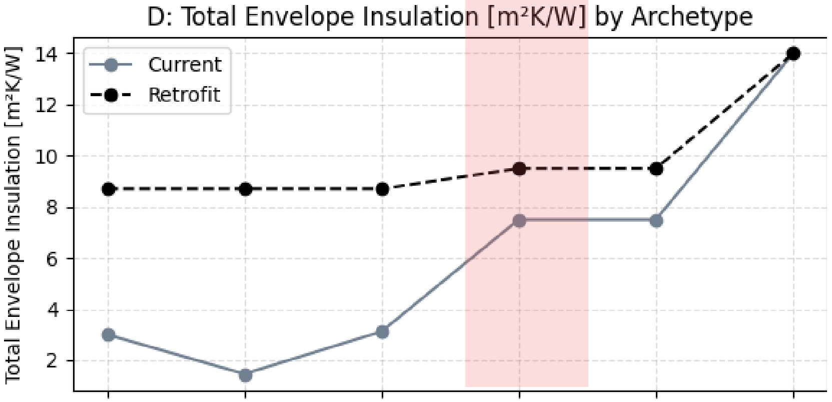
[2]

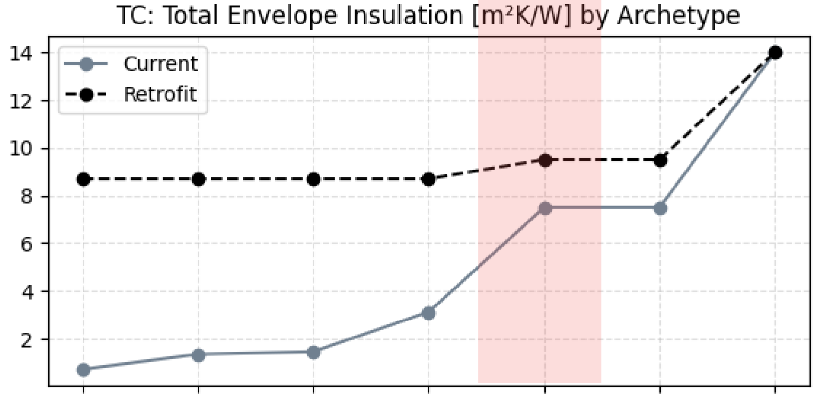
[9]

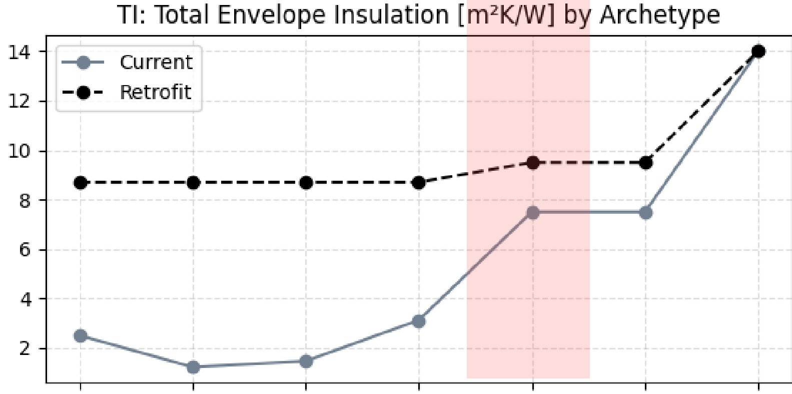










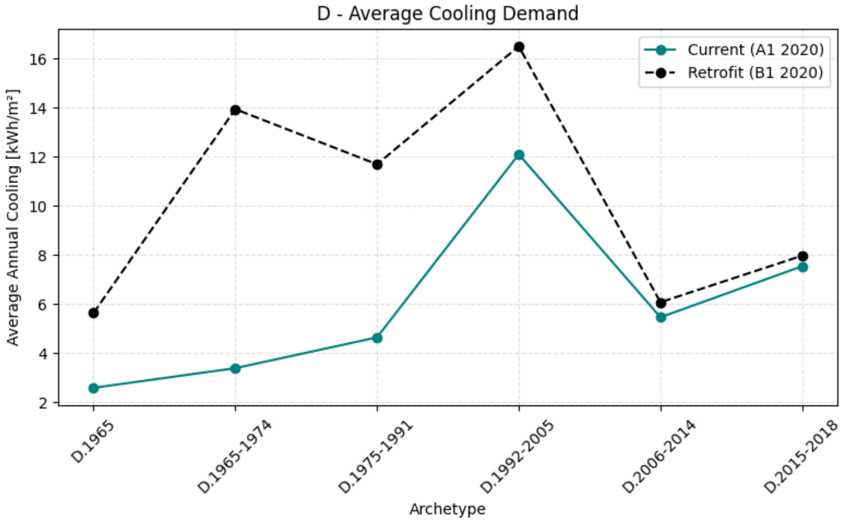


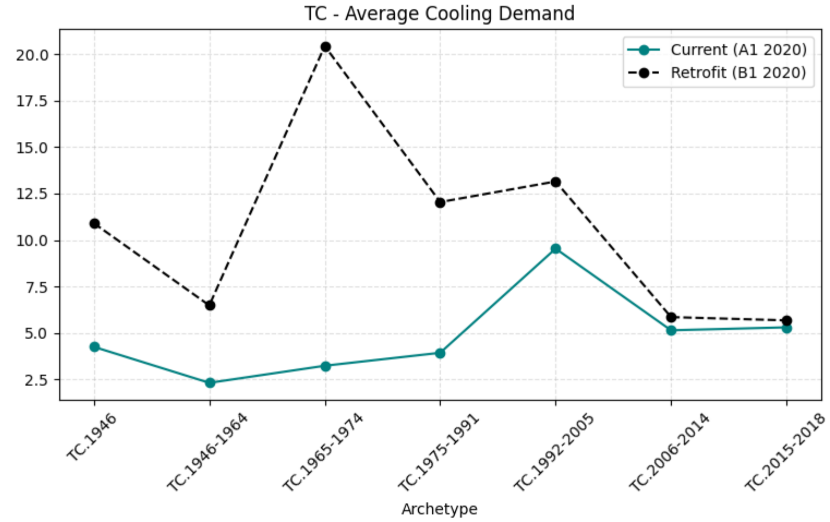
reduced heating demand influenced by increased envelope insulation (floor, facade, roof).

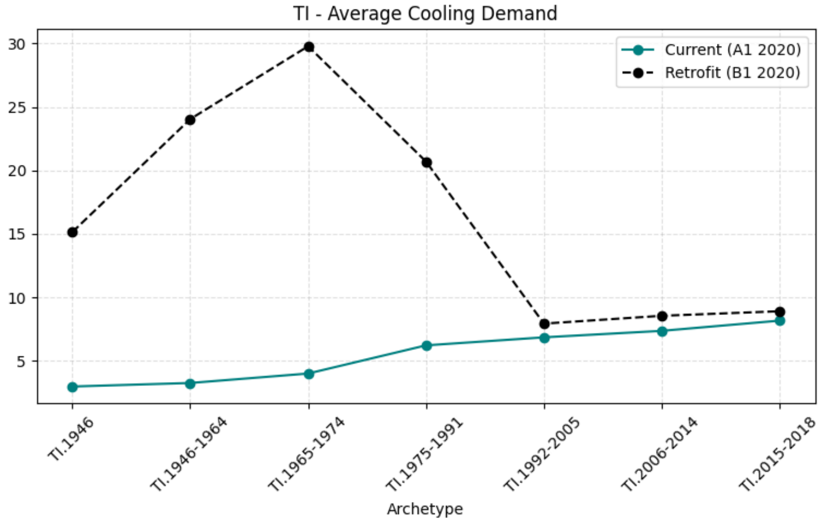
[10]

[2]

[9]







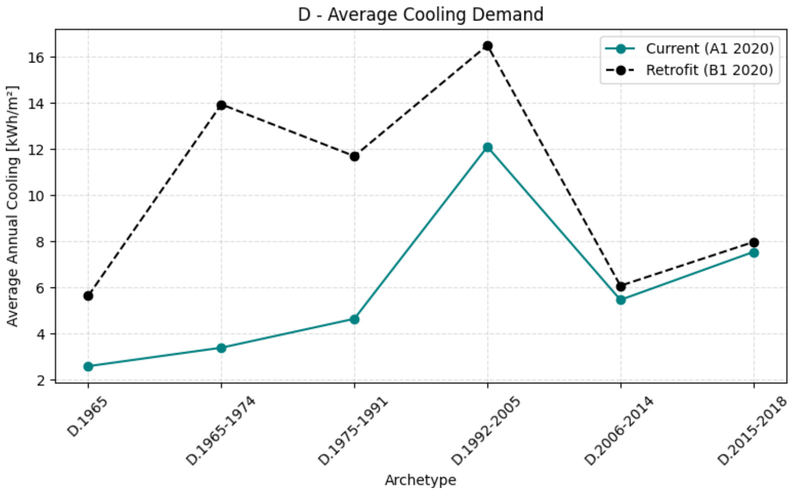
more variation in cooling demand between the archetypes.

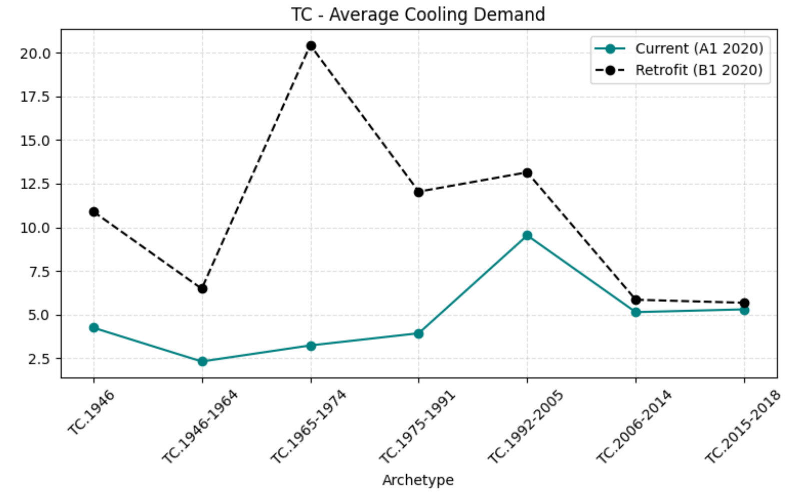
retrofit measures significant increase the cooling demand for all building types.

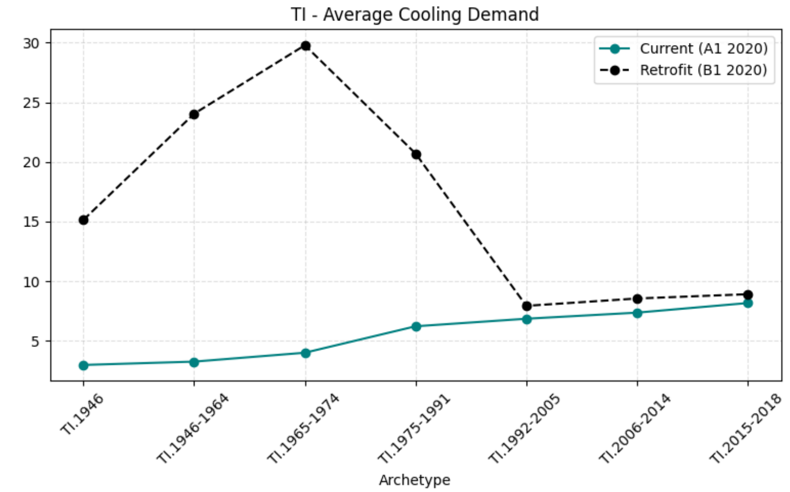
Higher SHGC = more solar radiation passes through window. increased cooling demand (summer)

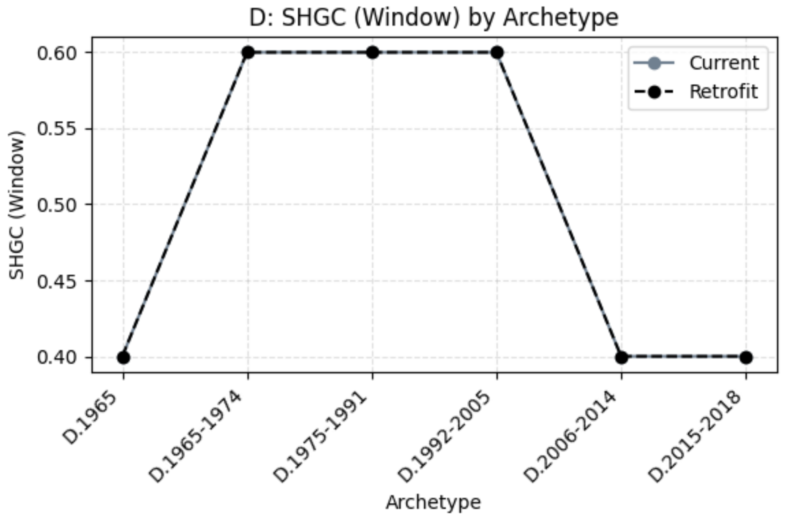
**Need to consider also effect of U factor, Insulations, Infiltrations.*

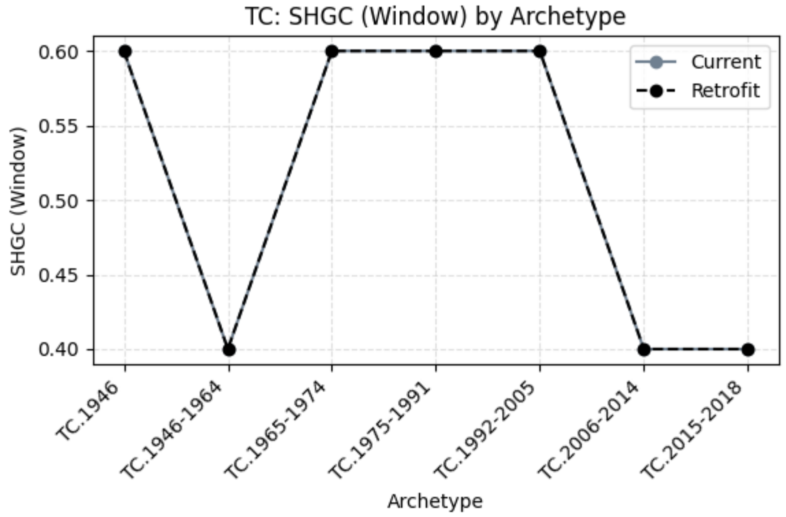
SHGC constant between retrofit and current

