Decarbonizing residential building energy use - demand reduction optimization under uncertainty

Jan Hensen

www.tue.nl/en/research/researchers/jan-hensen/

Technische Universiteit Eindhoven University of Technology

Design stage residential energy demand reduction optimization under uncertainty ....

- Context
- Simulation based parametric optimization
- Uncertainties – and how relevant
- Simulation based robustness analysis
- Design vs operations optimization
- Conclusions

Challenges – Netherlands context

- EU and NL 2030 - 2050 decarbonization goals
- NL 6 million residences/houses from different periods and corresponding building (energy) regulations
- Various renovation (energy efficiency) needs
- 60% owner occupied; 40% rental

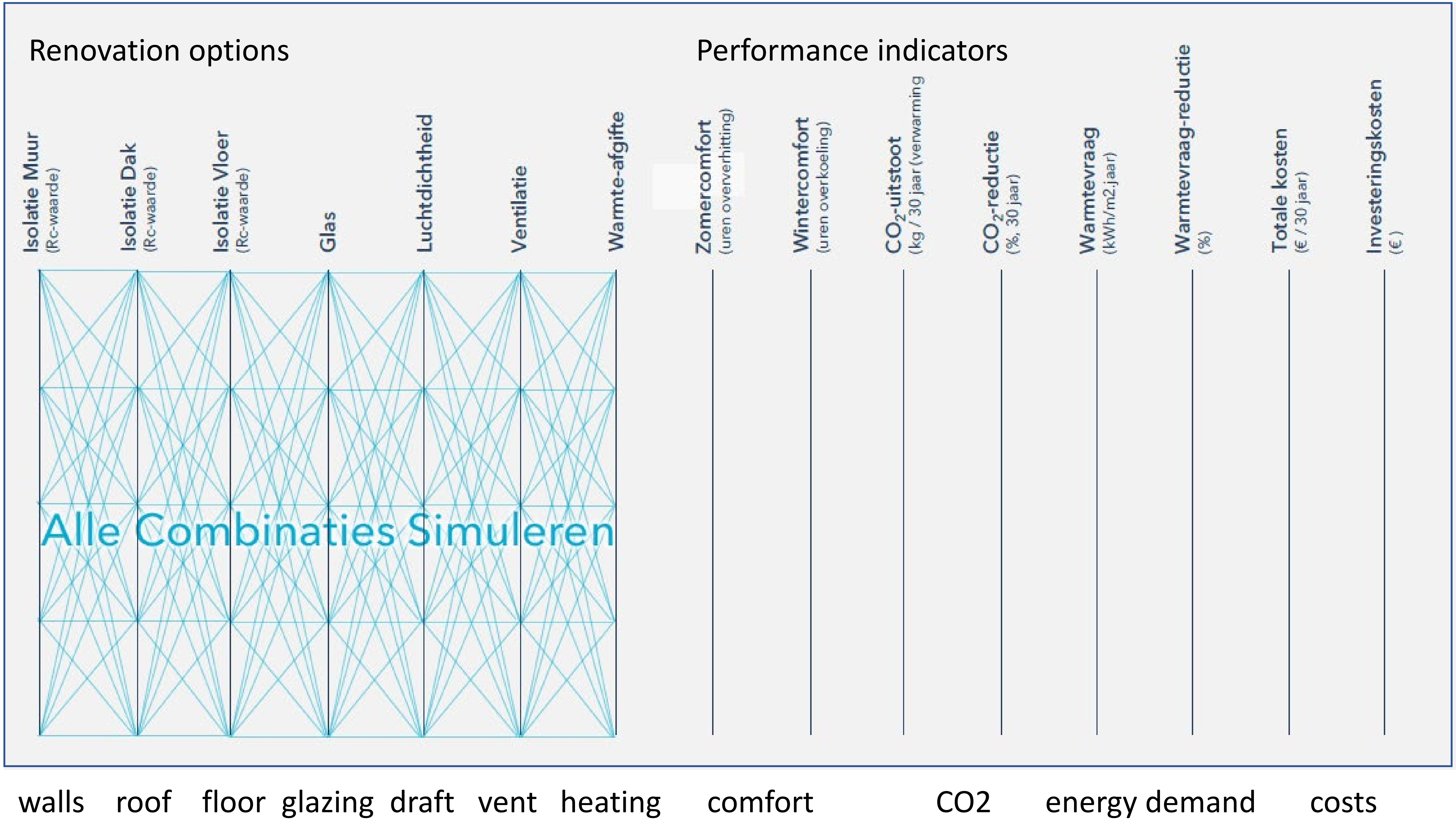
- What are optimal renovation solutions ?

NL housing stock renovation

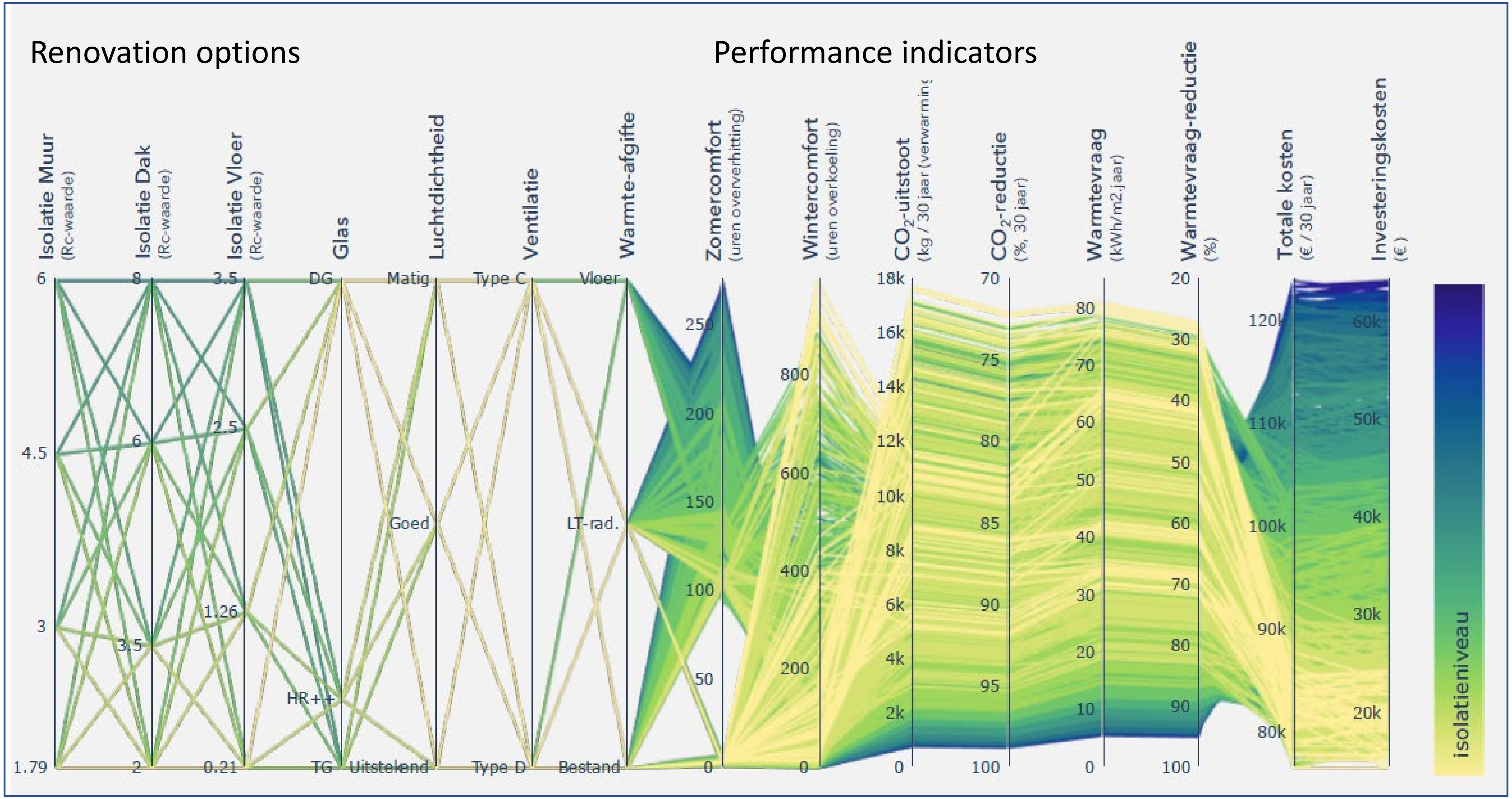
- Simulation based decision support
- “Classic” parametric optimization

- Typical Dutch house example:
  - Various shell renovation options
  - Various heating systems options
  - 3 Occupant behavior profiles

