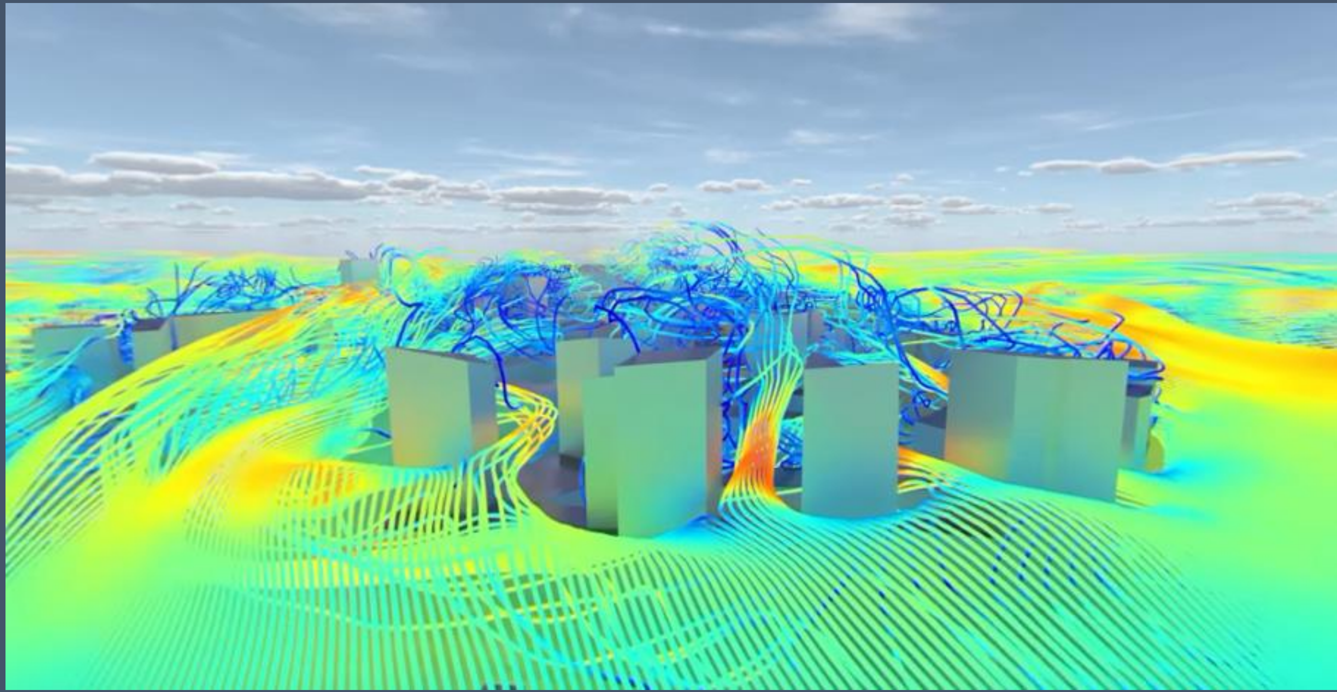
KATJA RODIONOVA RI(AMK)

STRUCTURAL KINESTHESIA:

BUILDING PHYSICS

FOR SMART BUILDINGS



PREDICTIVE MODELLING
COMFORT AND STRUCTURAL RESILIENCE

Challenge: moisture in structures

Laaksolahden jäähallin purkuaikataulu täysin auki – Matinkylä matalaksi jouluun mennessä

URHEILU Kaupungin omistama Laaksolahden areena on ollut käyttökiellossa ja tyhjän panttina jo lähes viisi vuotta.

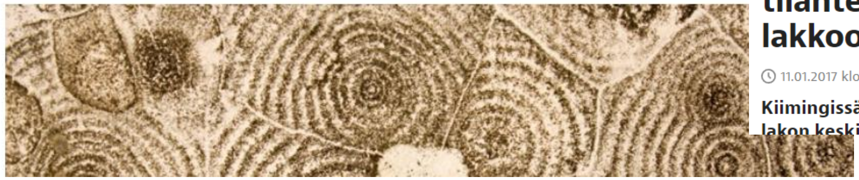
Luetuimmat

HEALTH

The Looming Consequences of Breathing Mold

Flooding means health issues that unfold for years.