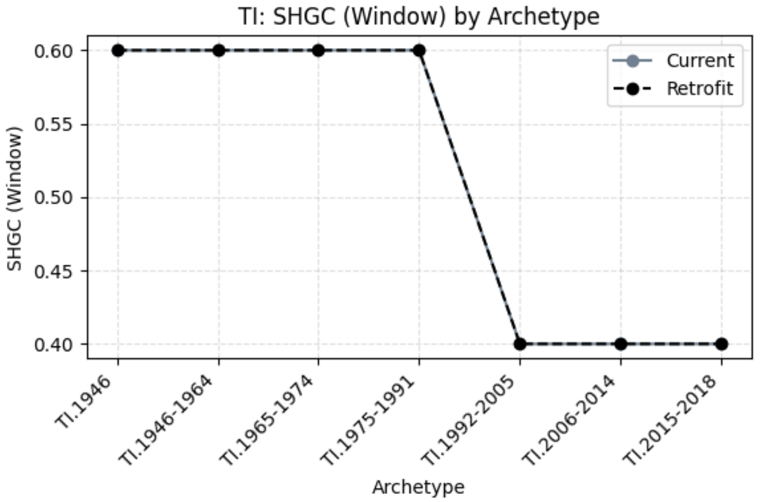








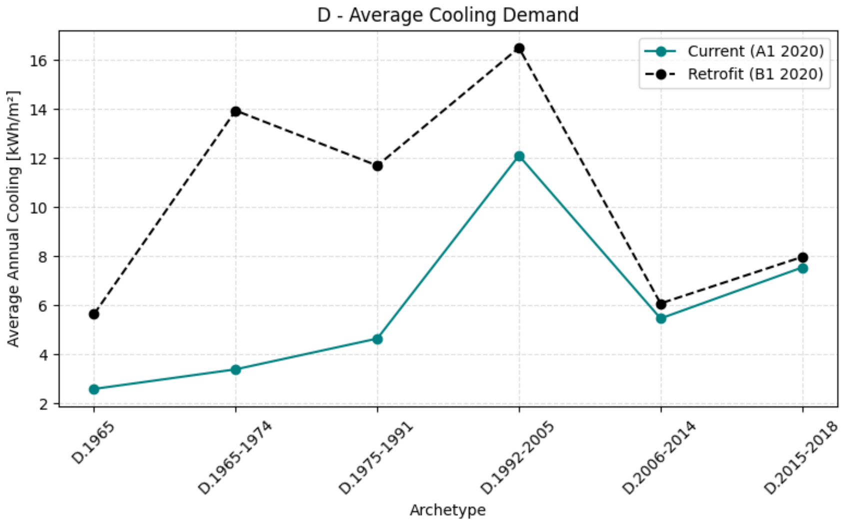


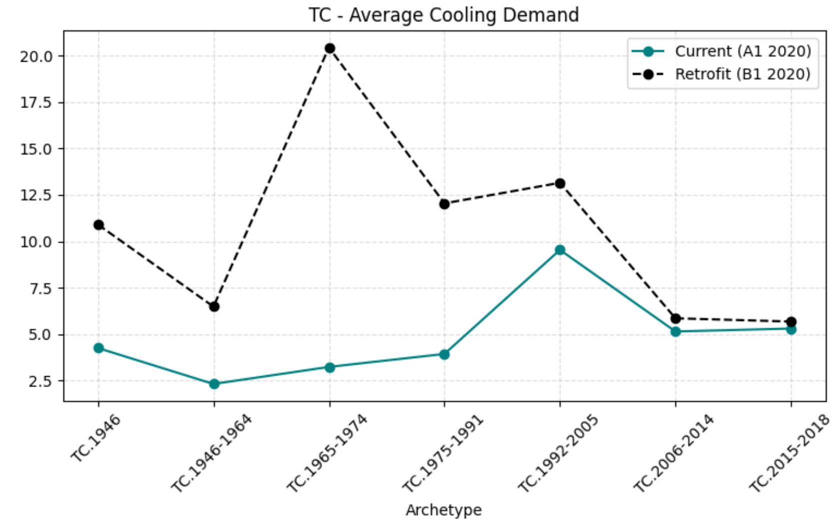


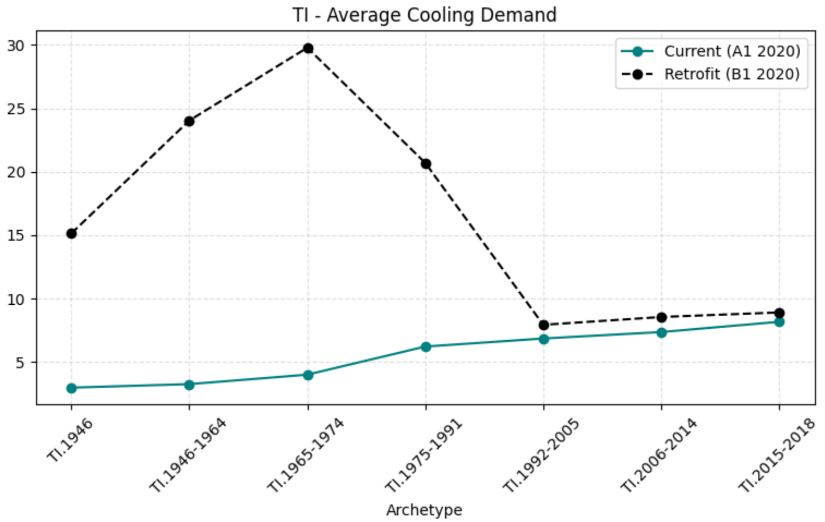
Higher WWR = more solar radiation passes through window.
increased cooling demand (summer)

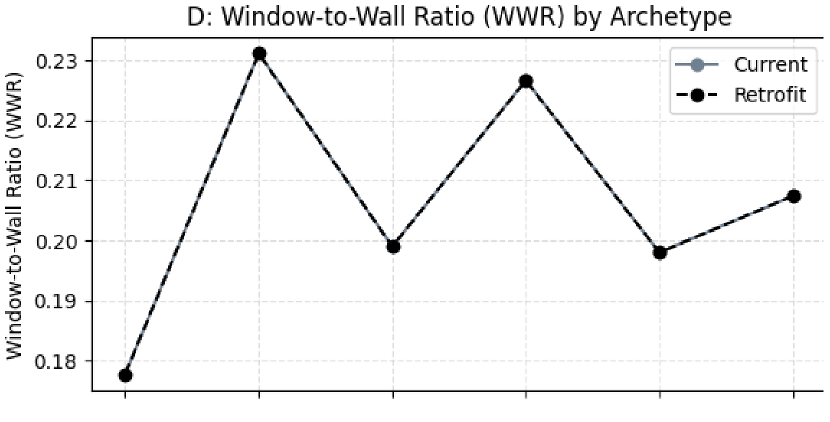
WWR constant between retrofit and current

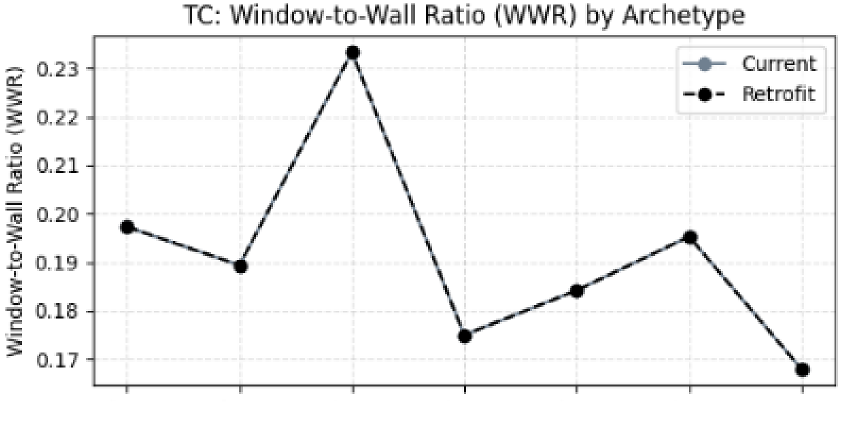
**Retrofit differences result from combined retrofit effect from lower U factor, higher insulations, lower infiltration*

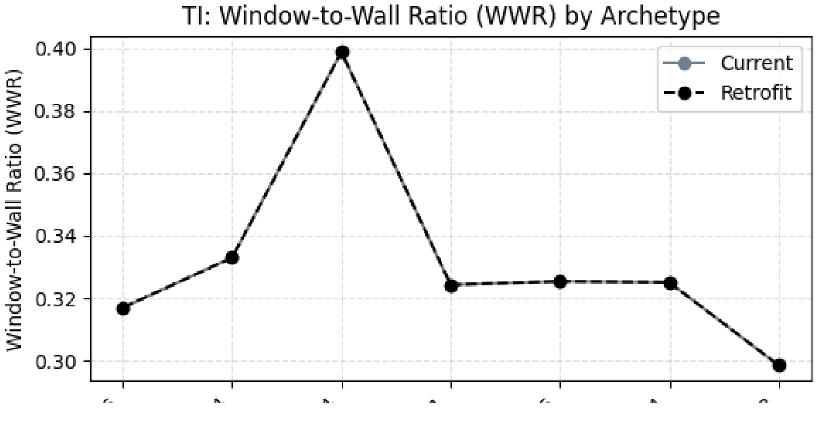








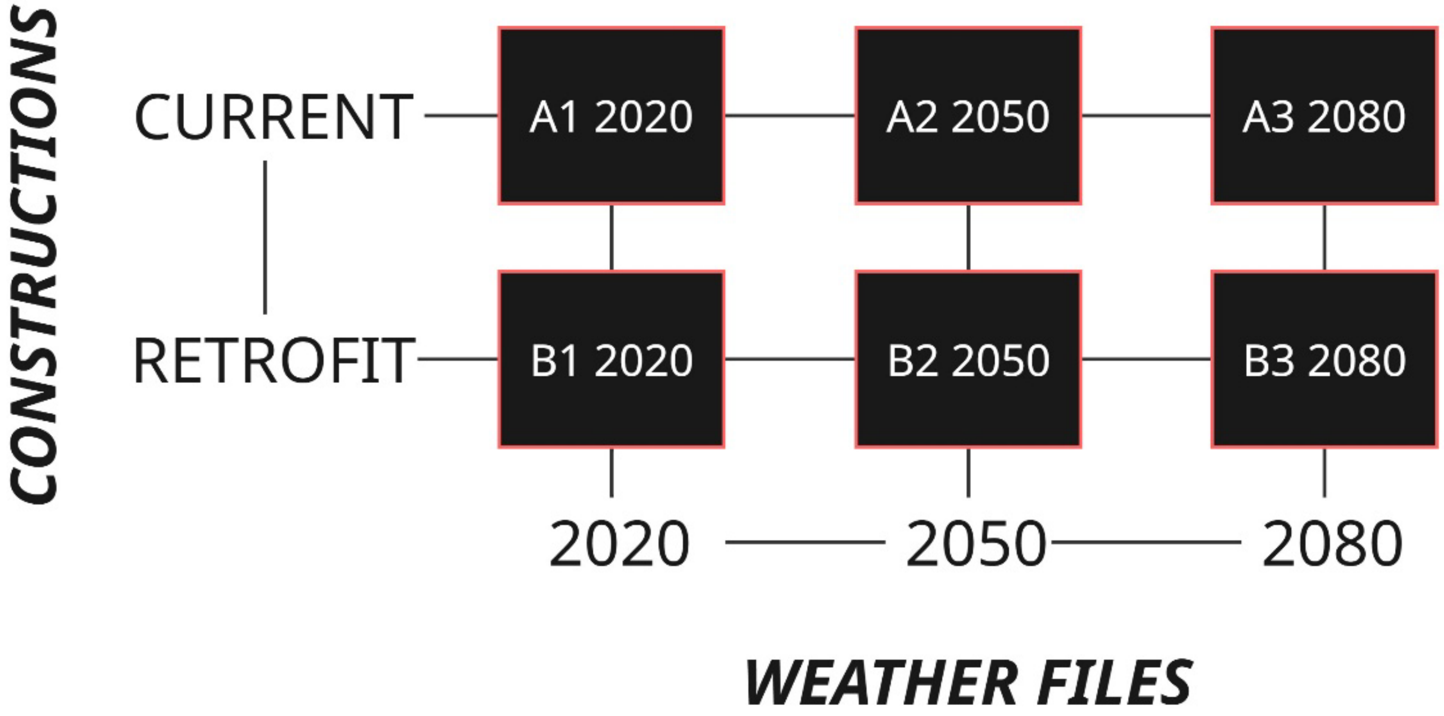




[10]

[2]

[9]



how do the energy demands for each archetype change in the future?

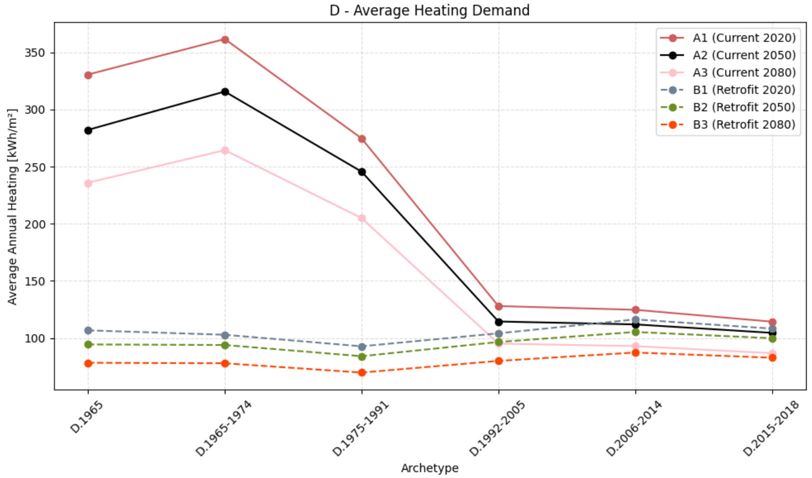
[10]

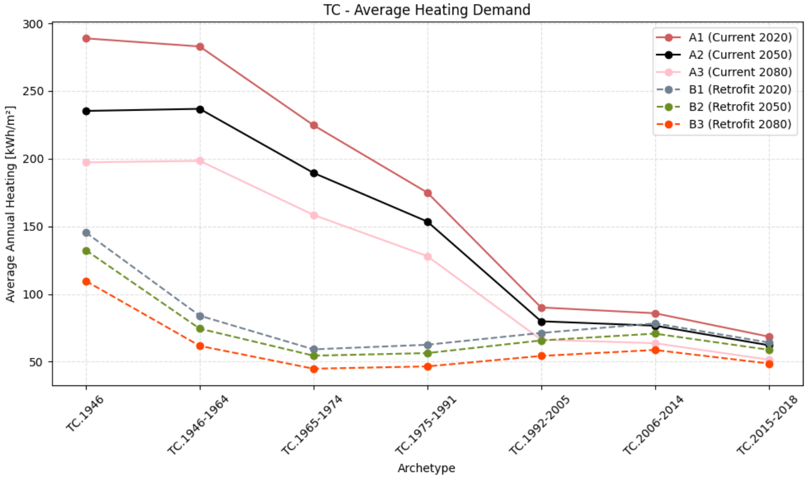
[2]

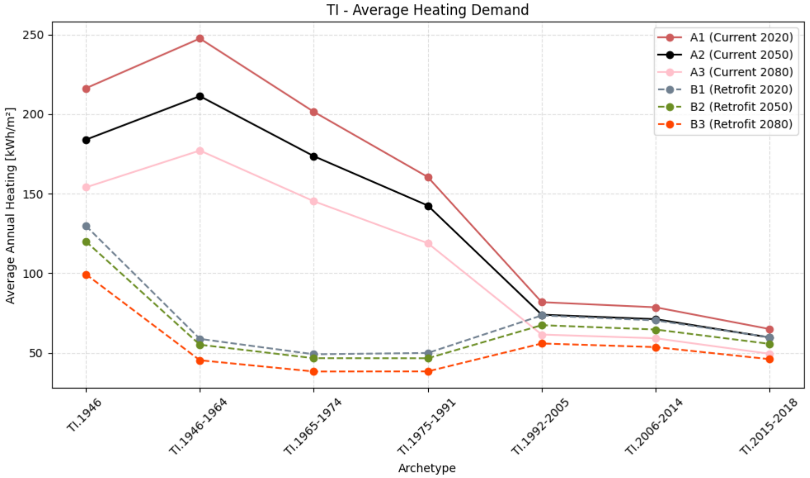
[9]

reduction in average heating demand when projecting to the 2050 and 2080 weather scenarios