  - Cost-optimal solutions

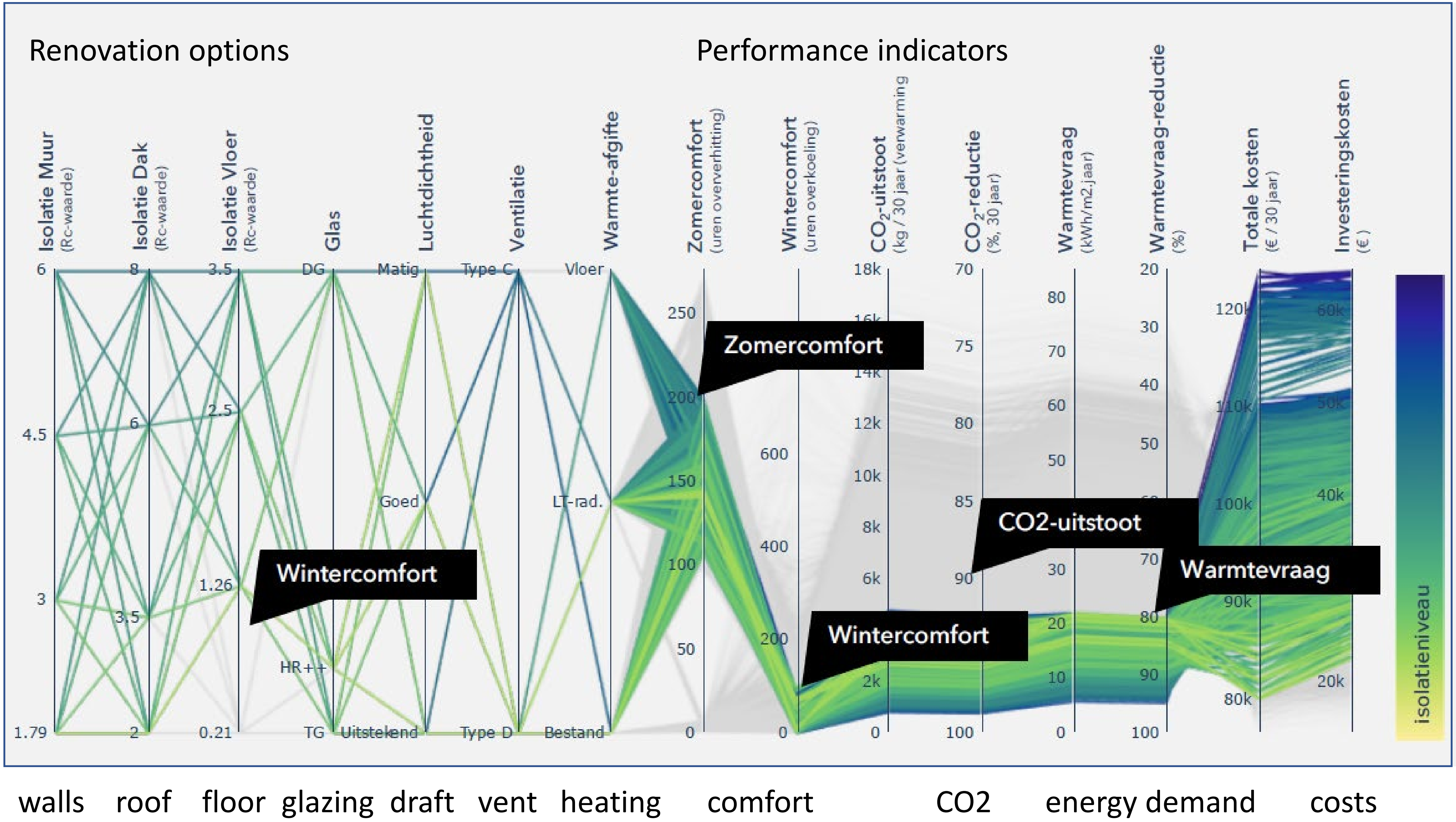


Renovation options
Performance indicators
Isolatie Muur (Rc-waarde)
Isolatie Dak (Rc-waarde)
Isolatie Vloer (Rc-waarde)
Glas
Luchtdichtheid
Ventilatie
Warmte-afgifte
Zomercomfort (uren oververhitting)
Wintercomfort (uren overkoeling)
CO2-uitstoot (kg / 30 jaar (verwarming
CO2-reductie (%, 30 jaar)
Warmtevraag (kWh/m2.jaar)
Warmtevraag-reductie (%)
Totale kosten (€ / 30 jaar)
Investeringskosten (€)
Alle Combinaties Simuleren
walls
roof
floor
glazing
draft
vent
heating
comfort
CO2
energy demand
costs

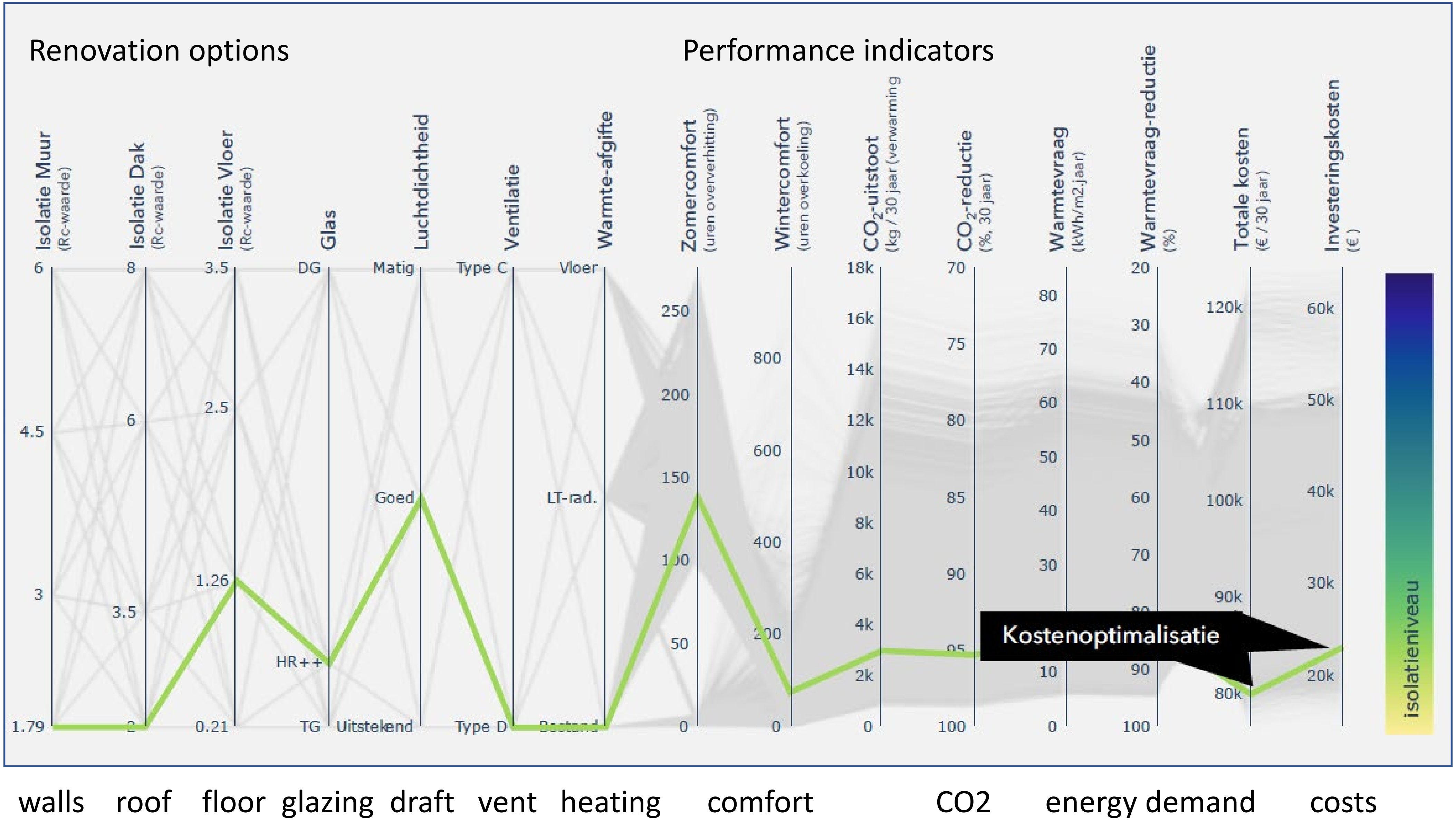


walls roof floor glazing draft vent heating comfort CO2 energy demand costs

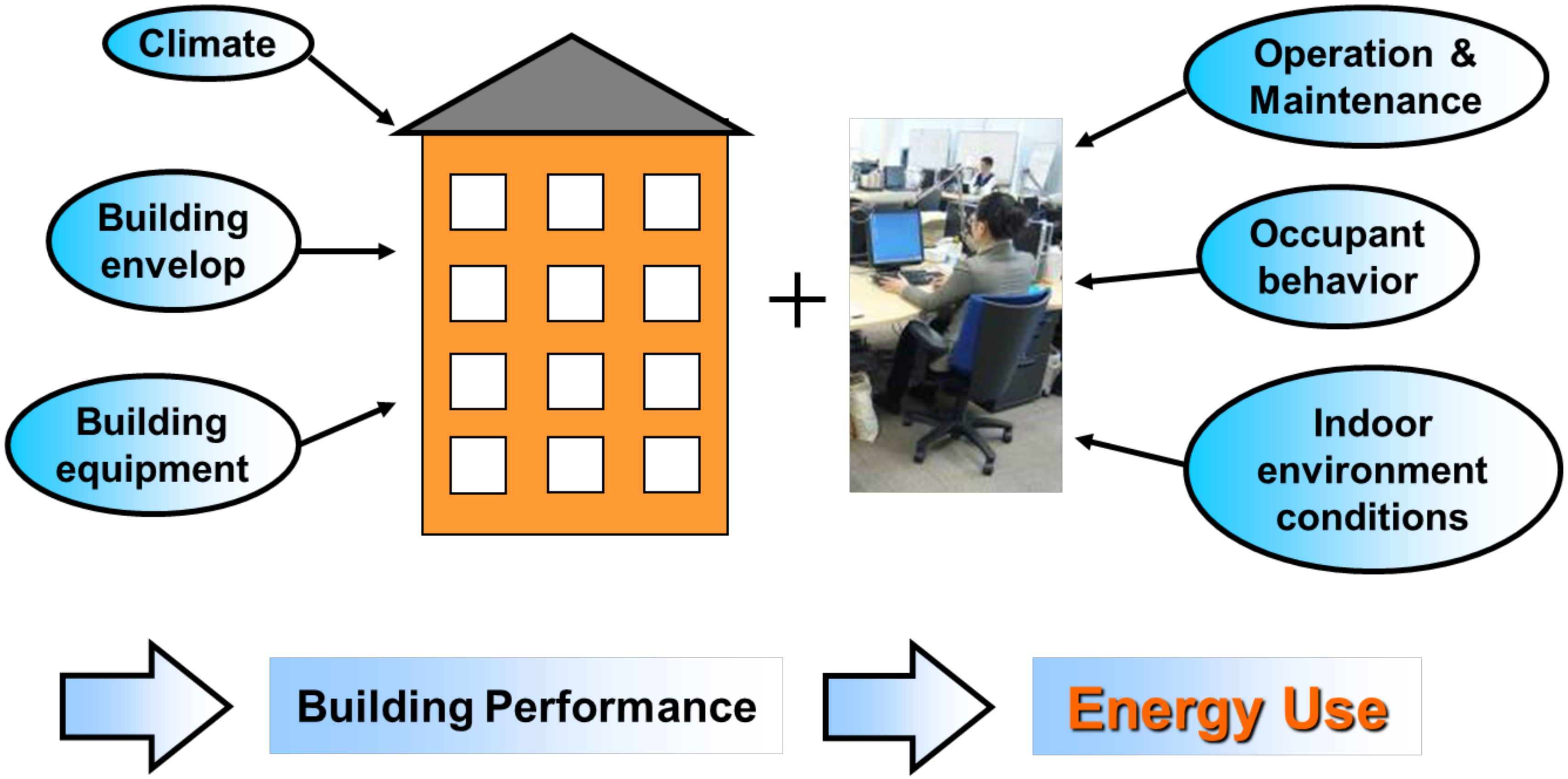
approx. 10000 combinations



Renovation options
Performance indicators
Isolatie Muur (Rc-waarde)
Isolatie Dak (Rc-waarde)
Isolatie Vloer (Rc-waarde)
Glas
Luchtdichtheid
Ventilatie
Warmte-afgifte
Zomercomfort (uren oververhitting)
Wintercomfort (uren overkoeling)
CO2-uitstoot (kg / 30 jaar (verwarming
CO2-reductie (%, 30 jaar)
Warmtevraag (kWh/m2.jaar)
Warmtevraag-reductie (%)
Totale kosten (€ / 30 jaar)
Investeringskosten (€)
6
4.5
3
1.79
8
6
3.5
2
3.5
2.5
1.26
0.21
DG
HR++
TG
Matig
Goed
Uitstekend
Type C
Type D
Vloer
LT-rad.
Bestand
Zomercomfort
Wintercomfort
CO2-uitstoot
Warmtevraag
isolatieniveau
walls
roof
floor
glazing
draft
vent
heating
comfort
CO2
energy demand
costs