JAMES HAMBLIN AUG 30, 2017



Uutiset

Mitta täyttyi homekoulun karmivaan tilanteeseen - yli 600 oppilasta ryhtyi lakkoon

11.01.2017 klo 20:10

Kiimingissä sijaitsevan Jokirannan homekoulun oppilaat aloittivat lakon keskiviikkoaamuna. Lakko kestää kolme päivää. Jokirannan

NEW ORLEANS METRO EDUCATION NEWS

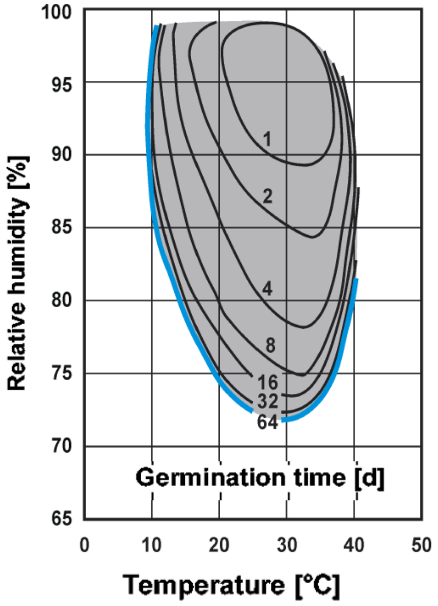
Did a moldy building kill 4 New Orleans college professors?

Updated Nov 15, 2016; Posted Jul 22, 2015

Problematics: air humidity effects

Risks:

- Surface mold
- Mold or water damage inside of structures
- Strength properties decline (timber cracking, creep; rust…)

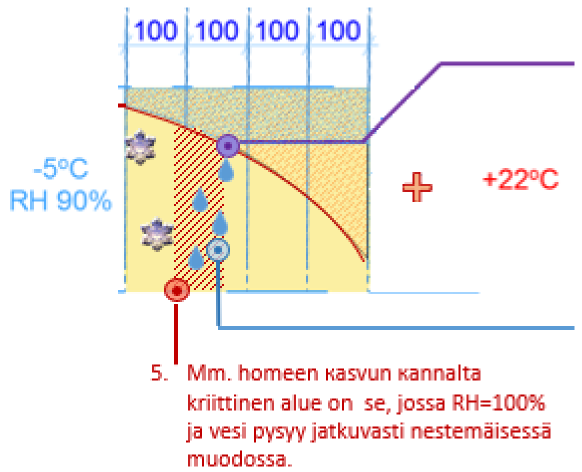


Mold development rates differ depending on temperature and humidity

Tarkastellaan tapaukset:

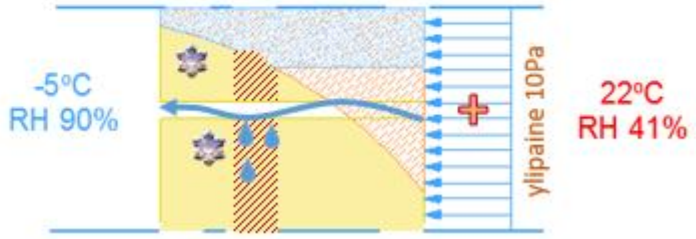
”lähijuna”

höyryn diffuusio rakenteen läpi



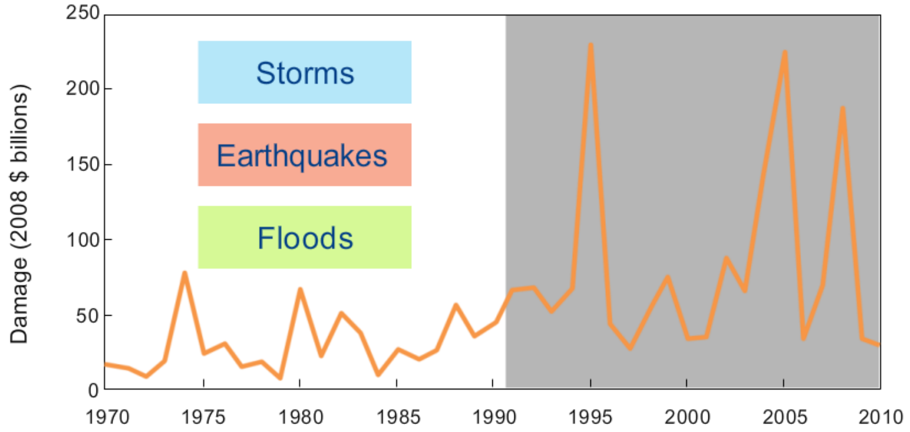
”pikajuna”