(retrofit measures constant between 2020 future weather)







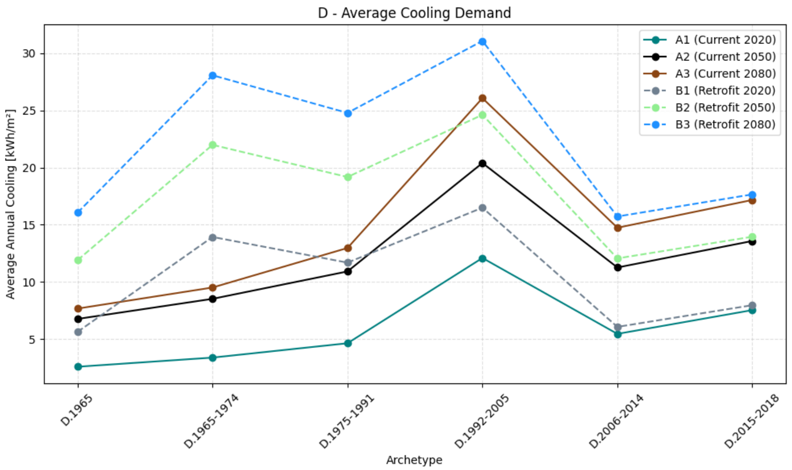
lowest heating demand for B3 (retrofit + 2080)

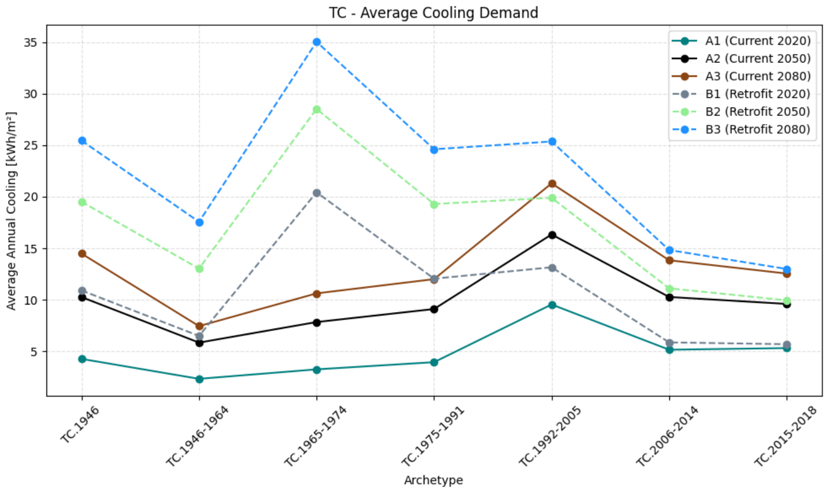
[10]

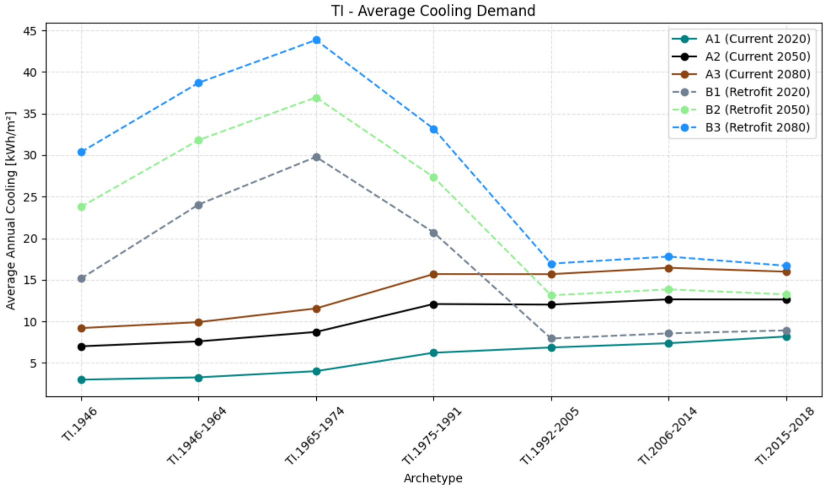
[2]

[9]

increase in average cooling demand under projected 2050 and 2080 weather scenarios.





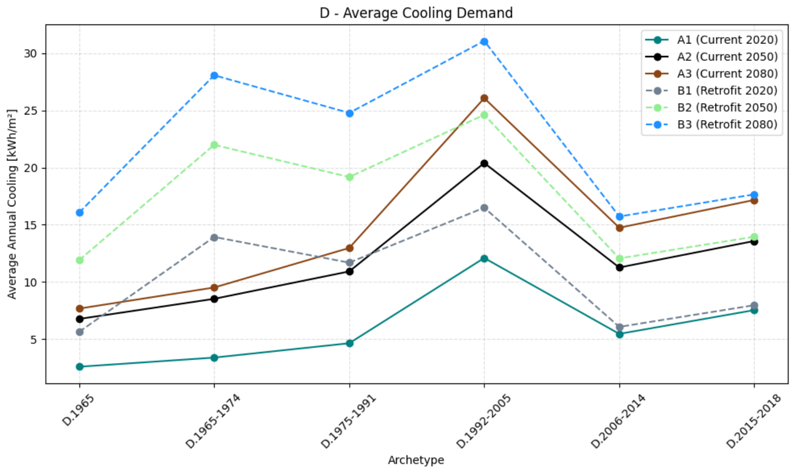


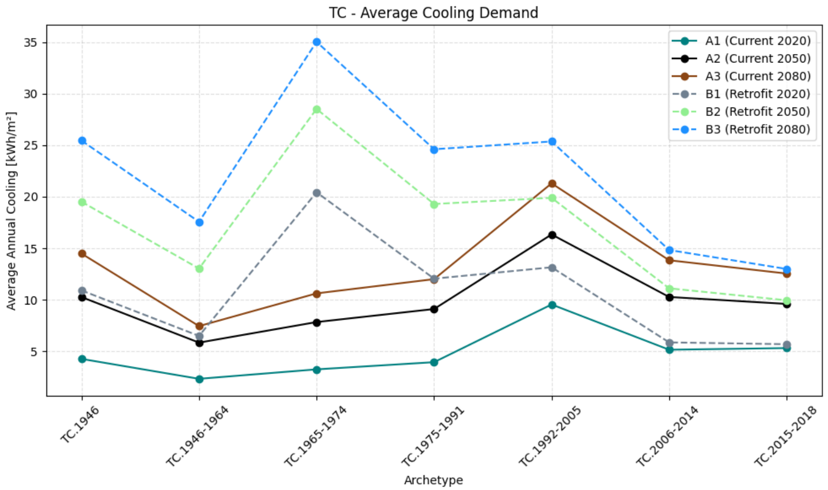
Unlike heating demand, where retrofits consistently reduce demand,
retrofit strategies results in an increased cooling demand.

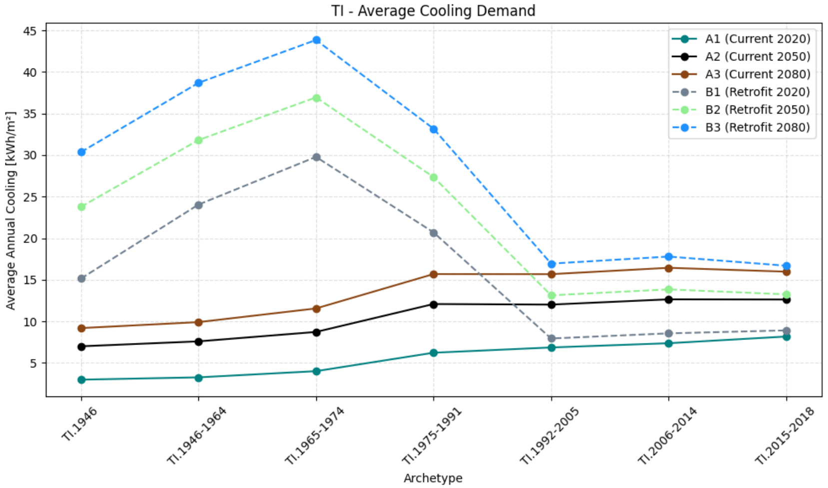
[10]

[2]

[9]







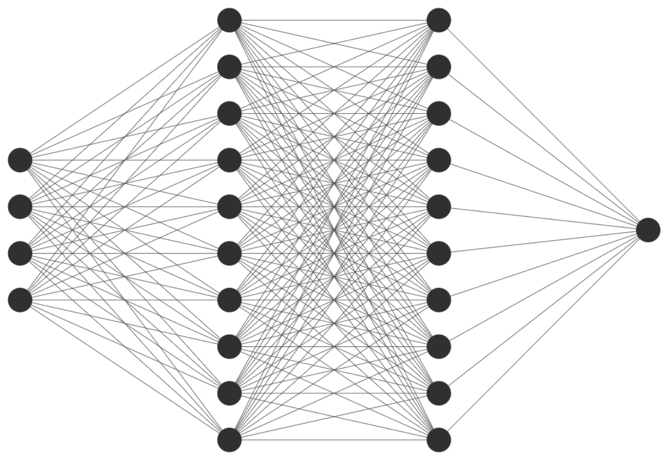
need to balance reductions in heating demand with mitigation of cooling loads

- ***can we use machine learning to predict these same energy demands?***

SIMULATIONS

[8] [7]

PREDICTION



COLLECT BUILDING + ENVIRONMENTAL DATA → GENERATE BUILDING ENERGY MODELS → ANALYZE ENERGY DEMANDS → PROCESS INPUT DATA FOR MACHINE LEARNING → TRAIN MODEL → EVALUATE PERFORMANCE

BUILDING ENERGY MODELLING

MACHINE LEARNING

BUILDING HEIGHT

BUILDING ORIENTATION

BUILDING VOLUME

NUMBER OF FLOORS

FLOOR AREA

WALL AREA

ROOF AREA

WINDOW AREA

INSULATIONS FLOOR

INSULATIONS ROOF

INSULAITIONS WALLS

U-VALUE WINDOWS

SOLAR

OUTDOOR TEMPERATURE

SOLAR RADIATION

WIND

HUMIDITY

BUILDING ENERGY MODELLING

[8] [7]

SIMULATIONS

HEATING DEAMND

COOLING DEMAND

replace
simulation engine
(EnergyPlus) with
prediction model

PREDICTION MODEL

BUILDING HEIGHT

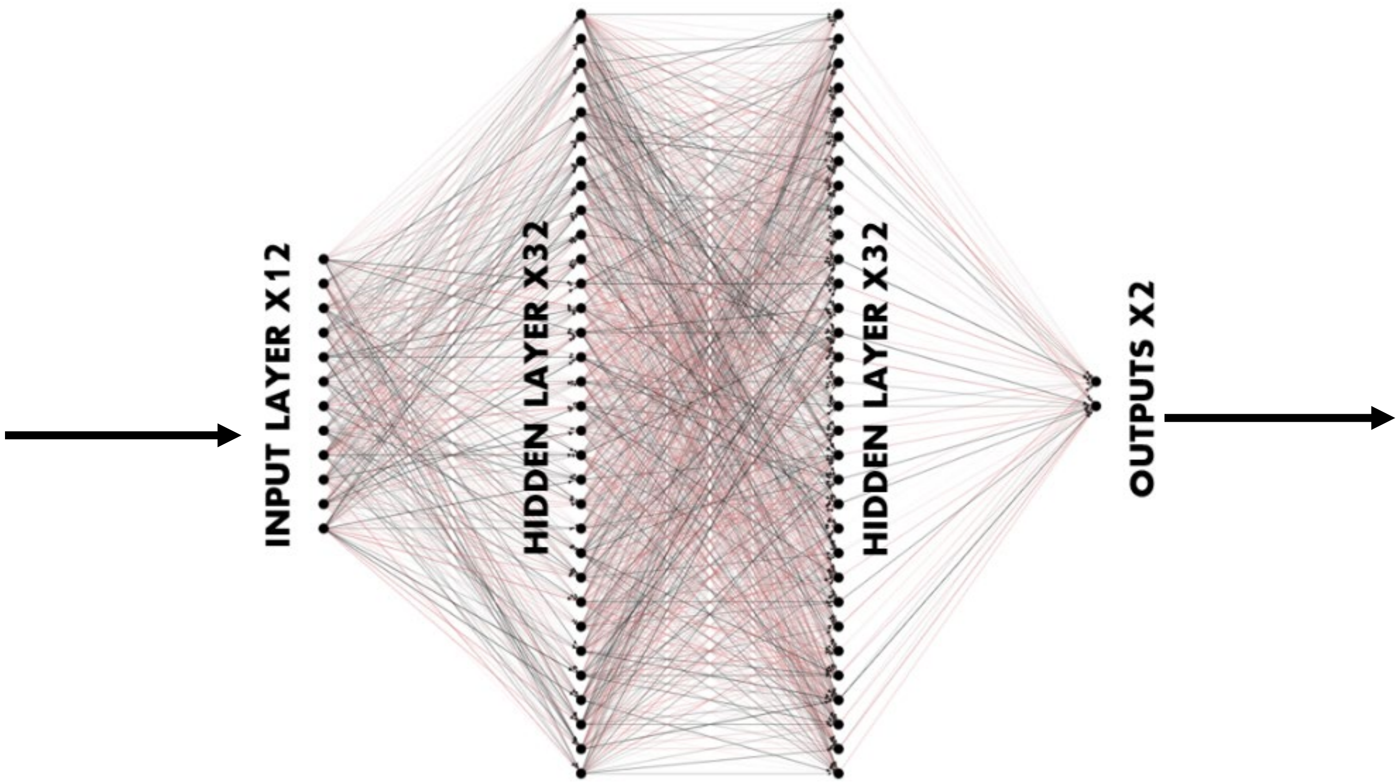
NUMBER OF FLOORS

FLOOR AREA

WALL AREA

INSULATIONS

OUTDOOR TEMPERATURE



HEATING DEAMND

COOLING DEMAND

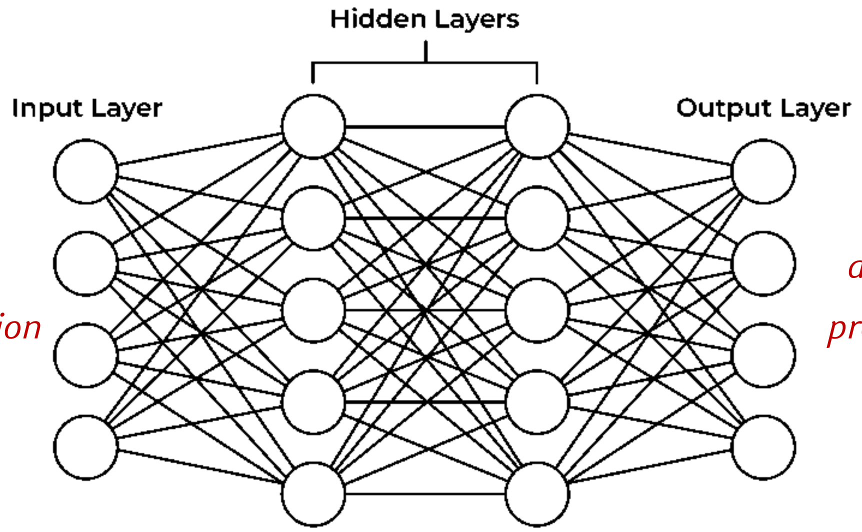
MACHINE LEARNING

ARTIFICIAL NEURAL NETWORK

ML model learn patterns and relationships in data to make predictions.