Renovation options
Performance indicators
Isolatie Muur (Rc-waarde)
Isolatie Dak (Rc-waarde)
Isolatie Vloer (Rc-waarde)
Glas
Luchtdichtheid
Ventilatie
Warmte-afgifte
Zomercomfort (uren oververhitting)
Wintercomfort (uren overkoeling)
CO2-uitstoot (kg / 30 jaar (verwarming
CO2-reductie (%, 30 jaar)
Warmtevraag (kWh/m2.jaar)
Warmtevraag-reductie (%)
Totale kosten (€ / 30 jaar)
Investeringskosten (€)
6
4.5
3
1.79
8
6
3.5
2
3.5
2.5
1.26
0.21
DG
HR++
TG
Matig
Goed
Uitstekend
Type C
Type D
Vloer
LT-rad.
Bestand
250
200
150
100
50
0
800
600
400
200
0
18k
16k
14k
12k
10k
8k
6k
4k
2k
0
70
75
80
85
90
95
100
80
70
60
50
40
30
10
0
20
30
40
50
60
70
80
90
100
120k
110k
100k
90k
80k
60k
50k
40k
30k
20k
Kostenoptimalisatie
isolatieniveau
walls
roof
floor
glazing
draft
vent
heating
comfort
CO2
energy demand
costs

Assumptions for many uncertain aspects



Relevance of uncertainties

Assuming absence of modeling method errors / software bugs / user input errors:

- “Minor”:
  - Uncertain construction material and equipment properties
  - …..
- Major:
  - Future climate / actual weather conditions
  - Future user behavior
  - …

Climate / weather uncertainties

- Actual vs typical weather data
- Climate change
- ….

Typical Meteorological Year vs Actual MY

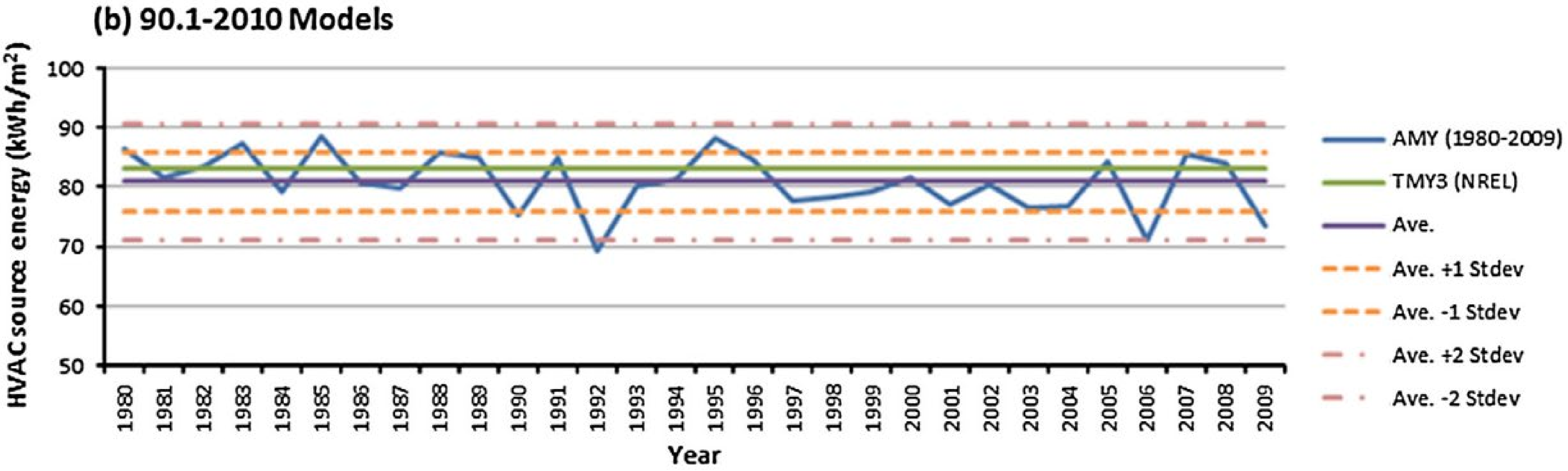
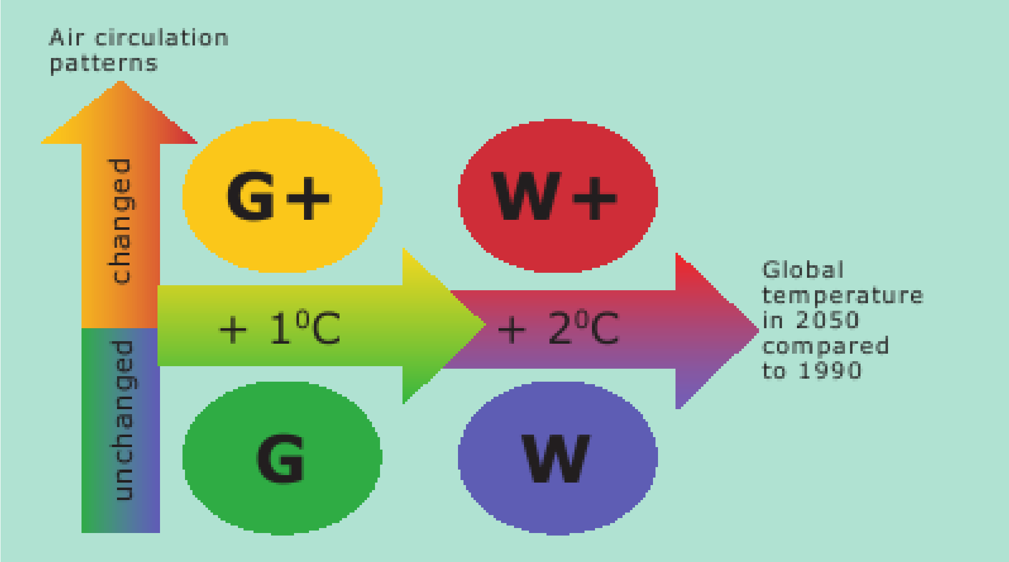


Fig. 4. Variations of HVAC source energy of the large office buildings in Chicago from year 1980 to 2009.

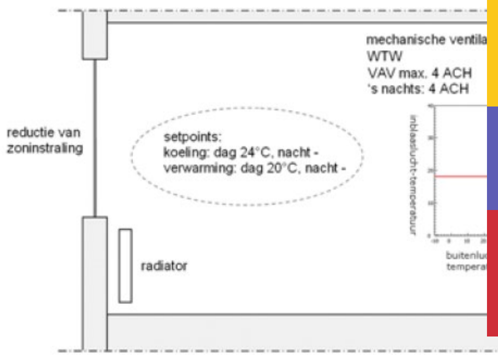
[Hong, Tianzhen, Wen-Kuei Chang, and Hung-Wen Lin. "A fresh look at weather impact on peak electricity demand and energy use of buildings using 30-year actual weather data." Applied Energy 111 (2013): 333-350.]

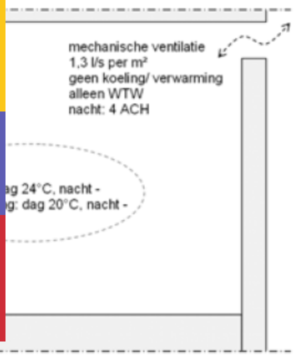
Climate change scenarios (NL)



[KNMI (2014) KNMI'14 climate scenarios for the Netherlands, A guide for professionals in climate adaptation, KNMI, De Bilt, The Netherlands]

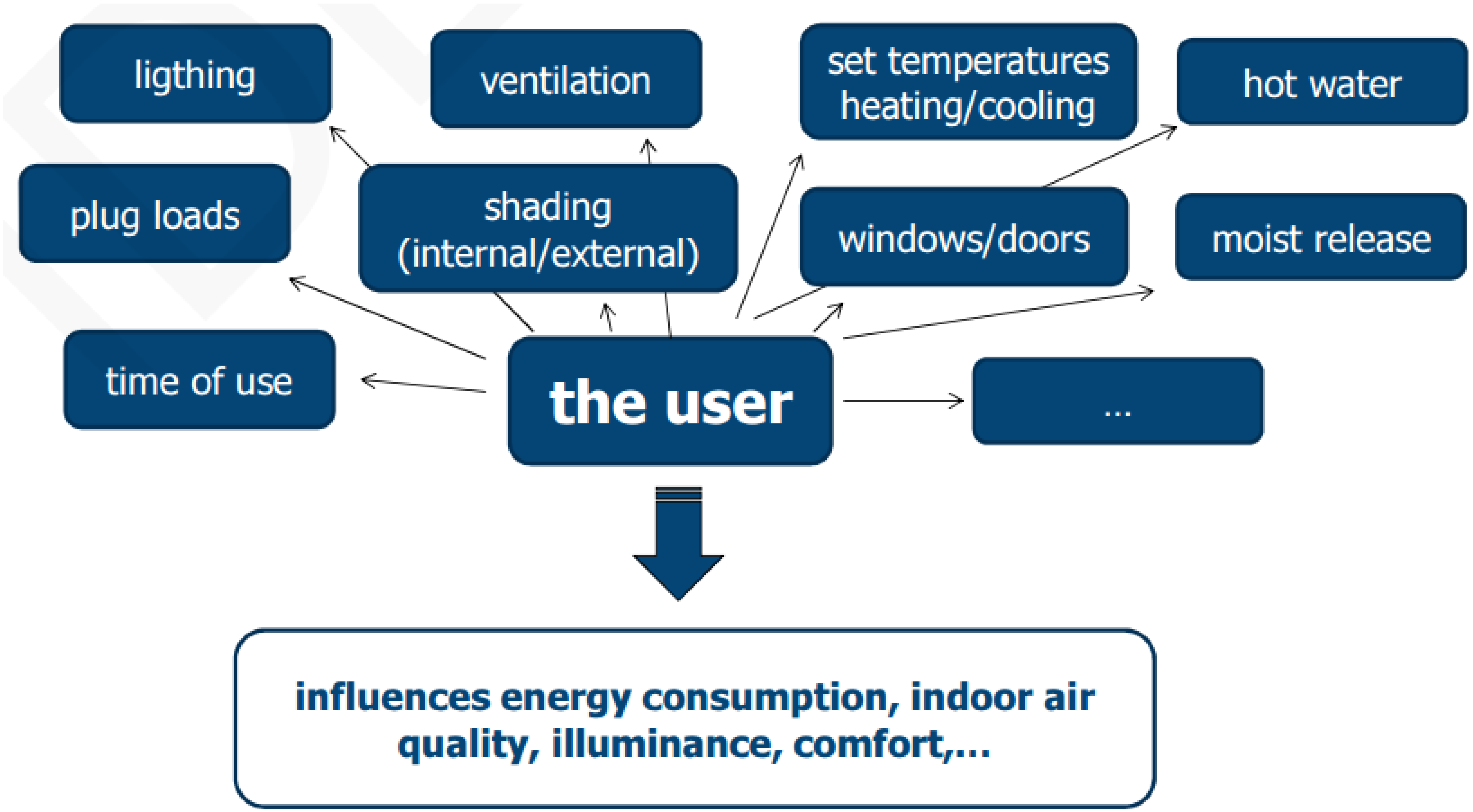
G	Moderate*	1°C temperature rise on earth in 2050 compared to 1990 no change in air circulation patterns in Western Europe
G+	Moderate +	1°C temperature rise on earth in 2050 compared to 1990 + milder and wetter winters due to more westerly winds + warmer and drier summers due to more easterly winds
W	Warm	2°C temperature rise on earth in 2050 compared to 1990 no change in air circulation patterns in Western Europe
W+	Warm +	2°C temperature rise on earth in 2050 compared to 1990 + milder and wetter winters due to more westerly winds + warmer and drier summers due to more easterly winds