experts: analyze

generalists: collect information



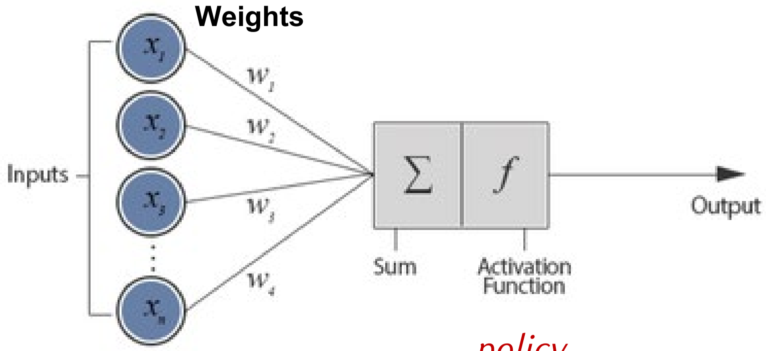
decision makers: produce final result

Neurons

team members

[16]

importance

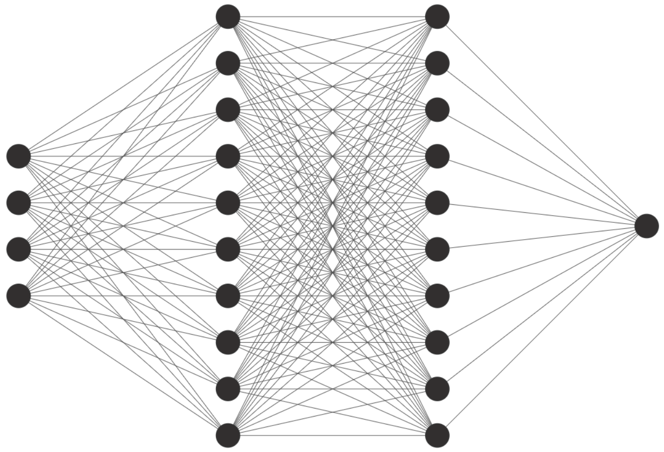


decision

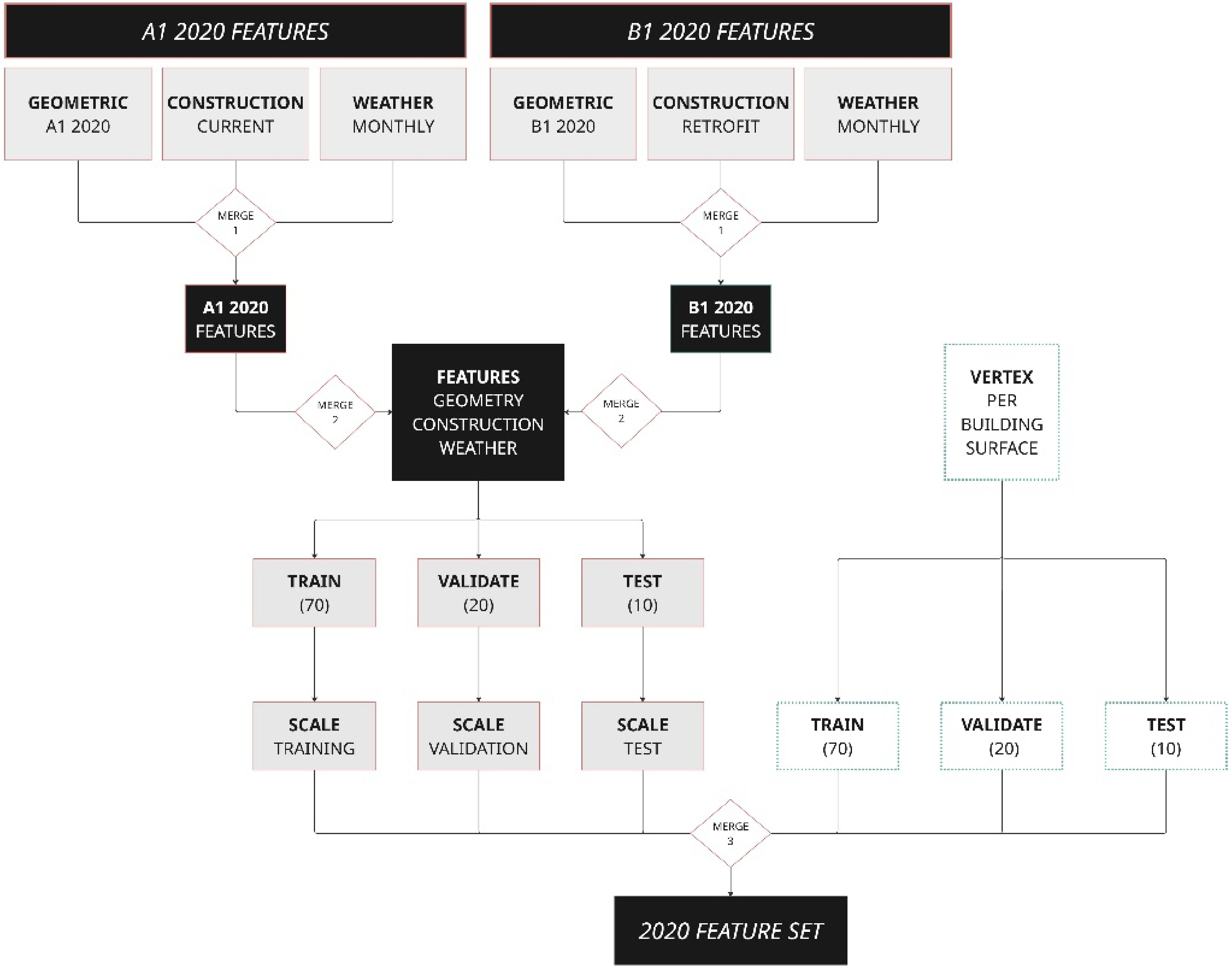
policy

[17]

PREDICTION



MACHINE LEARNING



DATA STRUCTURING WORKFLOW

1. MERGE GEOMETRIC CONSTRUCTION WEATHER FEATURES.
2. MERGE CURRENT / RETROFIT
3. SPLIT DATA
4. SCALE DATA
5. COMBINE WITH VERTEX DATA

geometric

Number of Floors	-
Wall Area	m^2
Roof Area (Flat)	m^2
Roof Area (Sloped)	m^2
Floor Area	m^2
Shared Wall Area	m^2
Building Height (70%)	m
Building Volume	m^3
Total Floor Area	m^2
Compactness Ratio	m^{-1}

constructions

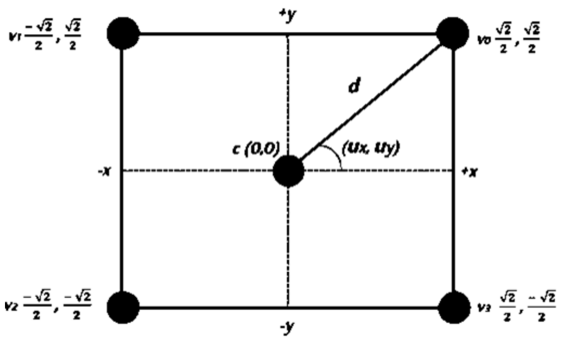
Ground Floor Insulation	m^2K/W
Facade Insulation	m^2K/W
Roof Insulation	m^2K/W
Infiltration	m^3/sm^2
Window to Wall Ratio (WWR)	m^2/m^2
U Factor (Windows)	W/m^2K
SHGC	-

temperature

Monthly average temperature	°C
Monthly average solar radiation	$kWh/m^2/day$

** constants. reserved for future weather training.*

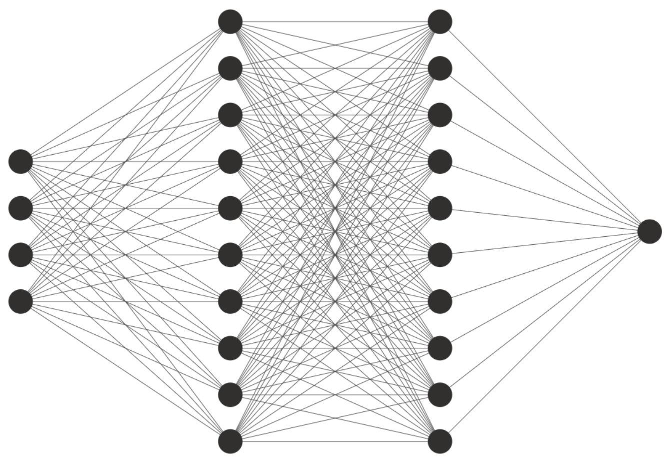
vertex features

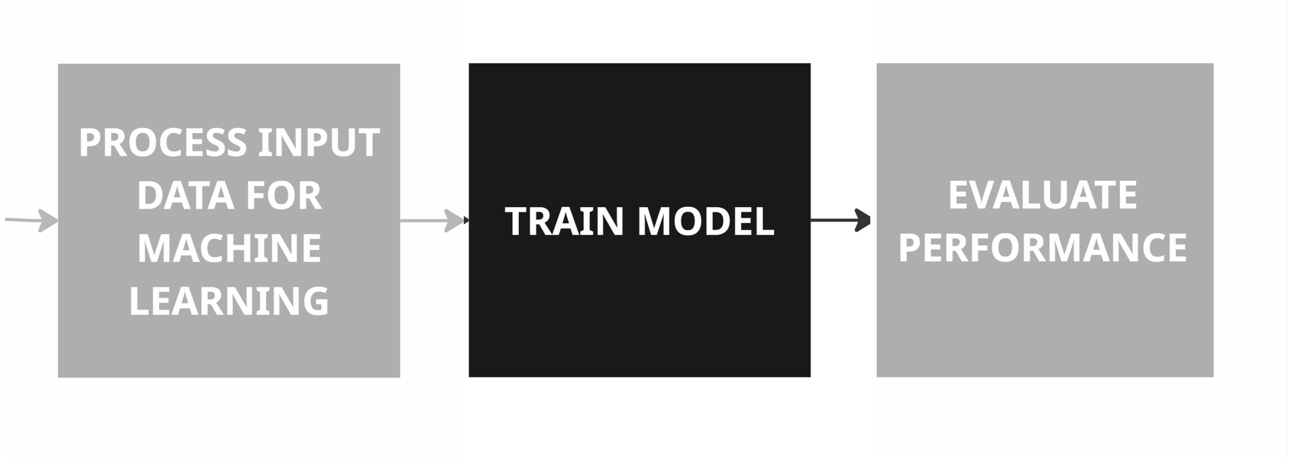


Distance (d) from centroid	-
Angle (u_x)	-
Angle (u_y)	-

Pand ID	Surface Index	Surface Type	d_1	ux_1	uy_1
0599100000013430	0	G	d_{G1}	ux_{G1}	uy_{G1}
0599100000013430	1	F	d_{F1}	ux_{F1}	uy_{F1}
0599100000013430	2	F	d_{F1}	ux_{F1}	uy_{F1}
0599100000013430	3	F	d_{F1}	ux_{F1}	uy_{F1}
0599100000013430	4	F	d_{F1}	ux_{F1}	uy_{F1}
0599100000013430	5	R	d_{R1}	ux_{R1}	uy_{R1}

PREDICTION





MACHINE LEARNING

[10]

NUMBER OF FLOORS

WALL AREA

SHARED WALL AREA

BUILDING HEIGHT

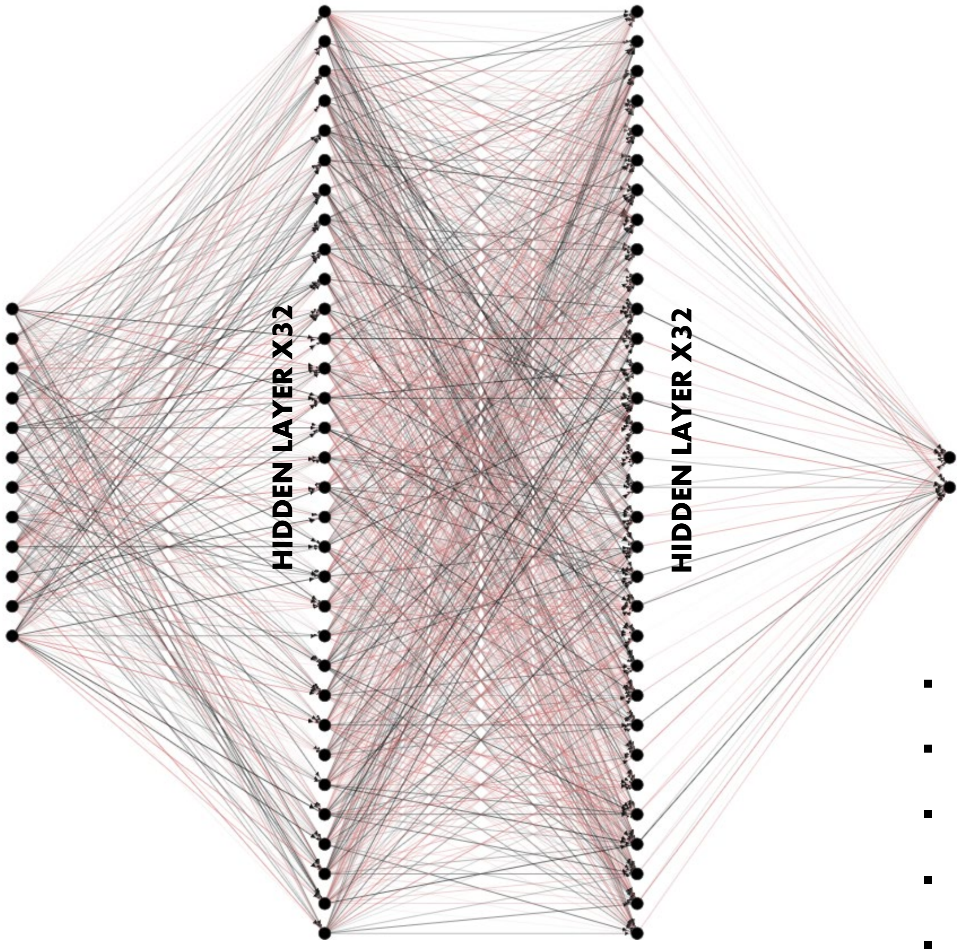
INSULATIONS

INFILTRATION

WWR

UFACTOR

SHGC



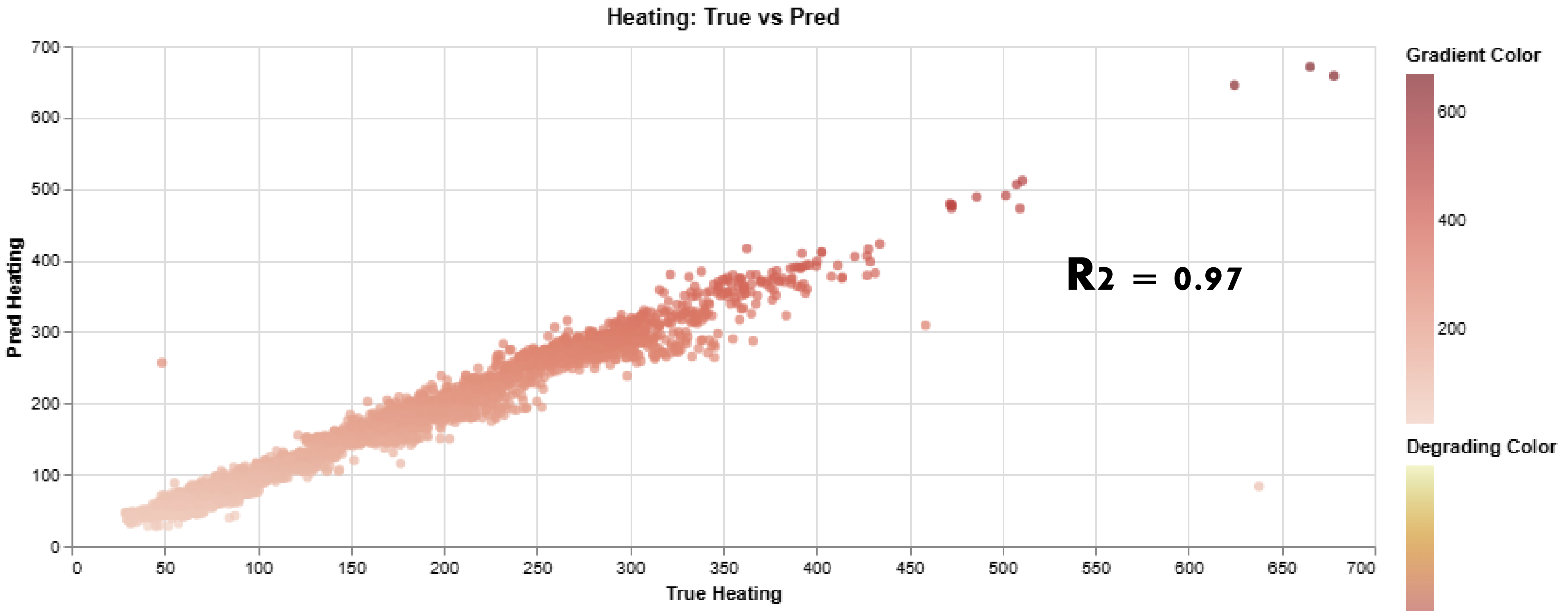
HEATING DEMAND

COOLING DEMAND

final model

- ***Training set size:*** *20,000 buildings*
- ***Learning rate:*** *1e-4*
- ***Hidden neurons per layer:*** *32*
- ***Epochs (max):*** *20,000*
- ***Early stopping patience:*** *400 epochs*
- ***Early stopping validation:*** *0.0 (strict improvement)*

Strong performance for heating predictions.



$R^2 = 0.97$

HEATING PREDICTION ERRORS					
RUN	EPOCH	RMSE	MAE	R2	MAPE
V4	9033	12.926	7.719	0.975	6.86%

final model

DETACHED *[10]*

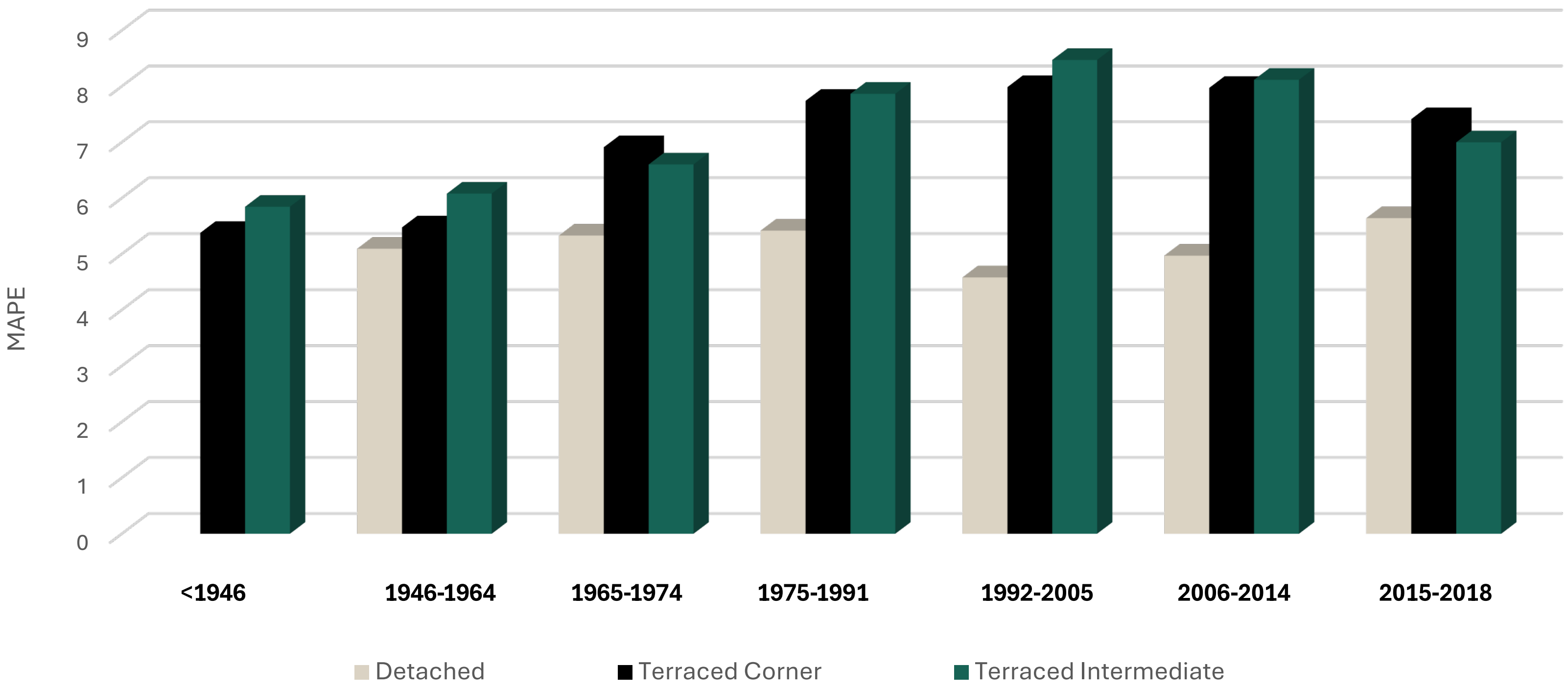
TERRACED CORNER *[2]*

TERRACED INTERMEDIATE *[9]*

Detached lowest MAPE between archetypes. median MAPE between 2-4%

Highest MAPE for Terraced Intermediate. Median MAPE between 5-6%

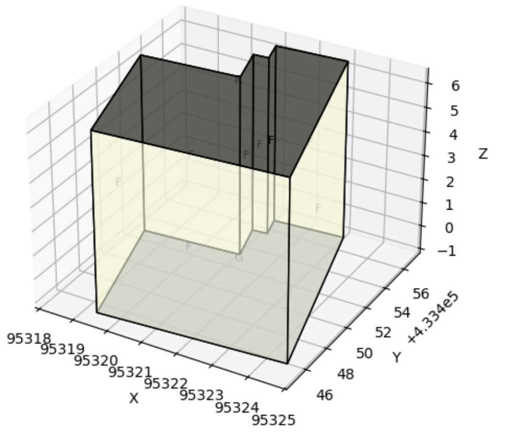
AVERAGE HEATING MAPE PER ARCHETYPE



TEST HEATING PREDICTION ERRORS

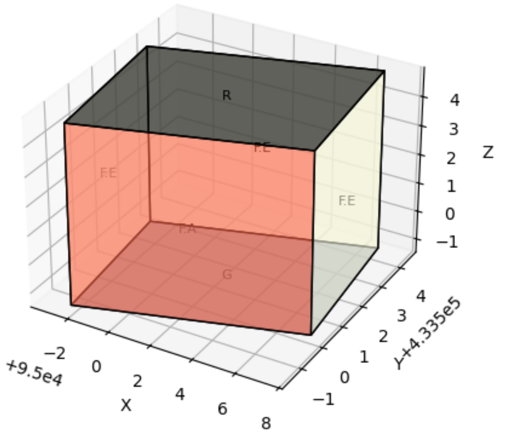
RUN	EPOCH	RMSE	MAE	R2	MAPE
V4	9033	12.926	7.719	0.975	6.86%

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - \hat{Y}_i\right|$$



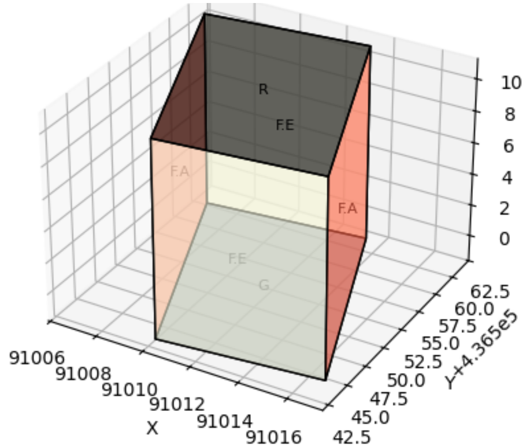
[10]

1000 buildings



[2]

11,000 buildings



[9]

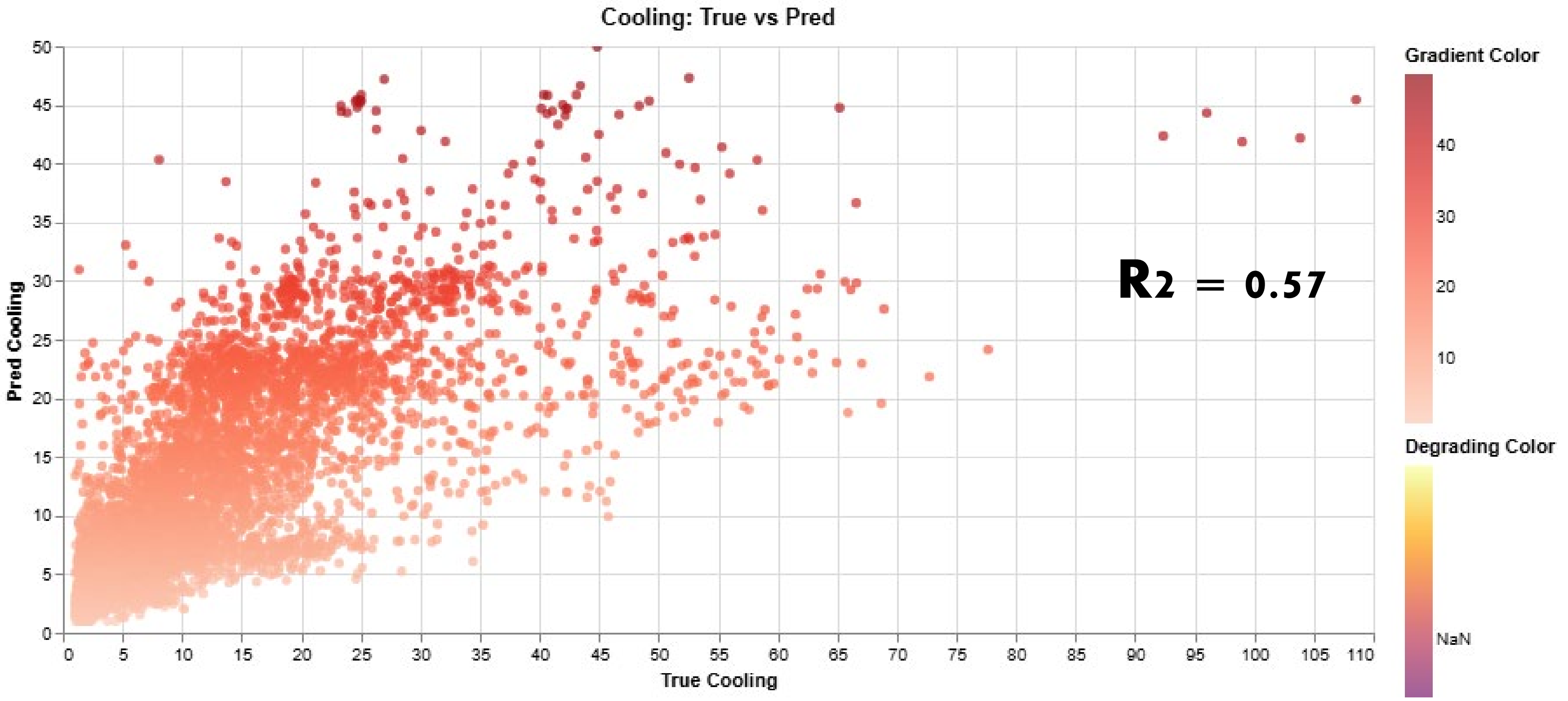
8,000 buildings

Detached, less represented, higher geometric complexity, but more accurate predictions?

- handling vertex data
- no adiabatic surfaces, more straightforward
- thermal performance closely related to wall area input feature

- terraced houses have multiple adiabatic wall surfaces
- only represented through shared wall area input feature
- relationships more complex

Moderate performance for cooling predictions.



R2 = 0.57

COOLING PREDICTION ERRORS					
RUN	EPOCH	RMSE	MAE	R2	MAPE
V4	9033	6.785	4.007	0.579	51.09%

DETACHED [10]

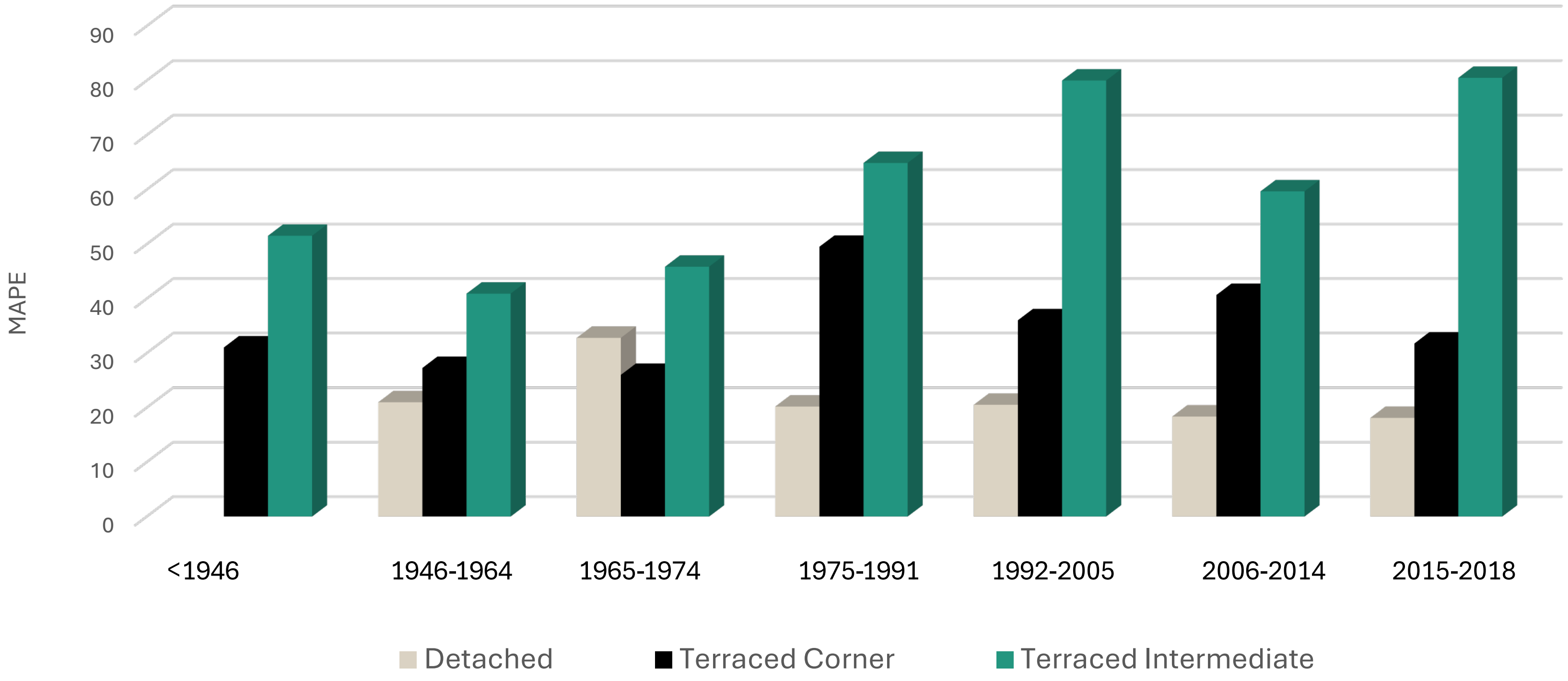
TERRACED CORNER [2]

TERRACED INTERMEDIATE [9]

Detached archetypes generally show the lowest median and spread in cooling MAPE

Terraced Intermediate showing highest MAPE and extremely high outliers.