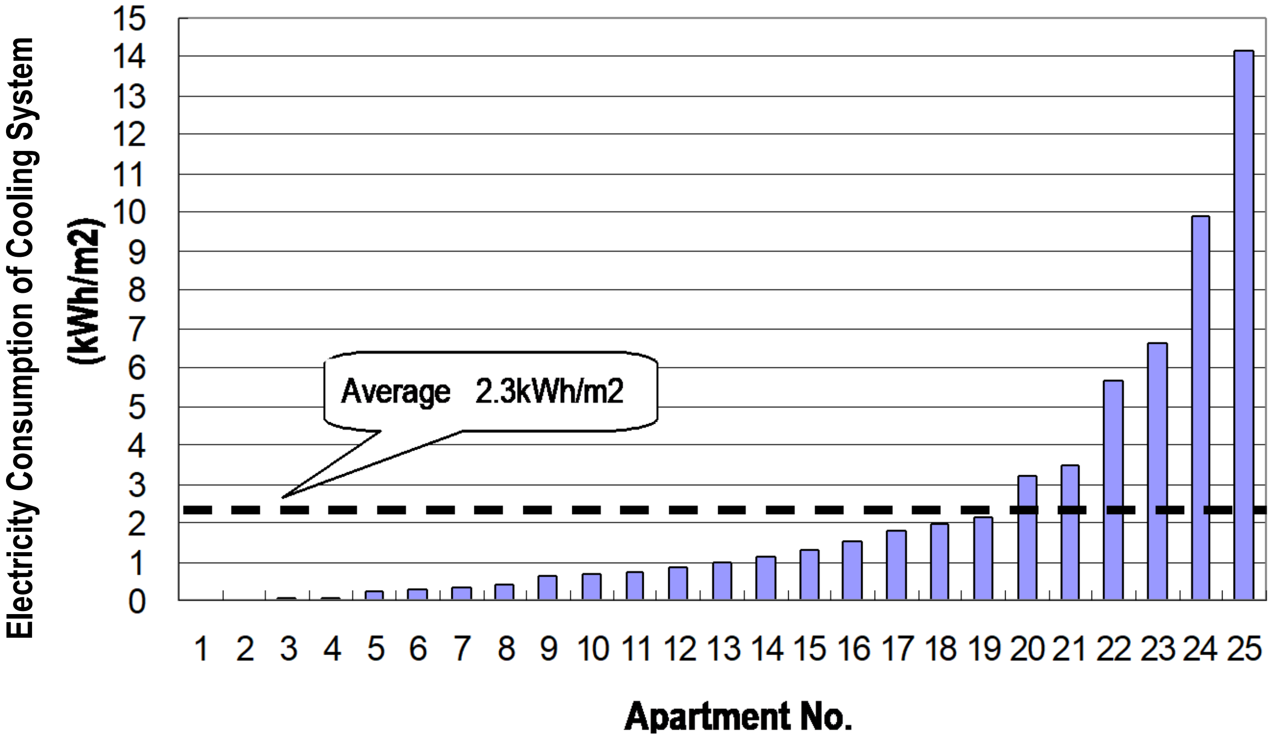
Verkerk-Evers, J. E. J., Struck, C., Herpen, R. A. P., Hensen, J. L. M., Wijsman, A. J. T. M. & Plokker, W. 2010. "Klimatiseringsconcepten voor de toekomst", TVVL Magazine, vol. 39, no. 7/8, 22-26.

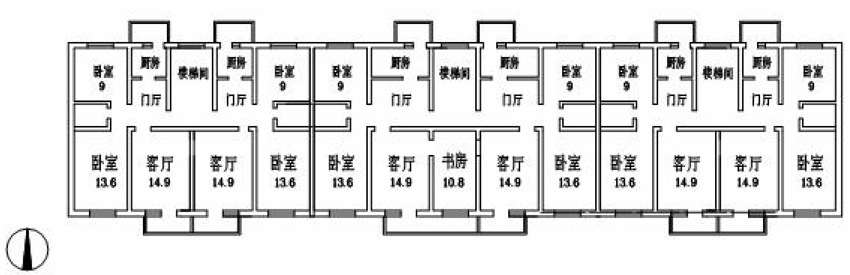
Occupant behavior uncertainties



[IDES-EDU, 2012]

Occupant behavior uncertainties

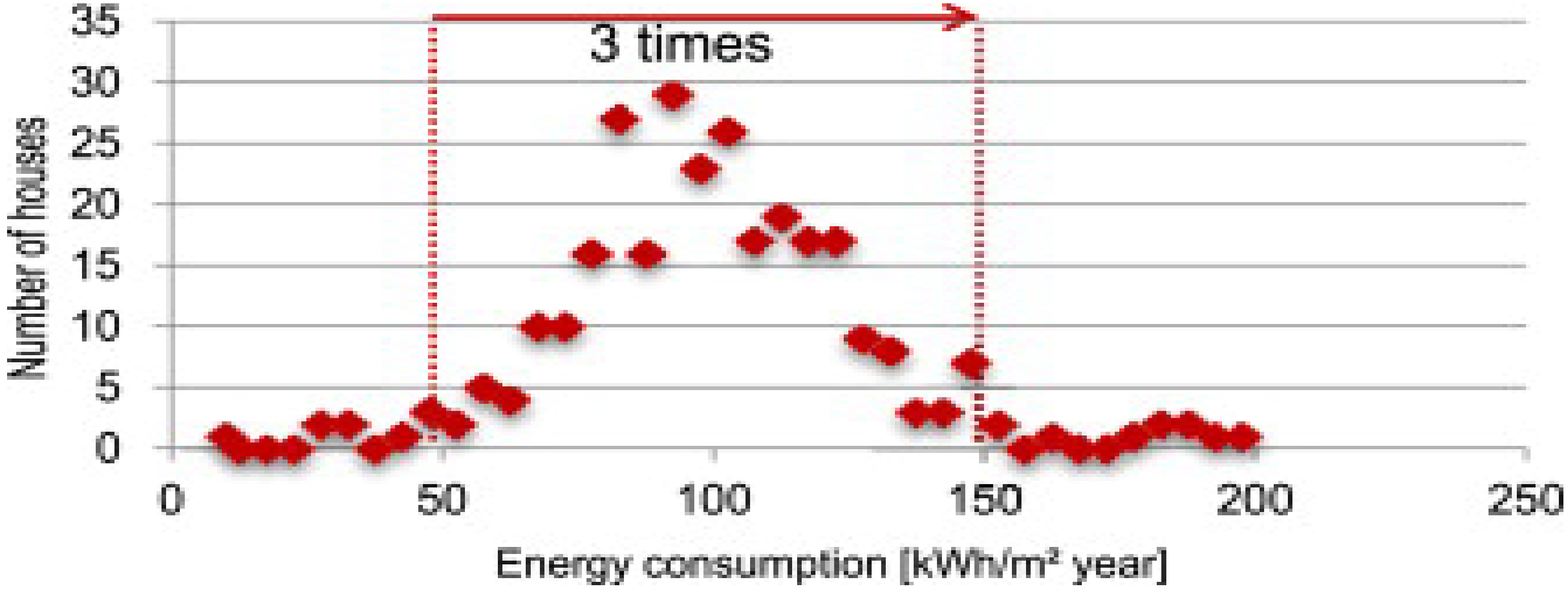




Cooling energy consumption of 25 similar apartments in Beijing, 2006

Chuang WANG. Research of energy-consumption-related occupant behavior.
Ph.D. Thesis, Tsinghua University, 2015.

Occupant behavior uncertainties

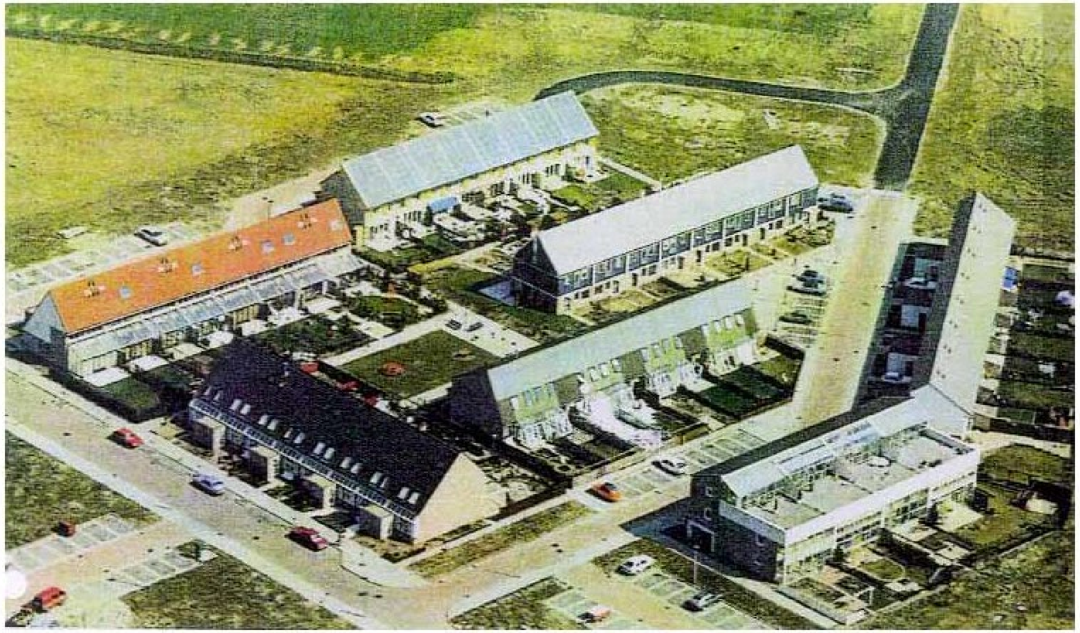


Energy consumption of 290 identical houses in Copenhagen, Denmark

[LBNL Building Performance Database, 2015]