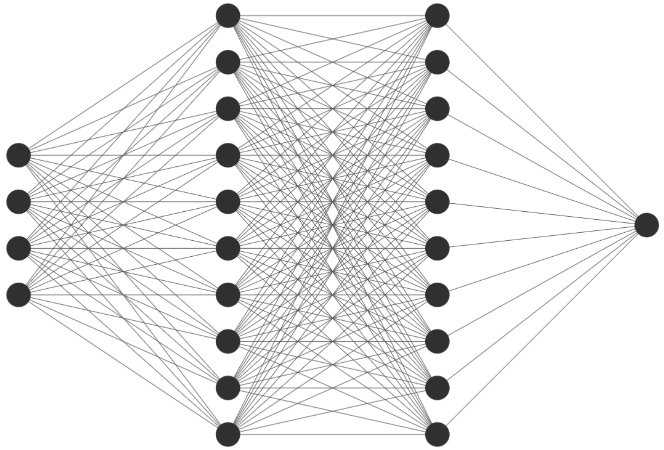
AVERAGE COOLING MAPE PER ARCHETYPE



COOLING PREDICTION ERRORS					
RUN	EPOCH	RMSE	MAE	R2	MAPE
V4	9033	6.785	4.007	0.579	51.09%

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - \hat{Y}_i\right|$$

PREDICTION

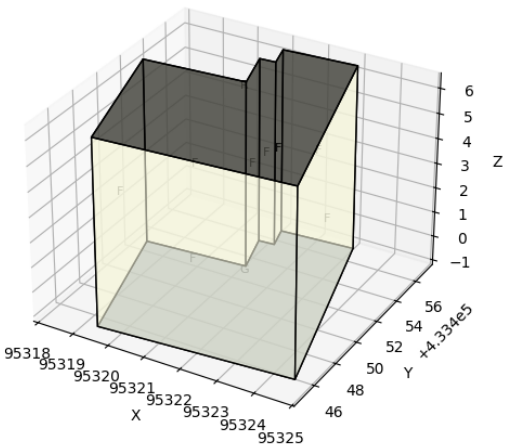


- ***why does the model struggle with cooling loads?***

MACHINE LEARNING

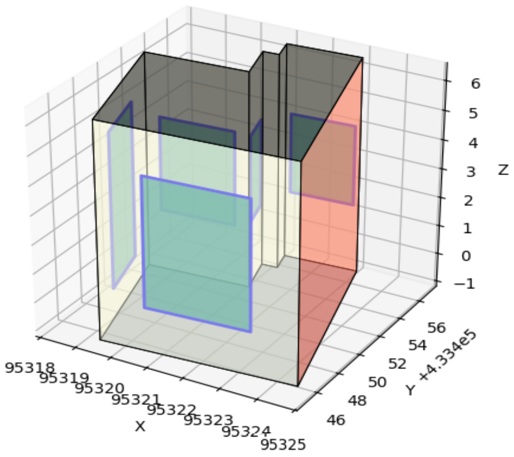
** before windows + adiabatic surfaces.*

SMALL DATA SETS
MINIMAL FEATURES
HYPERPARAMETERS
CURRENT VS. RETROFIT DISTINCTION
FEATURE STUDY



** after windows and adiabatic surfaces.*

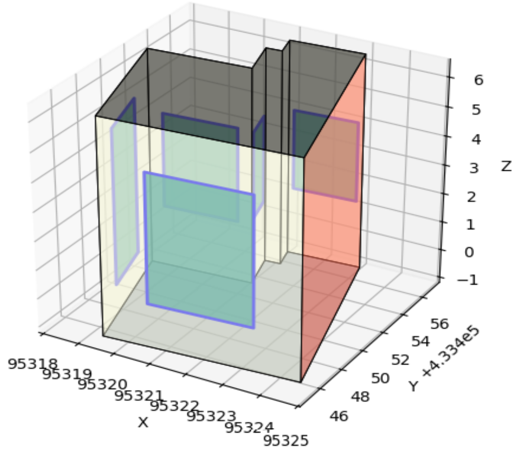
FEATURE STUDY
FINAL STUDY



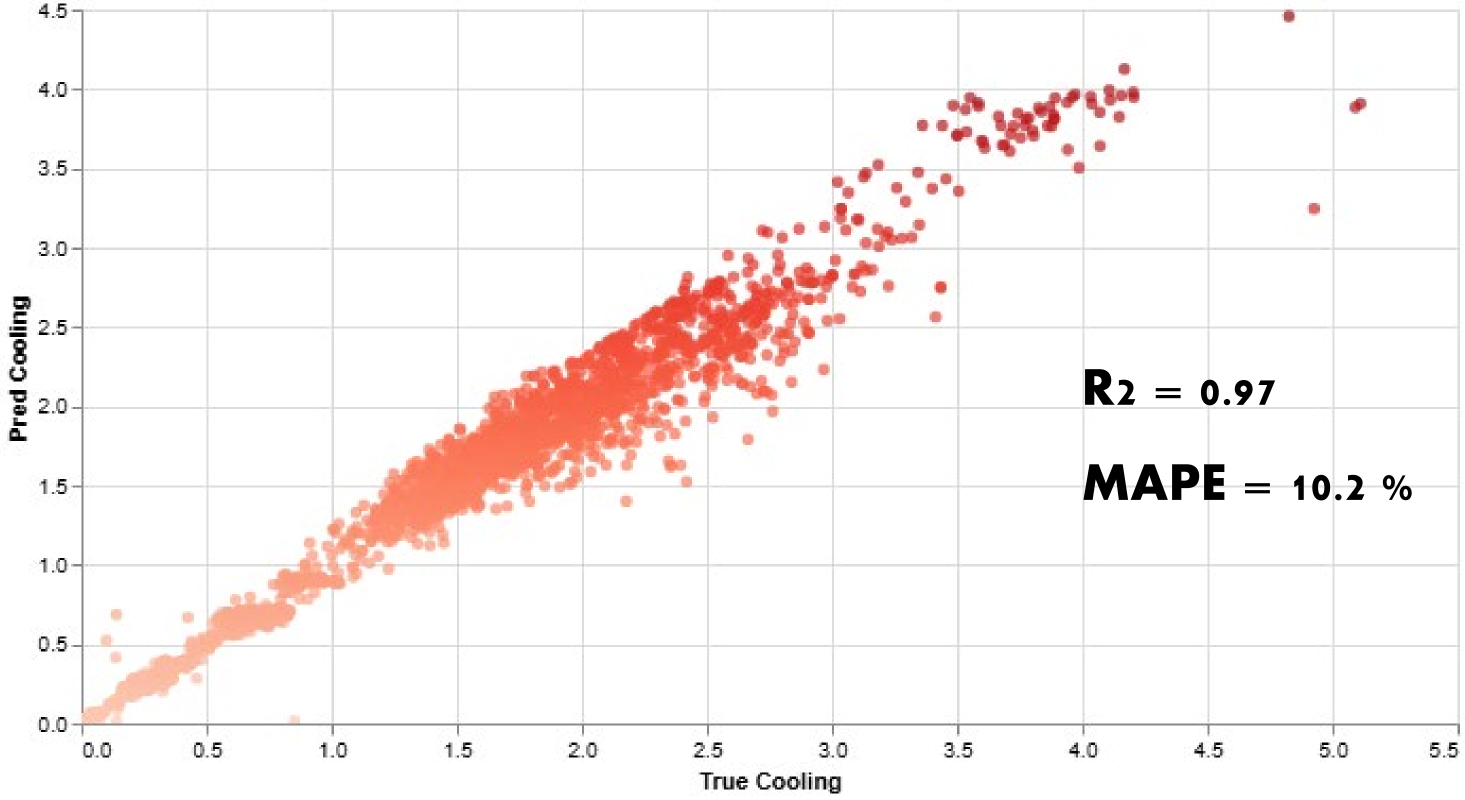
** after windows and adiabatic surfaces.*

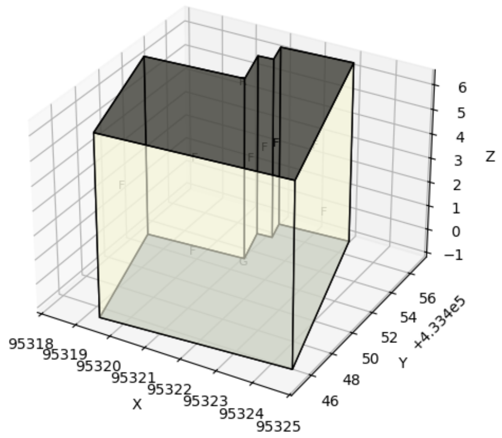
ADDED FEATURES

Shared wall area
Window to Wall Ratio (WWR)
U Factor (Windows)
SHGC



Strong predictions for cooling before windows, adiabatic surfaces.

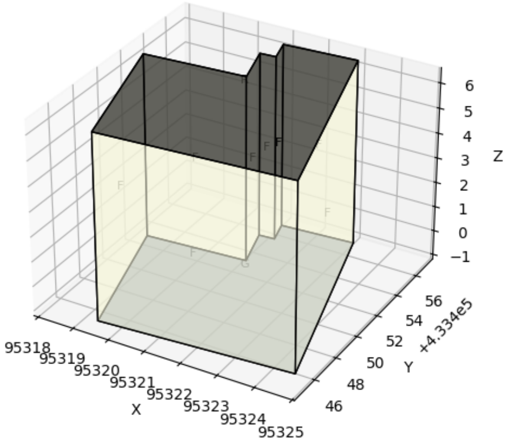




** before windows + adiabatic surfaces.*

Number of Floors	-
Wall Area	m^2
Floor Area	m^2
Building Height	m

Ground Floor Insulation	**m^2K/W**
Facade Insulation	m^2K/W
Roof Insulation	m^2K/W
Infiltration	m^3/sm^2

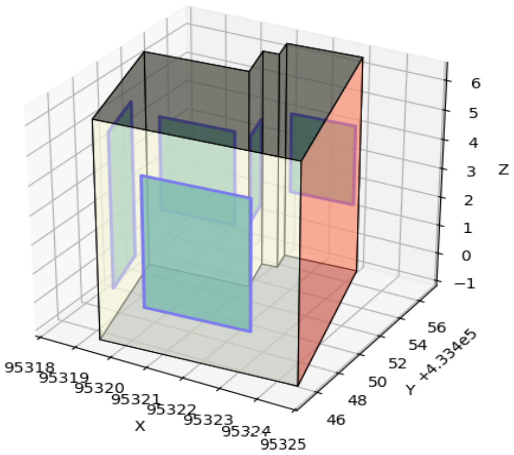


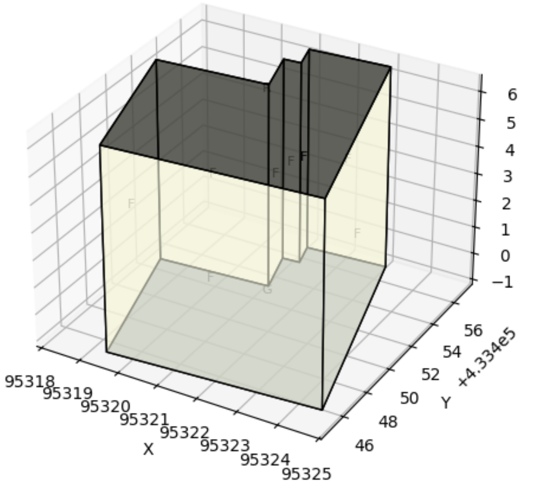
what are the differences in features?.

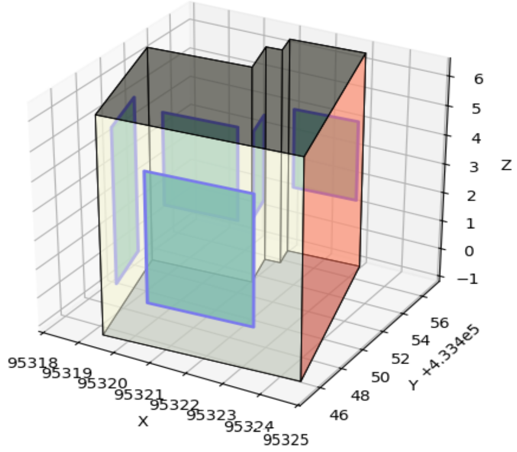
** after windows and adiabatic surfaces.*

Number of Floors	-
Wall Area	m^2
Floor Area	m^2
Shared Wall Area	m^2
Building Height	m

Ground Floor Insulation	**m^2K/W**
Facade Insulation	m^2K/W
Roof Insulation	m^2K/W
Infiltration	m^3/sm^2
Window to Wall Ratio (WWR)	m^2/m^2
U Factor (Windows)	W/m^2K
SHGC	-





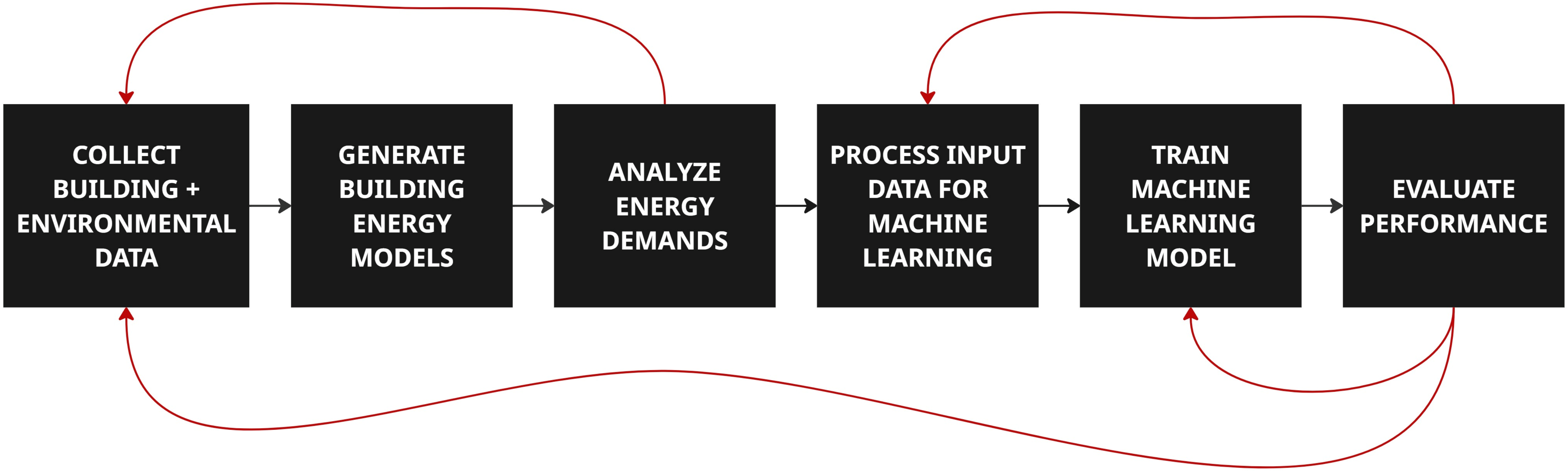


Reasons for poor cooling predictions.

1. Adiabatic surfaces are inferred through the shared wall area.
2. Terraced Intermediate houses have a higher WWR, introducing greater variability and complexity in cooling performance (added features U-value, solar heat gain).

- ***conclusions on methodology.***

COLLECT BUILDING + ENVIRONMENTAL DATA → GENERATE BUILDING ENERGY MODELS → ANALYZE ENERGY DEMANDS → PROCESS INPUT DATA FOR MACHINE LEARNING → TRAIN MACHINE LEARNING MODEL → EVALUATE PERFORMANCE


COLLECT BUILDING + ENVIRONMENTAL DATA
GENERATE BUILDING ENERGY MODELS
ANALYZE ENERGY DEMANDS
PROCESS INPUT DATA FOR MACHINE LEARNING
TRAIN MACHINE LEARNING MODEL
EVALUATE PERFORMANCE

How can ML be used to assess the impact of retrofit strategies across different building typologies?

IS THE MODEL ABLE TO PREDICT DIFFERENT ARCHETPES WITH ACCURACY ?

- Heating strong performance across all archetypes.
- Cooling predictions moderate. Poor prediction for terraced houses. Influenced by complexity of input features.

SUB QUESTION. / RETROFITS.

How can ML be used to assess the impact of retrofit strategies across different building typologies?

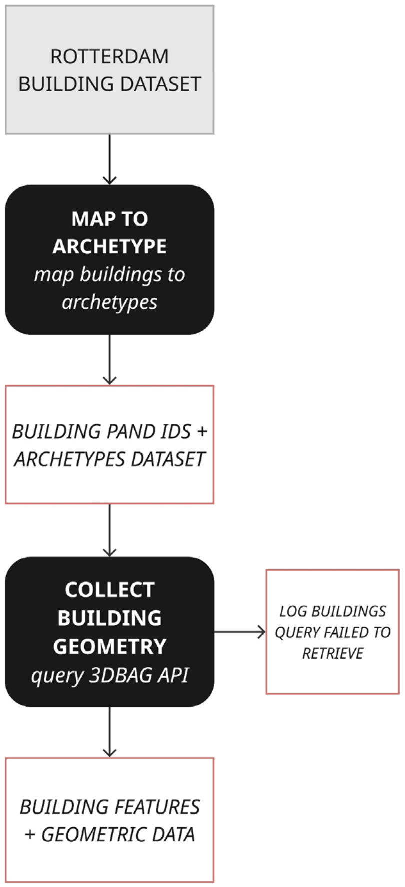
IS THE MODEL ABLE TO PREDICT GIVEN RANGE OF INPUT FEATURES RELATED TO RETROFITS?

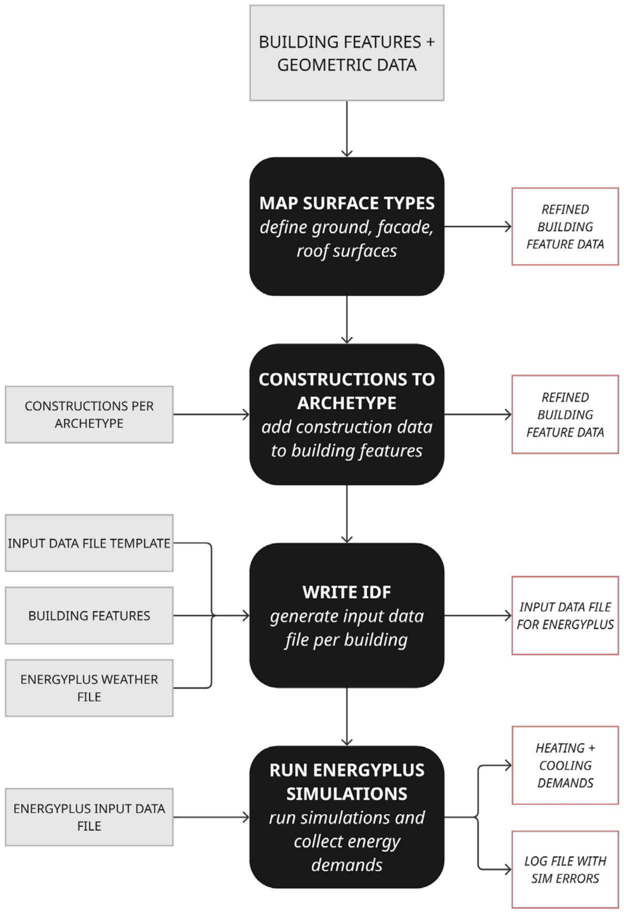
- Strong prediction when considering retrofits related to envelope air tightness, inputs governing envelope transmission and infiltration losses
  - **Rc and Infiltration**
- Cooling prediction accuracy drops when considering retrofit measures related to windows.
  - **U factor, SHGC**

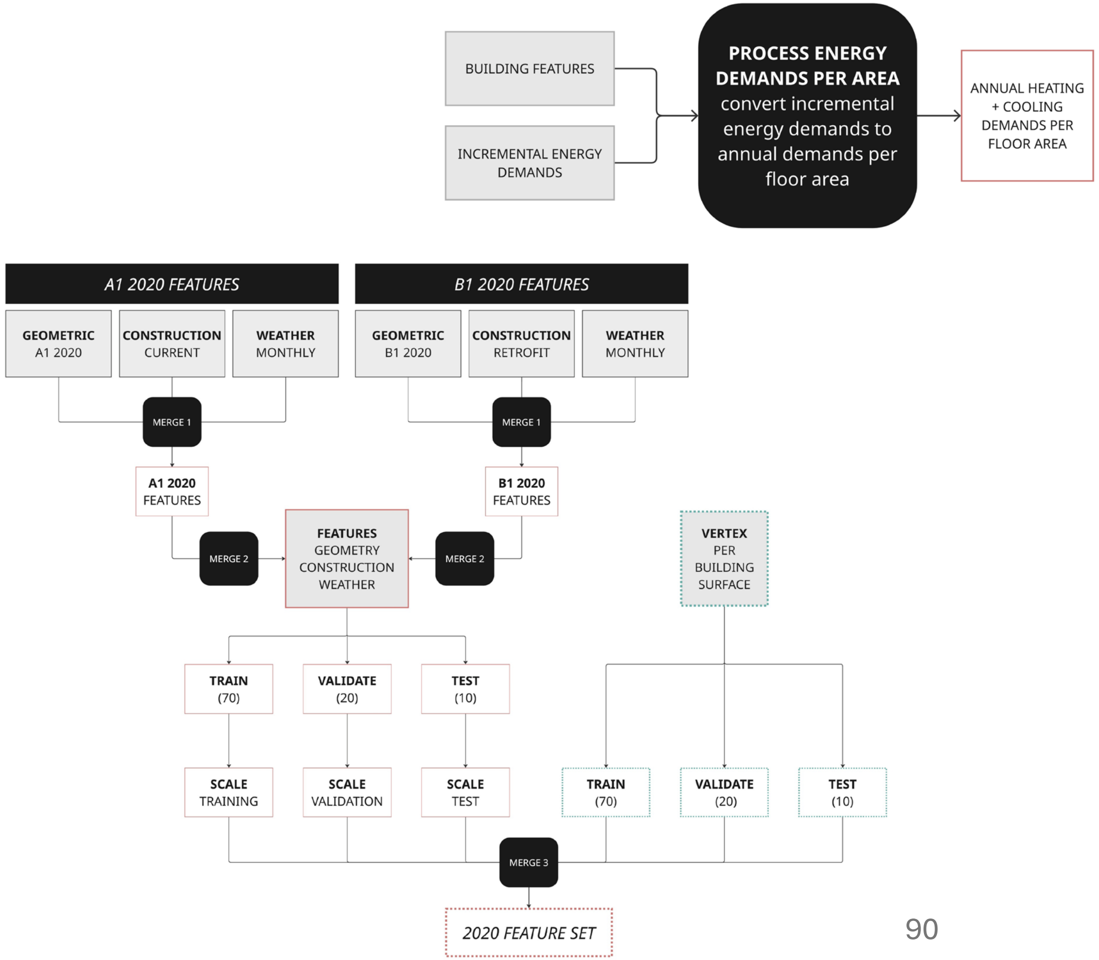
SUB QUESTION / AT CITY SCALE.

How can computational methods be leveraged for energy modelling at city-scale?

Collection, simulation, structuring, prediction, evaluation.





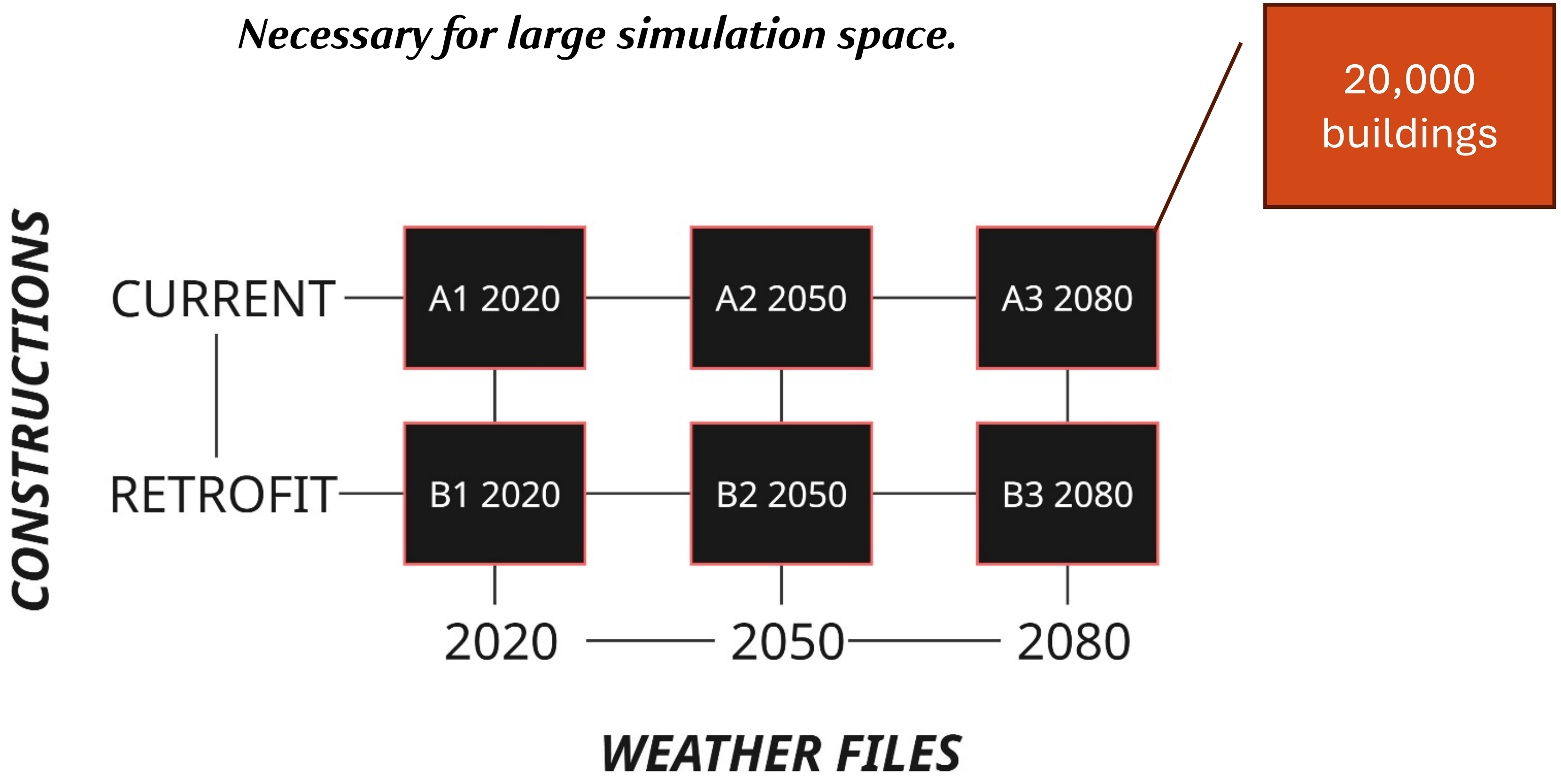


SUB QUESTION / AT CITY SCALE.

How can computational methods be leveraged for energy modelling at city-scale?

Collection, simulation, structuring, prediction, evaluation.

Necessary for large simulation space.



120,000 simulations

SUB QUESTION / MACHINE LEARNING.

How can ML models improve the efficiency of building energy modelling?

BUILDING HEIGHT

BUILDING ORIENTATION

BUILDING VOLUME

NUMBER OF FLOORS

FLOOR AREA

WALL AREA

ROOF AREA

WINDOW AREA

INSULATIONS FLOOR

INSULATIONS ROOF

INSULAITIONS WALLS

U-VALUE WINDOWS

SOLAR

OUTDOOR TEMPERATURE

SOLAR RADIATION

WIND

HUMIDITY

Many inputs for EnergyPlus simulation, time + computational intensity.

HEATING DEMAND

COOLING DEMAND

SUB QUESTION / MACHINE LEARNING.

How can ML models improve the efficiency of building energy modelling?

Reduced inputs and instant prediction.