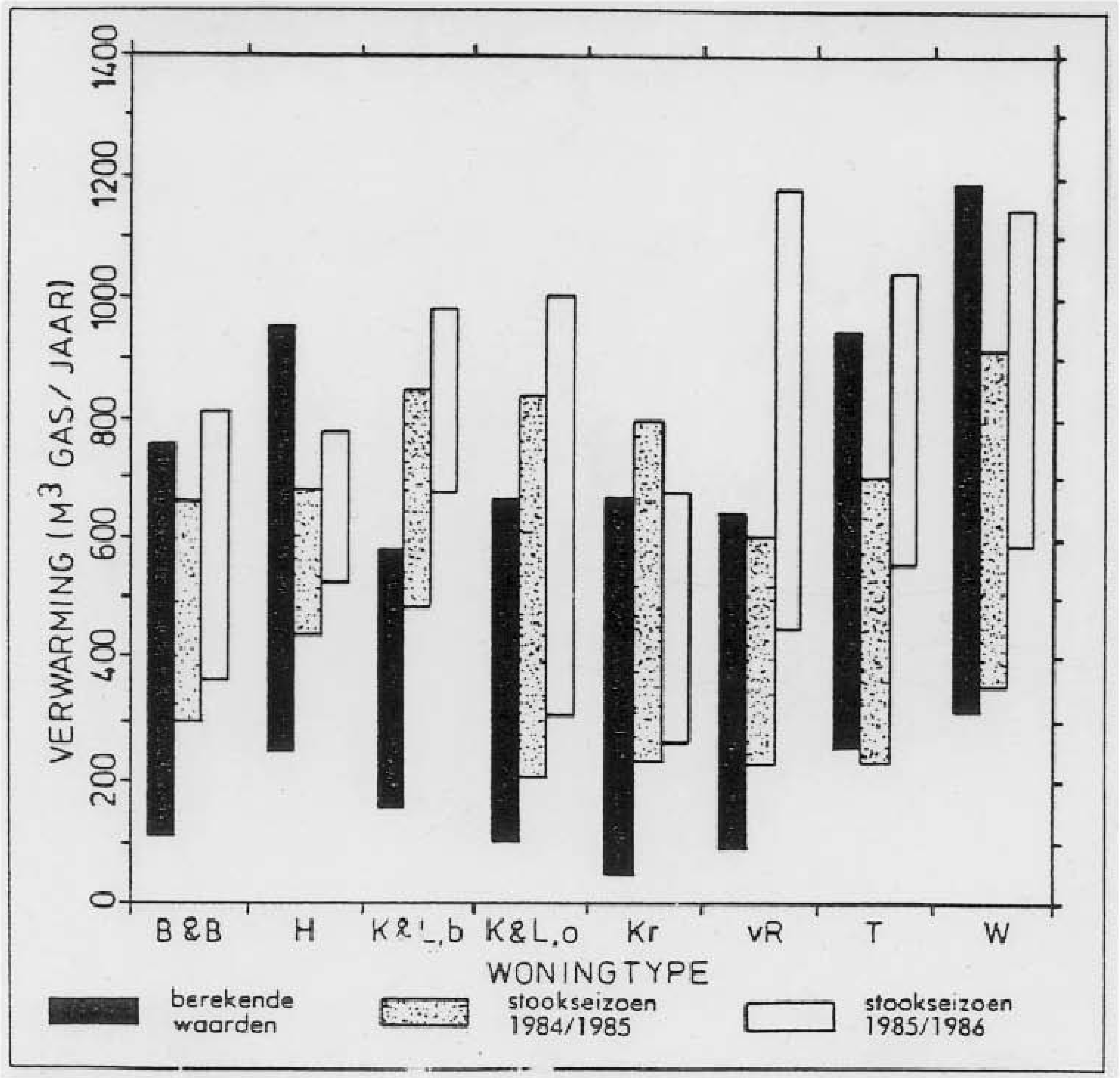
[Hong, T., D'Oca, S., Turner, W. J., & Taylor-Lange, S. C. (2015). An ontology to represent energy-related occupant behavior in buildings. Part I: Introduction to the DNAs framework. Building and Environment.]

“1984 Occupancy Uncertainty Analysis”

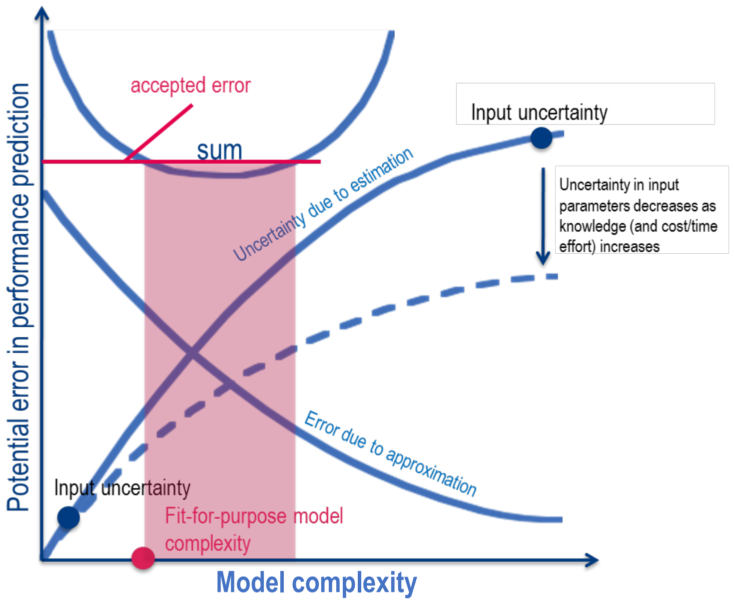


Low-energy houses near Amsterdam

Simulation experiments assuming small variations in Tset, Qgain, Vent



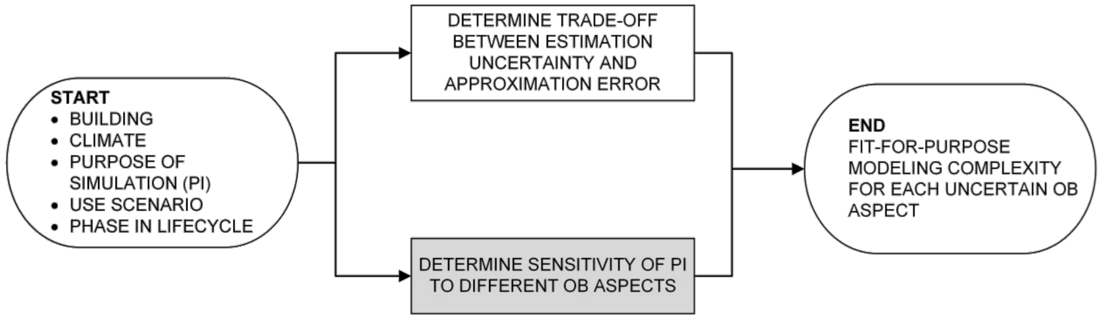
Fit-for-purpose occupant behavior modeling

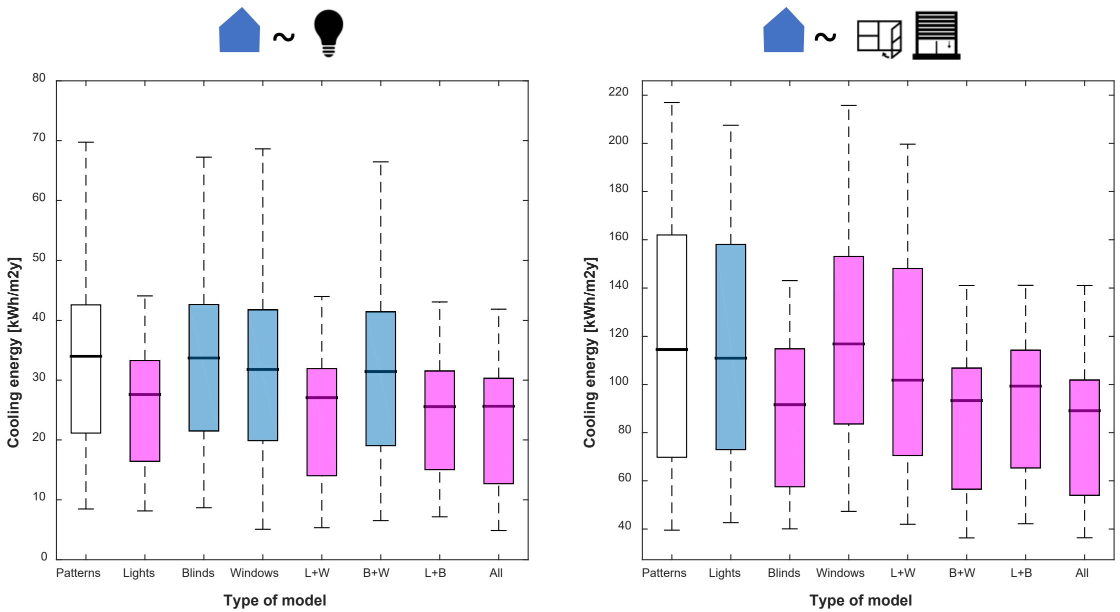


Trcka and Hensen, 2009

→ Increasing modeling complexity does not necessarily produce more accurate results

→The modeling complexity of each uncertain OB aspect should depend on the sensitivity of the results





Gaetani , I., Hoes, P. & Hensen, J.L.M. (2016). Occupant behavior in building energy simulation: Towards a fit-for-purpose modeling strategy. Energy and Buildings, 121, 188-204

Robustness (optimization under uncertainty)

- ➢ the ability of a system/design to have minimum sensitivity to variations in uncontrollable factors (Taguchi, 1950; Phadke, 1989)
- ➢ the potential for system success under varying future circumstances or scenarios *(Bettis and Hitt, 1995)*
- ➢ the ability of a system to continue to operate correctly across a wide range of operational conditions *(Gribble et al., 2001)*
- ➢ the output of a system varies little when some of the inputs vary (*Csete and Doyle 2002*).
- ……

Robustness assessment methods

- Probabilistic approach
- Non-probabilistic approach

Probabilistic approach

- Uncertainties - probabilities known
- Mostly, mean and variance are used to assess the robustness
- Many studies are carried out on robustness assessment using probabilistic approach in
    - Manufacturing/mechanical design (Caro et al., 2005; Wang et al., 2015)
    - Structural design (Haung et al., 2007; Baker et al., 2008)
    - Building performance (Hoes et al., 2009; Fabi et al., 2013; Gelder et al., 2014; Nik et al., 2015)

Non-probabilistic approach

- Probabilities - not known or hard to predict

- Scenarios are formulated

- Very limited studies are available on robustness assessment using non-probabilistic approach.
    - Best case and worst-case method (*Hoes, 2014*)
    - Relative performance variation method (*Kotireddy et al., 2015*)
    - Mini-max regret method (Bell, 1982; *Averbakh, 2000; Chein and Zang, 2010; Gang et al., 2015*)

Relative performance variation method

- In the best case and worst-case method, only performance deviation is considered as measure of robustness

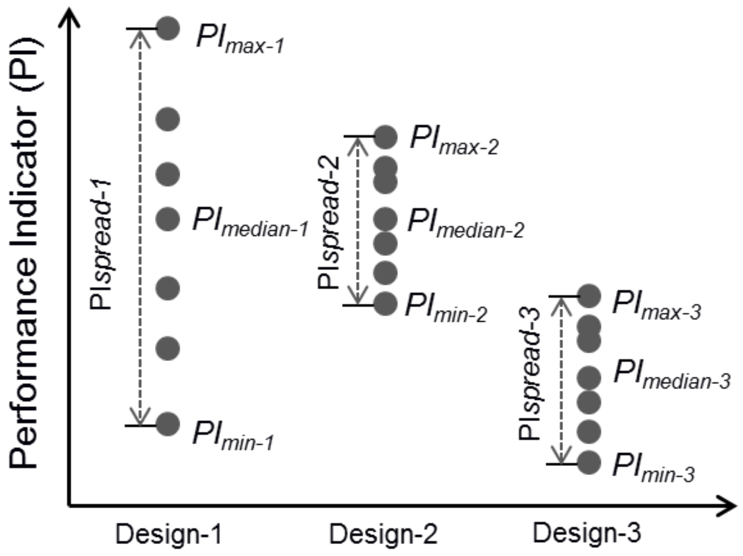
- In RPV method, robust design selection is based on low median value with minimum relative performance variation of a performance indicator for all scenarios

- **Performance spread**

$$PIspread = PImax - PImin$$

- **Relative performance variation (RPV)**

$$PI\ RPV = PIspread : PImedian$$



Relative performance variation method

- Conservative approach
- Does not take all scenarios into account
- Robustness assessment considering scenarios that causes maximum, median and minimum performance
- …….