NUMBER OF FLOORS

WALL AREA

SHARED WALL AREA

BUILDING HEIGHT

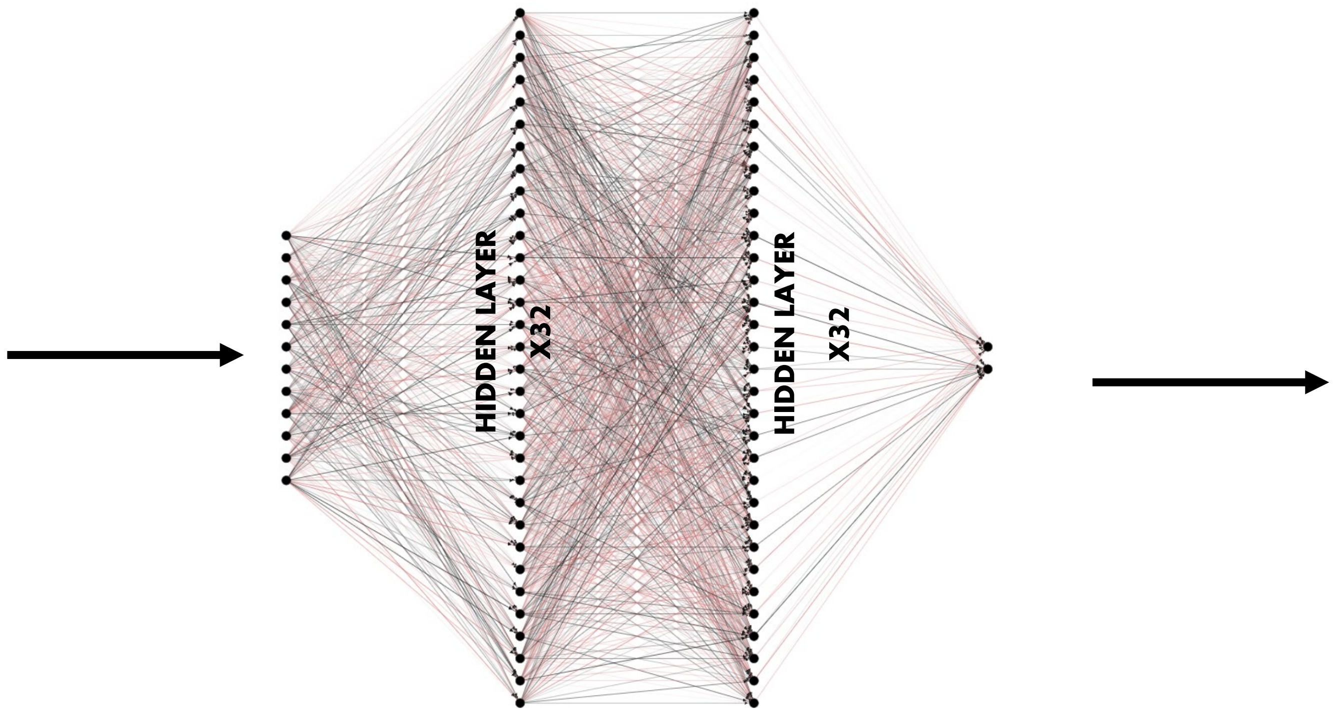
INSULATIONS

INFILTRATION

WWR

UFACTOR

SHGC



HEATING DEMAND

COOLING DEMAND

**** intensive data structuring process, training development.***

SUB QUESTION / MACHINE LEARNING.

What is an effective ML model (in terms of time efficiency, useability) for predicting building energy performance?

Artificial Neural Network.

- Relatively simply structure to set up with minimal lines of code.
- Performed strongly for heating predictions, moderate for cooling.
- Consideration for separate heating and cooling networks.

What are the limitations of ML models compared to traditional energy modelling?

Data.

- Amount of data required for training.
- Data structuring.
- Different models may need to be defined for heating and cooling, separate development process compared to EnergyPlus, where heating and cooling is all in one.

MAIN QUESTION.

How can machine learning be used to predict energy performance for residential buildings at city scale to reduce heating and cooling demands, considering future weather scenarios from climate change?

By ***automating the collection*** *of building geometry, generation of EnergyPlus input data files, and* ***training an artificial neural network with minimal layers****.*

Reduces *the* ***time and computational resources*** *needed from hours or days to run traditional EnergyPlus simulations to minutes when calling predictions from the surrogate model.*

THANK YOU.

[9] [2]

TU Delft Delft University of Technology

next.

next steps.

How can machine learning be used to predict energy performance for residential buildings at city scale to reduce heating and cooling demands, considering future weather scenarios from climate change?

Incorporating a broader range of Rc and infiltration values, enabling the ANN to generalize better to different retrofit scenarios.

next steps.

How can machine learning be used to predict energy performance for residential buildings at city scale to reduce heating and cooling demands, considering future weather scenarios from climate change?

- *ML prediction for future energy demands.*
- *To fully capture the impacts of climate change, the weather input features need to be further explored.*
- *Change input features from average monthly temperatures and solar radiations to cooling degree days, heating degree days, and seasonal global horizontal irradiance.*

next steps.

How can machine learning be used to predict energy performance for residential buildings at city scale to reduce heating and cooling demands, considering future weather scenarios from climate change?

Representing input features including adiabatic surfaces and vertices to more accurately represent boundary conditions and geometries.

model improvements.

Cooling predictions:

- small range of current cooling demands.
- min-max compression: network sees little difference in scaled values (0-1)
- log-transforming the cooling values before training compresses the range of cooling values and dominance of large cooling values. Reduced skew ideally allows the model to better predict both high and low values.

Architecture:

- heating dominates network (broader range).
- 32 neurons to approximate two very different functions.

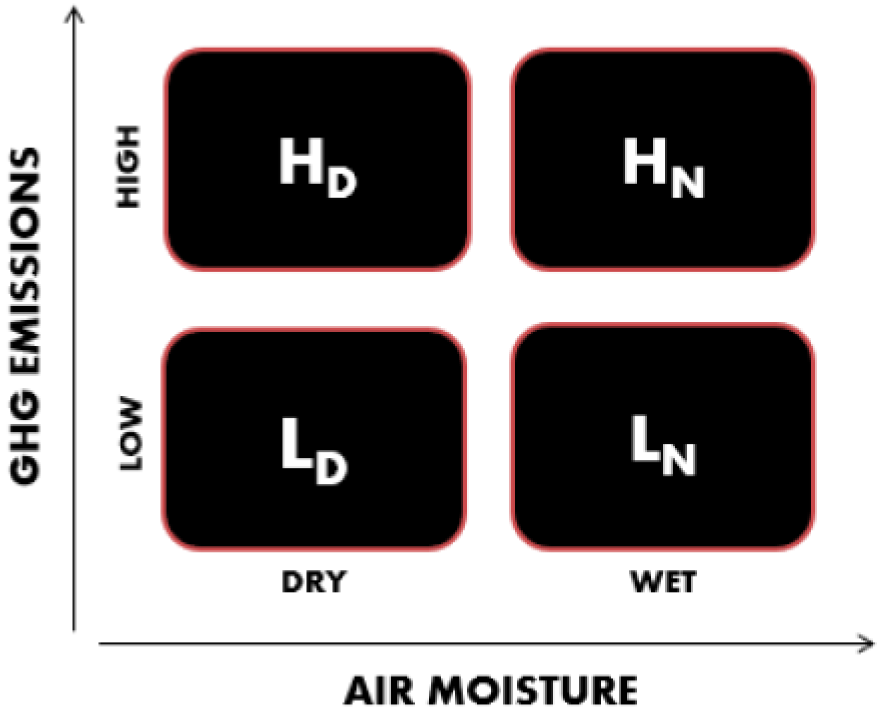
Range of Rc:

- For more recent construction periods, data for wall/floor/roof insulation and infiltration is the same for current and retrofit scenarios.

** **data structuring for merging surface data**

FEATURE SET A		
Geometry	**Weather**	**Constructions**
Number of Floors	Average annual temperature [°C]	Ground floor insulation [m^2K/W]
Wall Area [m^2]	Average annual radiation [$kWh/m^2/day$]	Façade insulation [m^2K/W]
Roof Area (Flat) [m^2]		Roof insulation [m^2K/W]
Floor Area [m^2]		Infiltration [m^3/sm^2]
Roof Area (Sloped) [m^2]		
Shared Wall Area [m^2]		
Absolute Height (70%) [m]		
Building Volume [m^3]		
Total floor area [m^2]		
Compactness ratio [m^{-1}]		
Vertices		

Pand ID	Surface Index	Surface Type	d_1	ux_1	uy_1
0599100000013430	0	G	d_{G1}	ux_{G1}	uy_{G1}
0599100000013430	1	F	d_{F1}	ux_{F1}	uy_{F1}
0599100000013430	2	F	d_{F1}	ux_{F1}	uy_{F1}
0599100000013430	3	F	d_{F1}	ux_{F1}	uy_{F1}
0599100000013430	4	F	d_{F1}	ux_{F1}	uy_{F1}
0599100000013430	5	R	d_{R1}	ux_{R1}	uy_{R1}



HIGH EMISSIONS (H) emissions increase sharply until 2080. Global warming of 4.9°C around 2100.

LOW EMISSIONS (L) emissions reduced to limit global warming below 2.0°C. Global warming of 1.7°C around 2100.

WET SCENARIO (N) Winters become very wet. Summers become slightly dry.

DRY SCENARIO (D) Winters become slightly wetter, summers become extremely dry.

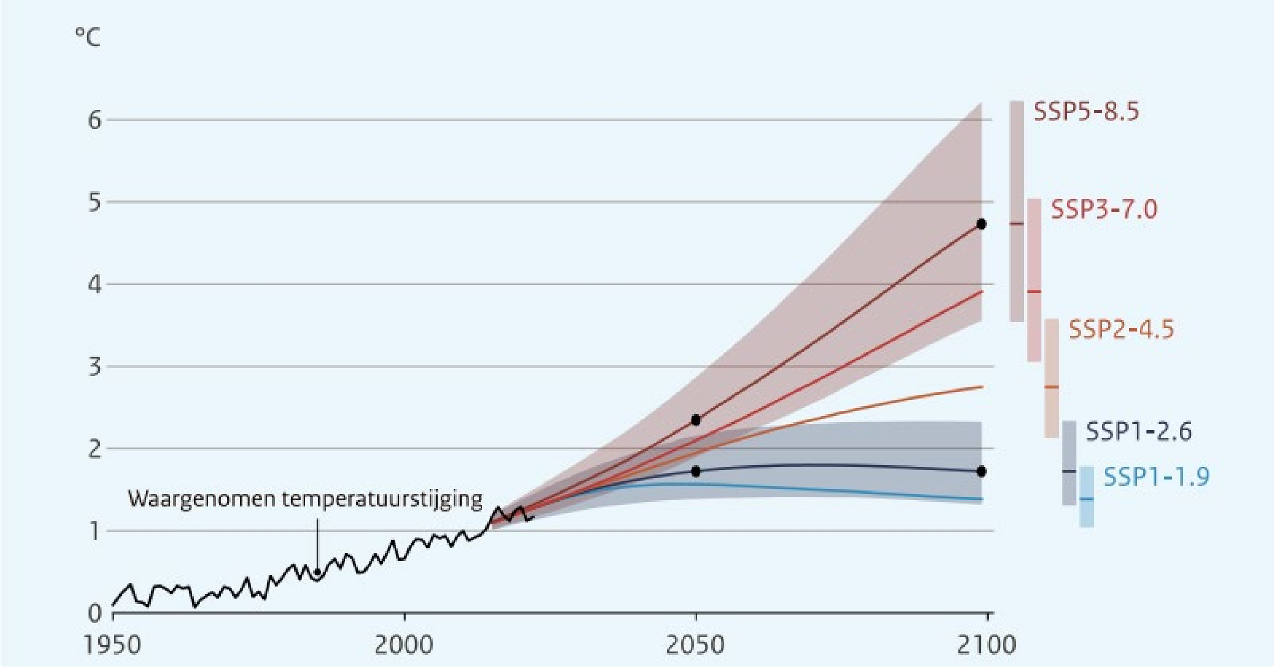
KNMI future climate scenarios.

KNMI future climate scenarios.

Season	Variable	Indicator	Climate in 1991-2020 = reference period	2050 (2036-2065)				2100 (2086-2115)			
				Ld	Ln	Hd	Hn	Ld	Ln	Hd	Hn
Spring	Temperature	average	9.6°C	+0.8°C	+0.7°C	+1.3°C	+1.1°C	+0.8°C	+0.7°C	+3.6°C	+3.3°C
		average daily maximum	13.7°C	+0.9°C	+0.8°C	+1.2°C	+1.0°C	+0.9°C	+0.8°C	+3.3°C	+2.9°C
		average daily minimum	5.5°C	+0.7°C	+0.7°C	+1.4°C	+1.3°C	+0.7°C	+0.7°C	+3.9°C	+3.7°C
	Precipitation	amount	153 mm	+1%	+3%	0%	+4%	+1%	+3%	+4%	+10%
	Solar radiation	average	161 W/m^2	+6.6 W/m^2	+5.2 W/m^2	+3.2 W/m^2	+0.8 W/m^2	+6.6 W/m^2	+5.2 W/m^2	-0.2 W/m^2	-4.8 W/m^2
	Humidity	average relative humidity [2]	78%	-1%	-1%	0%	0%	-1%	-1%	+1%	+2%
	Evaporation	potential evaporation (Makkink)	190 mm	+6%	+5%	+6%	+4%	+6%	+5%	+10%	+6%
	Drought	maximum precipitation deficit April and May	76 mm	+11%	+6%	+15%	+5%	+11%	+6%	+21%	+8%
	Wind	average wind speed	4.7 m/s	-0.1 m/s	-0.1 m/s	0.0 m/s	0.0 m/s	-0.1 m/s	-0.1 m/s	+0.1 m/s	0.0 m/s
Summer	Temperature	average	17.3°C	+1.2°C	+1.1°C	+2.1°C	+1.7°C	+1.2°C	+1.1°C	+5.1°C	+4.7°C
		average daily maximum	21.7°C	+1.4°C	+1.2°C	+2.2°C	+1.7°C	+1.4°C	+1.2°C	+5.4°C	+4.7°C
		average daily minimum	12.9°C	+1.0°C	+1.0°C	+1.9°C	+1.8°C	+1.0°C	+1.0°C	+5.0°C	+4.9°C
	Precipitation	amount	235 mm	-8%	-2%	-13%	-5%	-8%	-2%	-29%	-12%
		1-day total precipitation exceeded once every 10 years [4]	63 mm [3]	+4 (1-6)%	+5 (2-7)%	+6 (2-9)%	+9 (5-14)%	+4 (1-6)%	+5 (2-7)%	+15 (5-26)%	+26 (12-41)%
		hourly precipitation exceeded once per year [4]	16 mm [3]	+4 (2-6)%	+6 (3-8)%	+6 (2-9)%	+11 (6-16)%	+4 (2-6)%	+6 (3-8)%	+15 (5-26)%	+31 (17-46)%
	Solar radiation	average	206 W/m^2	+12 W/m^2	+9.1 W/m^2	+14 W/m^2	+7.4 W/m^2	+12 W/m^2	+9.1 W/m^2	+24 W/m^2	+11 W/m^2
	Humidity	average relative humidity [2]	77%	-2%	-1%	-2%	-1%	-2%	-1%	-4%	-1%
	Evaporation	potential evaporation (Makkink)	286 mm	+8%	+6%	+11%	+7%	+8%	+6%	+22%	+14%
	Drought	maximum precipitation deficit for April-September	160 mm	+22%	+13%	+35%	+15%	+22%	+13%	+79%	+37%
		maximum precipitation deficit for April-September exceeded once every 10 years	265 mm	+16%	+9%	+30%	+16%	+16%	+9%	+63%	+30%
	Wind	average wind speed	4.2 m/s	-0.1 m/s	-0.1 m/s	-0.1 m/s	-0.1 m/s	-0.1 m/s	-0.1 m/s	-0.2 m/s	-0.2 m/s

[3]

KNMI scenarios are based on the IPCC's global framework of Shared Socioeconomic Pathways, (SSPs), which result in different global greenhouse gas trajectories and temperature increases.



[3]

The SSP scenario with the highest emissions (SSP5-8.5) was taken for the high emission scenario (H). This scenario will result in 2.4 and 4.9°C of global warming by 2050 and 2100 respectively. The distribution in the coloured bands represents the uncertainty in climate sensitivity.

EPW R Package

1. **Pick a baseline EPW**

2. **Choose a climate projection**
an emissions pathway (SSP1-2.6, SSP2-4.5, SSP5-8.5, ...) AND future time-slice such as the 2050s.

3. **Shift the hourly weather**
For each variable epwshiftr computes the monthly delta (additive) between the future and historical climatology, applies it hour-by-hour to the baseline EPW.

4. **Write the future EPW(s)**

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