- Alternatively, mini-max regret method which takes all scenarios into account can be used for robustness assessment method

Mini-max regret method

Mini-max* : **Minimax** is a decision rule used in decision theory, game theory, statistics etc. for *mini*mizing the possible loss for a worst case

Regret theory* : Regret theory models choice (decision) under uncertainty taking into account the effect of anticipated regret

Mini-Max Regret Theory

- to minimize the worst-case regret

- to find a solution that performs reasonably well for all scenarios, i.e., solution having the best “worst-case" performance

- commonly used to find robust solutions (*Averbakh, 2000; Chein and Zang, 2010; Ehrgott et al., 2014; Gang et al., 2015)*

….

* From Wikipedia

Mini-max regret method

Mini-max approach

Return	Interest rates rise	Static rates	Interest rates fall	Worst return
Stocks	−4	4	12	−4
Bonds	−2	3	8	−2
Money market	3	2	1	1
Best return	3	4	12	

Mini-max regret approach *(regret = best return – actual return)*

Regret	Interest rates rise	Static rates	Interest rates fall	Worst regret
Stocks	7	0	0	7
Bonds	5	1	4	5
Money market	0	2	11	11

Mini-max regret method - in context

- Define design variants (d1, d2, d3….dm) and scenarios (s1, s2, s3….sn)
- Assess the performance of designs (dm) for all scenarios (sn) using performance indicator (P)

Scenarios → **Designs ↓**	s1	s2	s3	…	sn
d1	P11	P12	P13	…	P1n
d2	P21	P22	P23	…	R2n
d3	P31	P32	P33		
…	…	…	…	…	…
dm	Pm1	Pm2	…	…	Pmn

Mini-max regret method

- Find the best (optimal) performance per scenario

Scenarios → **Designs ↓**	s1	s2	s3	…	sn
d1	P11	P12	P13	…	P1n
d2	P21	P22	P23	…	R2n
d3	P31	P32	P33	…	…
…	…	…	…	…	…
dm	Pm1	Pm2	…	…	Pmn
Best/ Optimal performance	Min(P11, P21…Pm1)	Min(P12, P22…Pm2)	Min(P13, P23…Pm3)		Min (P1n, P2n…Pmn)

Mini-max regret method

- Calculate the performance regret (R) of a design (difference between performance of a design and the best performance for a scenario)

Scenarios → **Designs ↓**	s1	s2	s3	…	sn
d1	R11	R12	R13	…	R1n
d2	R21	R22	R23	…	R2n
d3	R31	R32	R33	….	R3n
…	…	…	…	…	…
dm	Rm1	Rm2	…	…	Rmn

Mini-max regret method

- Find the maximum (worst) performance regret per design

Scenarios → Designs ↓	s1	s2	s3	…	sn	Maximum regret
d1	R11	R12	R13	…	R1n	Max(R11, R12…R1n)
d2	R21	R22	R23	…	R2n	Max(R21, R22…R2n)
d3	R31	R32	R33	….	R3n	Max(R31, R32…R3n)
…	…	…	…	…	…	
dm	Rm1	Rm2	…	…	Rmn	Max(Rm1, Rm2…Rmn)

Mini-max regret method

- Find the design having minimum of maximum (best of the worst-case performance) performance regrets across all scenarios i.e., robust design

Scenarios → **Designs ↓**	s1	s2	s3	…	sn	Maximum regret
d1	R11	R12	R13	…	R1n	max(R11, R12…R1n)
d2	R21	R22	R23	…	R2n	max(R21, R22…R2n)
d3	R31	R32	R33	….	R3n	max(R31, R32…R3n)
…	…	…	…	…	…	
dm	Rm1	Rm2	…	…	Rmn	max(Rm1, Rm2…Rmn)
		Minimum of maximum regret				Rmin-max

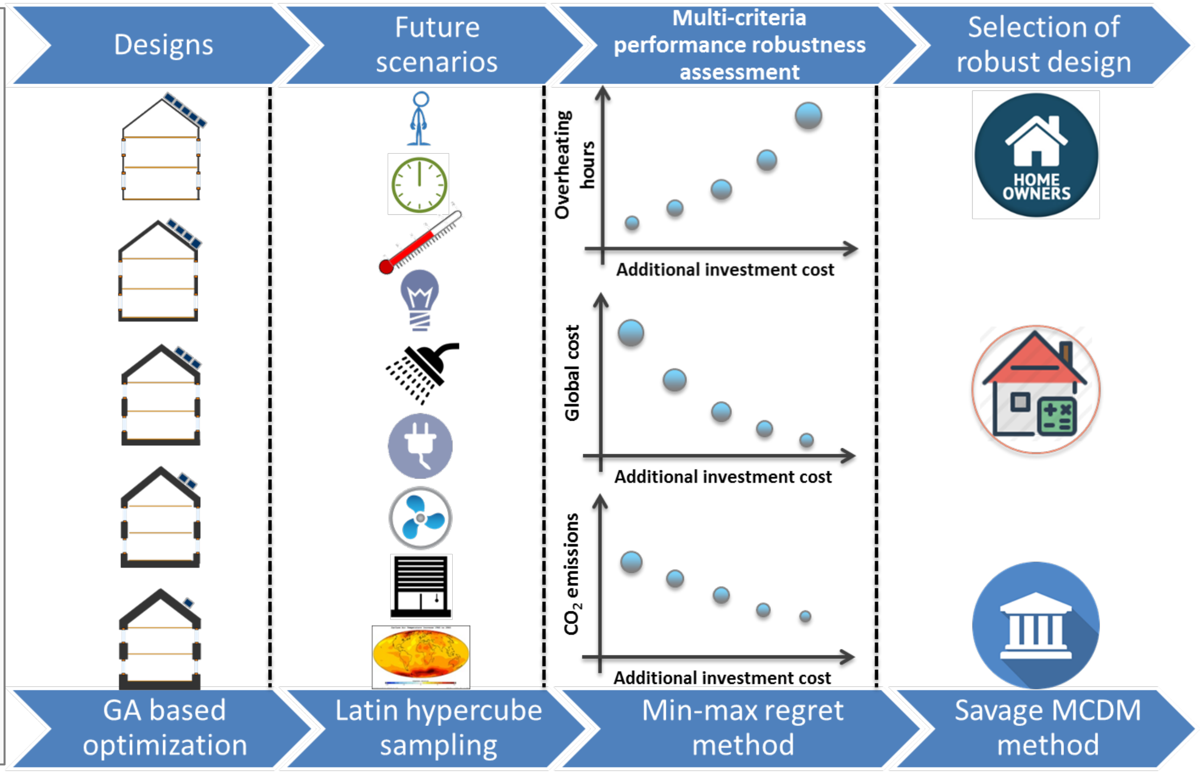
- Maximum performance regret is the measure of robustness; the lower the maximum performance regret, the higher the robustness

Example: performance robustness optimization

Highlights :

- Multi-criteria performance assessment
- Min-max regret method for robustness assessment
- Multi-criteria decision making
- Robust designs for different decision makers

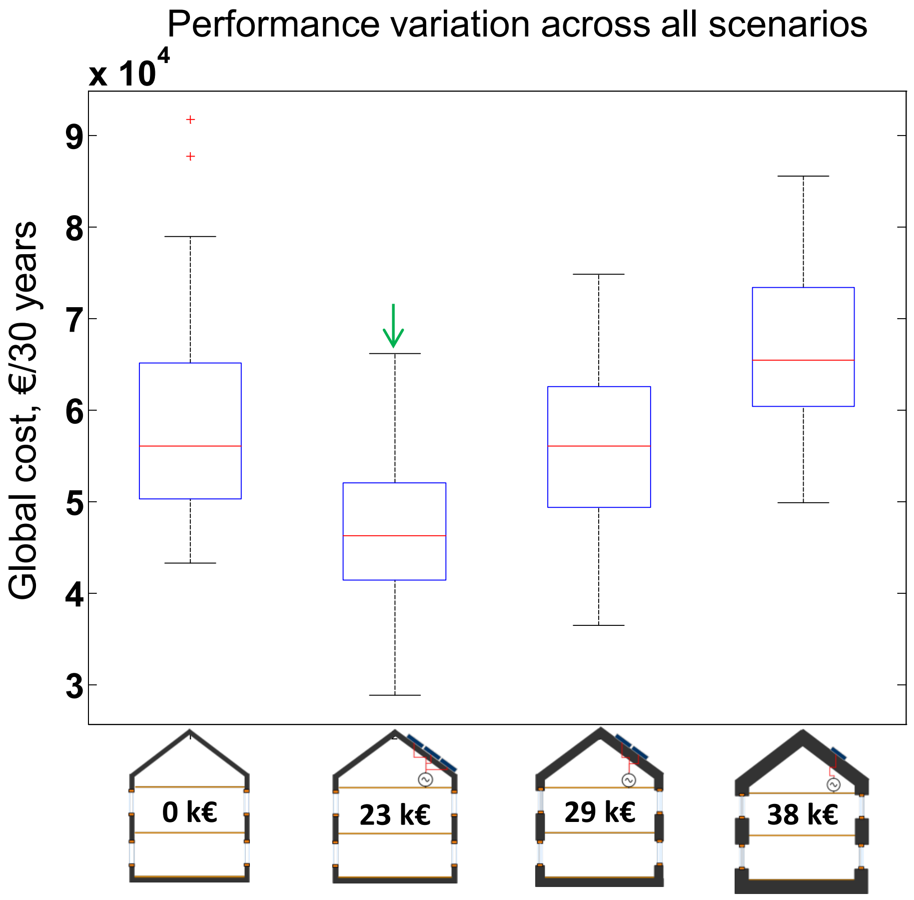
Methodology :

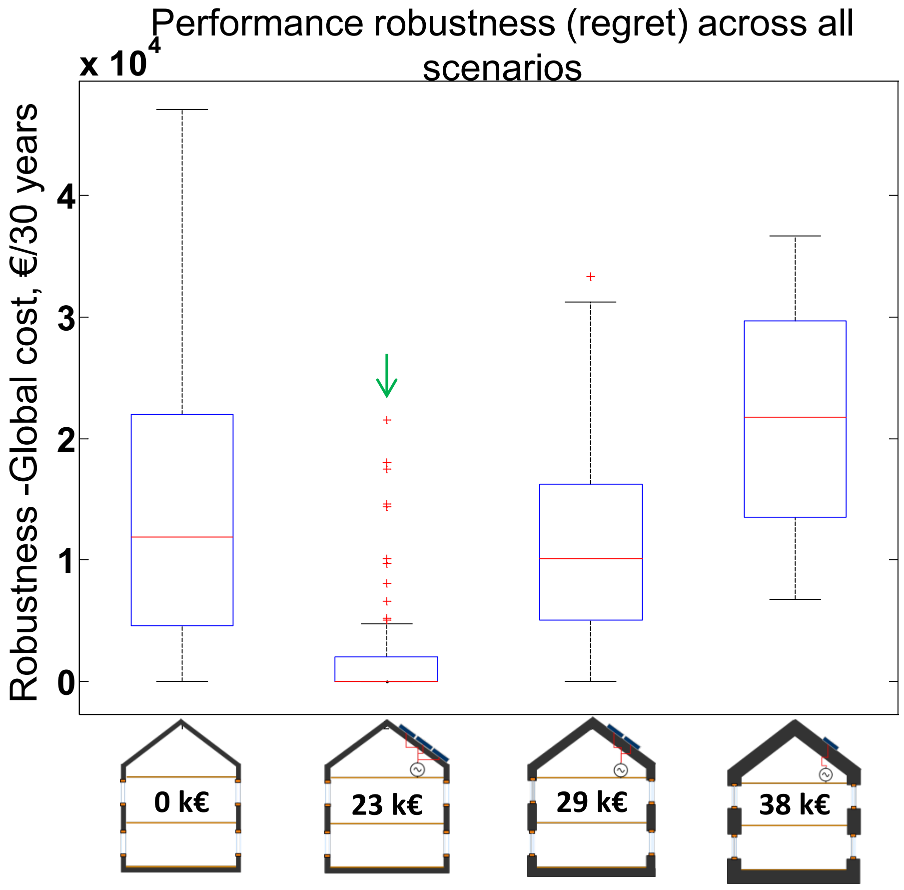


Kotireddy, R., Hoes, P., & Hensen, J. L. M. (2015). OPTIMAL BALANCE BETWEEN ENERGY DEMAND AND ONSITE ENERGY GENERATION FOR ROBUST NET ZERO ENERGY BUILDINGS CONSIDERING FUTURE SCENARIOS, Proceedings of IBPSA conference, 1970-77.

Global cost

- Cost of investment, replacement and operational
- Calculated for period of 30 years – service life span of energy systems





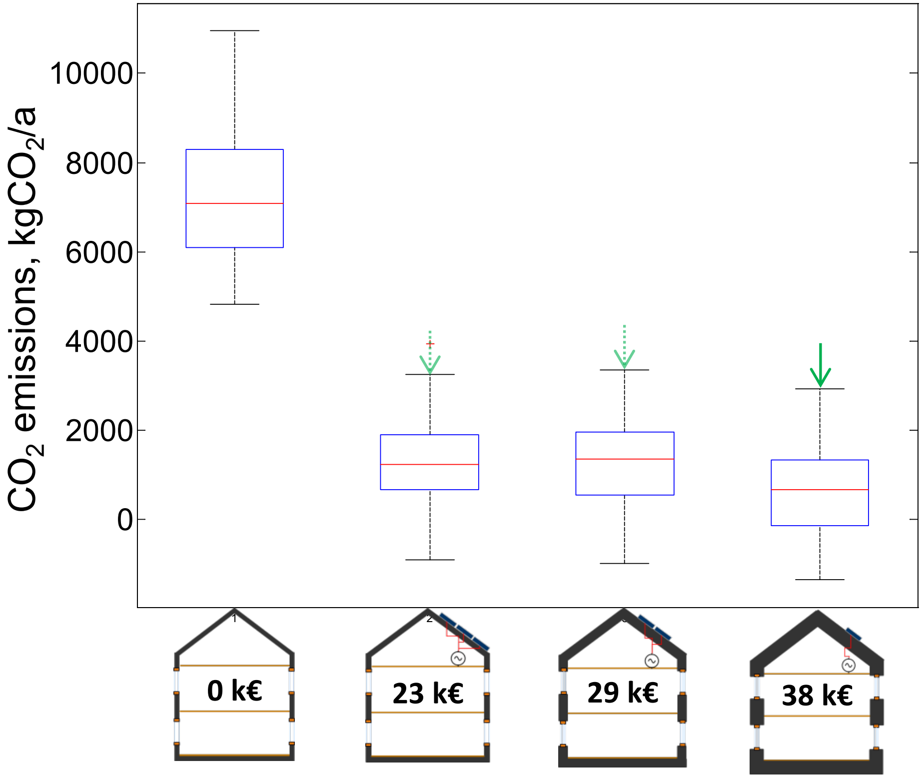
(regret = performance difference between the best solution and the solution considered for a particular scenario)

CO_2 emissions

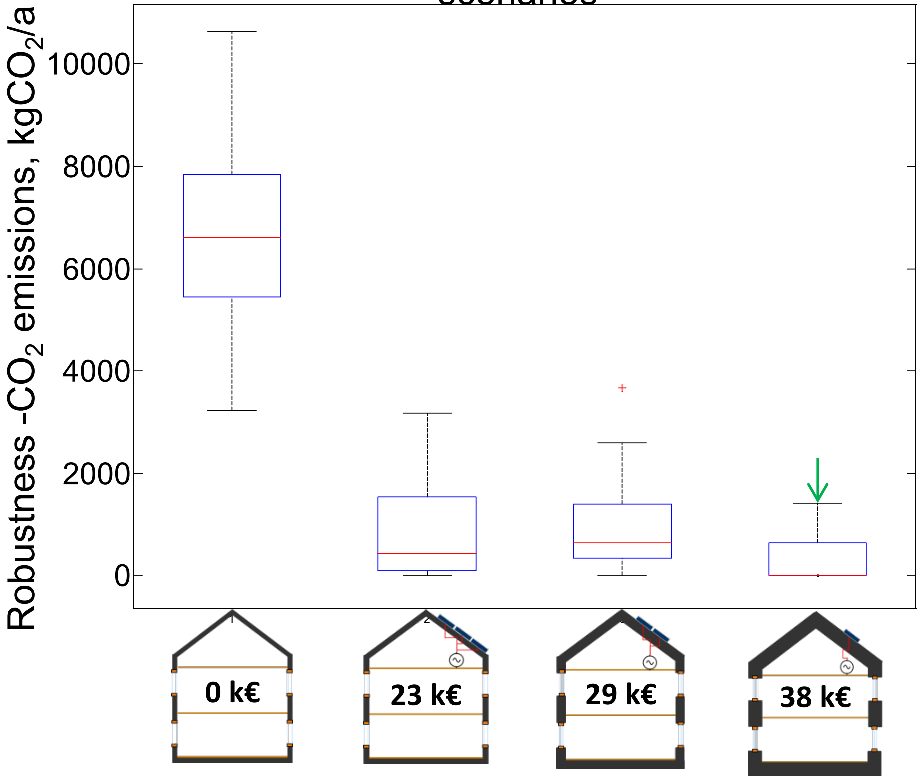
$$CO_2\,emissions = Energy\ consumption \times EF - Energy\ generation \times EF$$

- EF = CO_2 emission factor
- Embodied emissions are not taken into account

Performance variation across all scenarios



Performance robustness (regret) across all scenarios

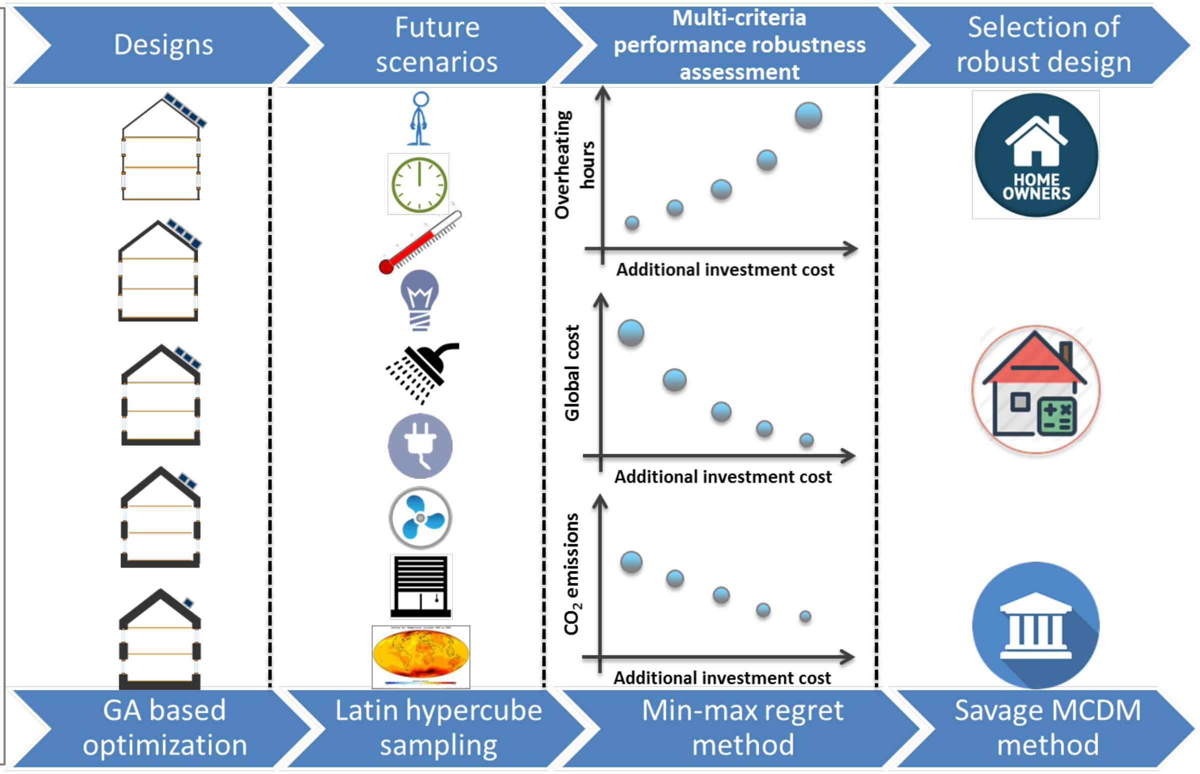


Example: performance robustness optimization

Highlights :

- Multi-criteria performance assessment
- Min-max regret method for robustness assessment
- Multi-criteria decision making
- Robust designs for different decision makers

Methodology :



Key findings :

- Active solutions are more robust compared to passive solutions
- Buildings with modest insulation and large PV systems are cost optimal robust solutions
- Buildings with very high insulation levels are prone to overheating risks in the future

Kotireddy, R., Hoes, P., & Hensen, J. L. M. (2015). OPTIMAL BALANCE BETWEEN ENERGY DEMAND AND ONSITE ENERGY GENERATION FOR ROBUST NET ZERO ENERGY BUILDINGS CONSIDERING FUTURE SCENARIOS, Proceedings of IBPSA conference, 1970-77.

Mini-max regret method - summary

- Non-conservative approach

- Non-probabilistic approach-independent of probabilities of outcome-the designs are ranked based on their worst outcomes

- Robust design performs reasonably well for all scenarios

Design optimization

- Is necessary, because buildings have a long lifetime, involve considerable investments, impact different stakeholders, and non-optimal design performance is very difficult to rectify by operational optimization later on
- Because of many future uncertainties, the objective should be to find robust design solutions that perform reasonably well for all scenarios and stakeholders
- For innovative solutions there is no performance date yet, so physics based computational models must be used

Operations optimization – digital twins

[https://www.bau.fraunhofer.de/en/fieldsofresearch/smartbuilding/digital-twin.html]

Operations optimization

Example: PV fault detection & performance guarantee

Panelen
12 stuks

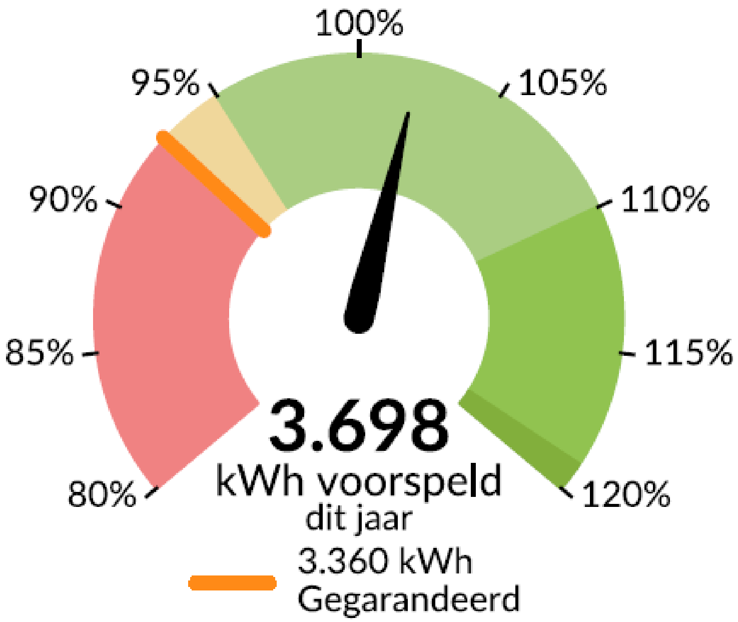
Totaal vermogen
3.900 wP

Paneeltype
Suntech STP325S - A20/Wfh

Omvormer
SolarEdge SE 3680H 1-fase HD

Installatiedatum
19-08-2020

Installateur
365Zon



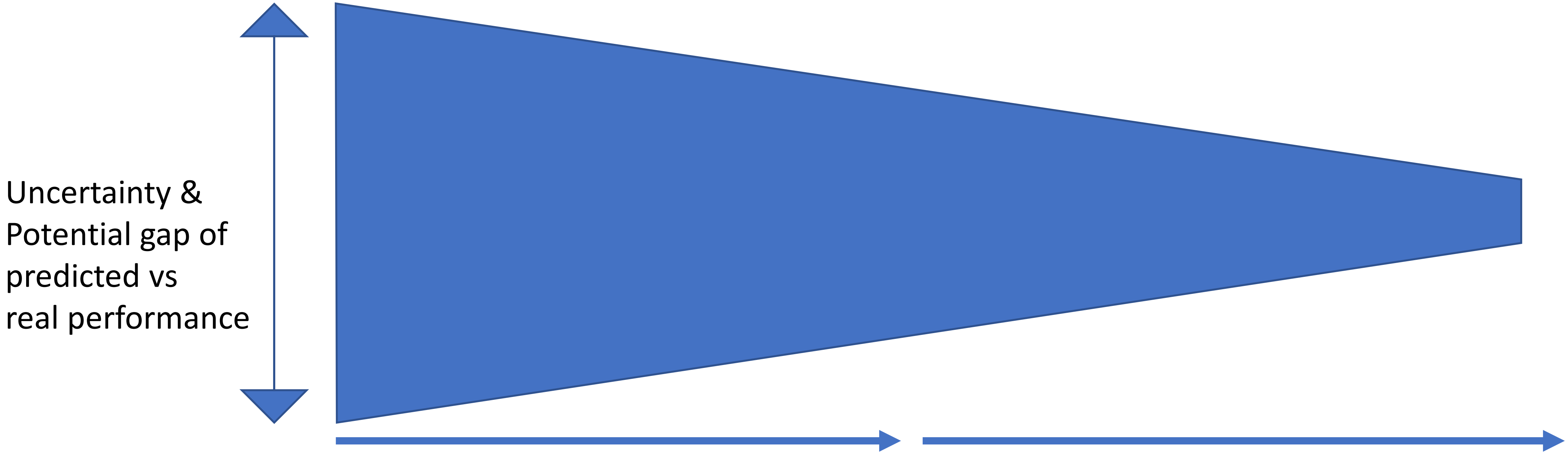
TU/E CAMPUS DIGITAL TWIN FOR SMART BUILDING MANAGEMENT AND CONTROL

Pieter Pauwels (BE), Elena Torta (ME), Gamze Dane (BE), Sonja Rijlaarsdam (RE), Thijs Meulen (RE), and Annemieke Pelt (ME)

- Build a Digital Twin system for the Atlas and Gemini buildings (Zero Emission Lab, Gemini building)
- Smart management of facilities through on-site anomaly detection and device monitoring
- Unsupervised robot navigation through semantic (model-driven) path detection and real-time data analysis (data-driven)
- Developing a 3D campus information system for digital accessibility of campus facilities and services in buildings and open spaces

www.tue.nl/en/research/institutes/eindhoven-artificial-intelligence-systems-institute/digital-twin-lab/

Summary



Design phase

- Prediction – long term
- Physics based modeling
- Input parameter uncertainty

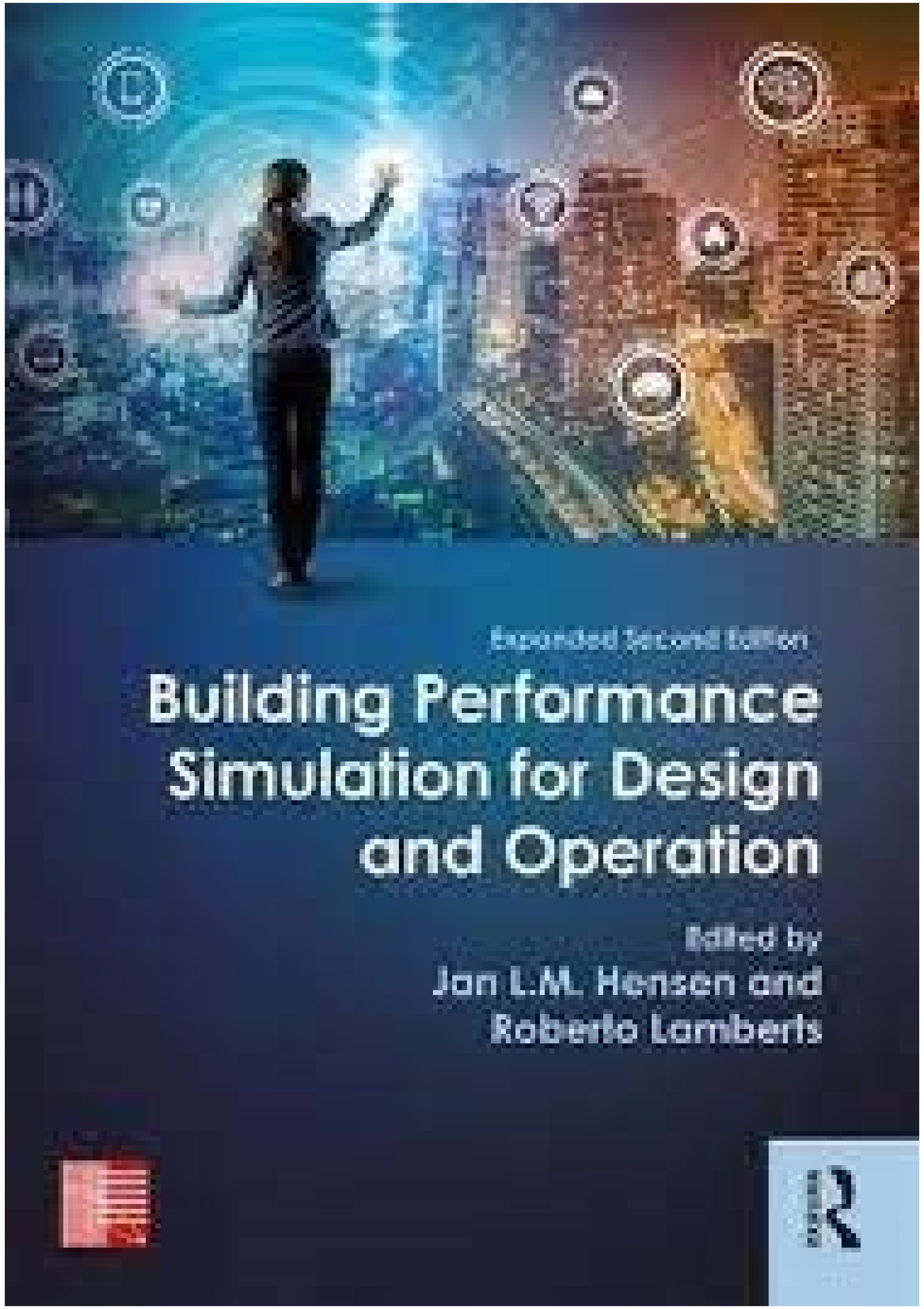
Operational phase

- Forecasting – short term
- Data driven modeling / AI
- Faults / non-optimal operation

Conclusions

- Building performance simulation is a very powerful engineering technique for optimization under uncertainty
- Mind the performance gap – be aware and quantify uncertainties; this could offer (business) opportunities
- Need knowledgeable people and intelligent approaches

Questions ?


Expanded Second Edition
Building Performance Simulation for Design and Operation
Edited by
Jan L.M. Hensen and
Roberto Lamberts