ilmavirta kuljettaa kosteutta rakoa pitkin

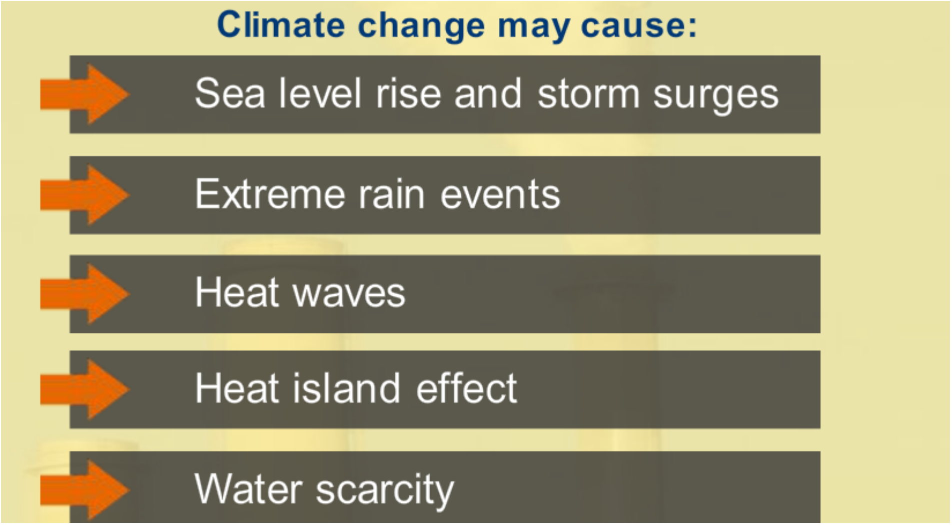


Other applications

Statistical analyses of structural data using deformation sensors



Source: NHUD Report 2010



Illustrations: World bank group, resilient city program

Though climate change is a global issue it implies that different areas are subject to different type of hazards

Rising of wind velocities and quantities of storm events is acknowledged as one of the globally detected factors.

It is reported 360M urban dwellers are positioned in regions sensitive to sea-level rise or storm surges

Post-processing buildings' and elements' deformation data

- Can serve as an in-situ design values' verification process
- Massive statictical input for technology development
- Help to insure the resilience of existing (historical structures) against changing weather conditions

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NABC

Need:

Stage 1. Utilize the existing sensor data, e.g. from building service appliances and elevators

Stage2. Ensure long-term financial resilience of the asset portfolio

Approach:

Stage 1. Digitalize building's risk assessments and provide user guide in digital form (app / automation connection) to mitigate unintentional misuse possibility

Stage 2. Provide predictive analyses of structural performance and incentivize additional sensor points for structural measurements

Counterparts:

Ruukki® Sensor Network: *Roof Sensor,* actual roof deformation under snow load, savings on snow removal works.

Trä group: building permits for non-standard massive timber townhouses based on sensor data

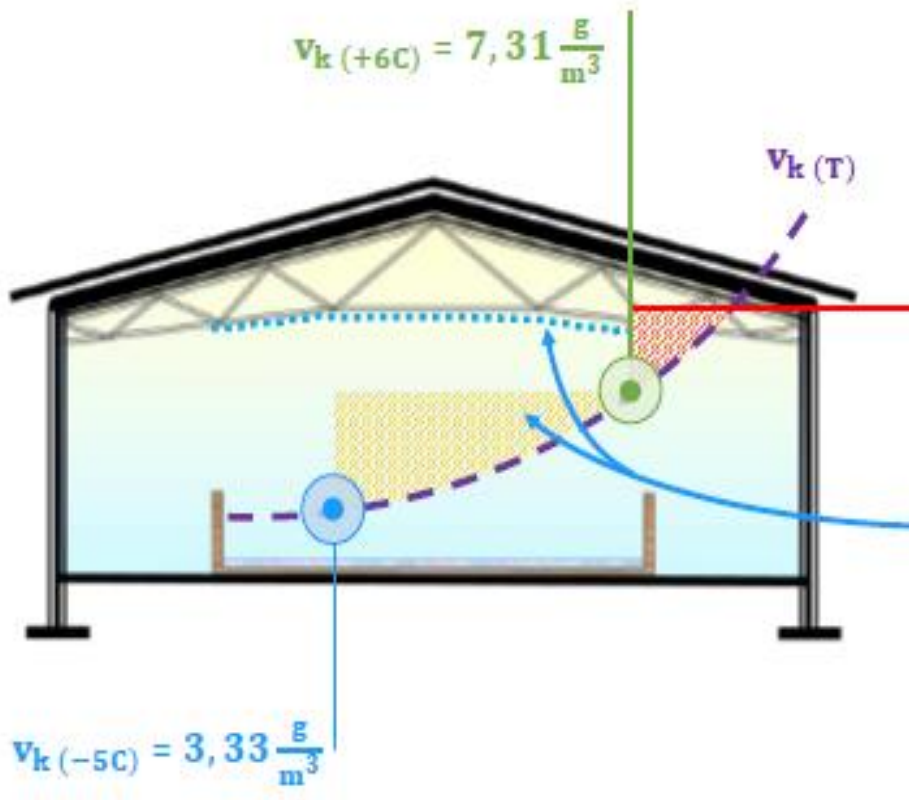
VTT: *LTDA Digital end-user toolset for Moisture assessment in Wooden buildings,* artificial dataset for weather-induced changes in glulam structural properties

Benefits:

Stage 1. Raising users' awareness of the proper ways to use the buildings

Stage 2. Collecting data for structural and energy optimization

Vision



Project with complex moisture safety features:

- The customer is offered extra safety level
- Digitized parametrical assessment instead of single-parameter paper-based

Case ice rinks

- Moisture loads from people + other aktivities
- During summer, massive moisture load from the ventilation (winter time, drying impact)
- Air ventilation / dehumidification effects need to be taken into account

- Also SPA, swimming pools, renovation projects…

Termperature defines the maximum amount of water vapor in the air

The ultimate goal

- theoretical and software framework for lifecycle risk assessment of building part under complex moisture loading conditions.
- Modularity: the ability to adapt for the use in simpler projects.
- Interoperability: interface ML and parametric design projects
- Transparency: convenient documentation and the use of e.g. “explainable AI” and similar methods in IoT-related applications.

Intelligent asset management: service levels

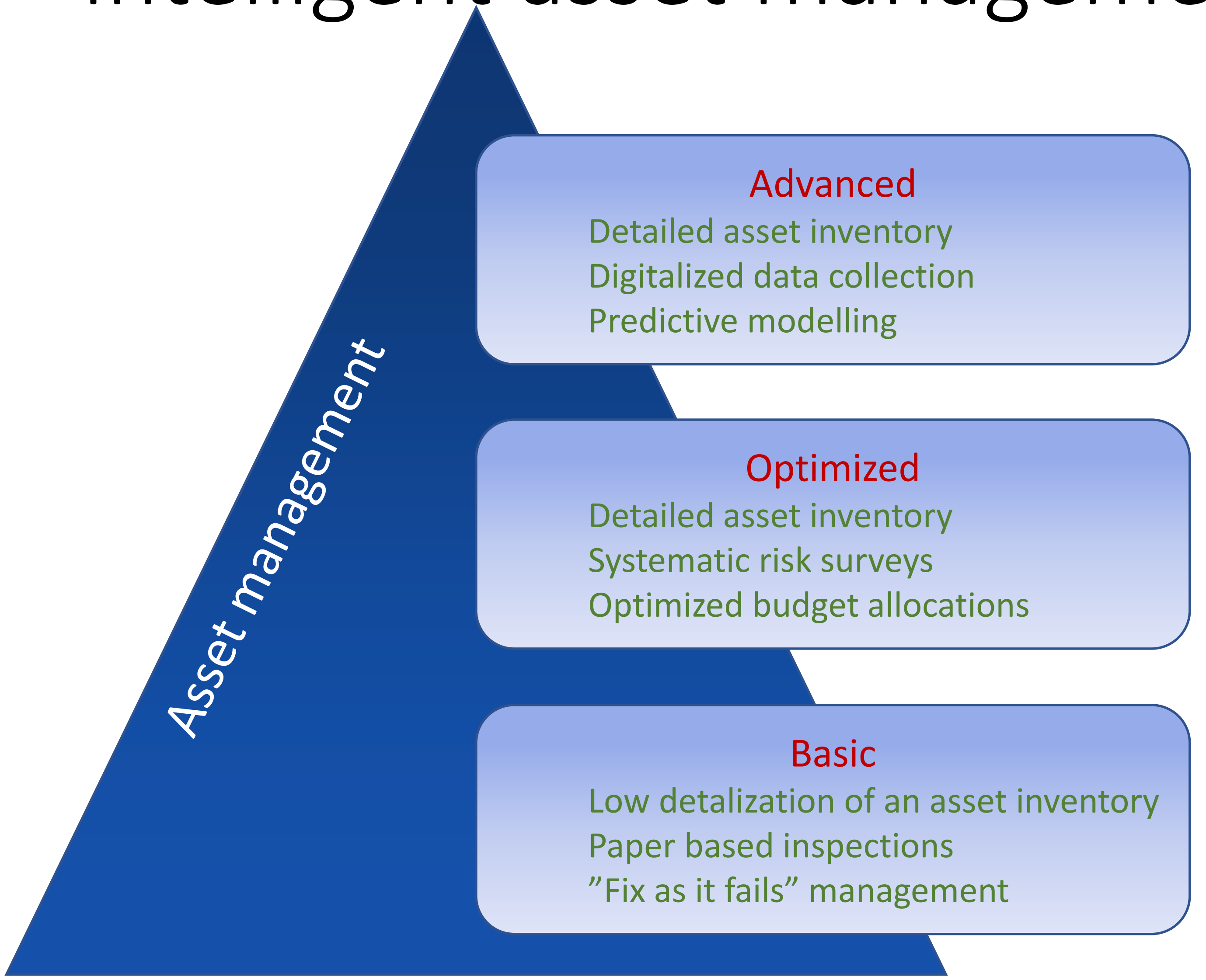
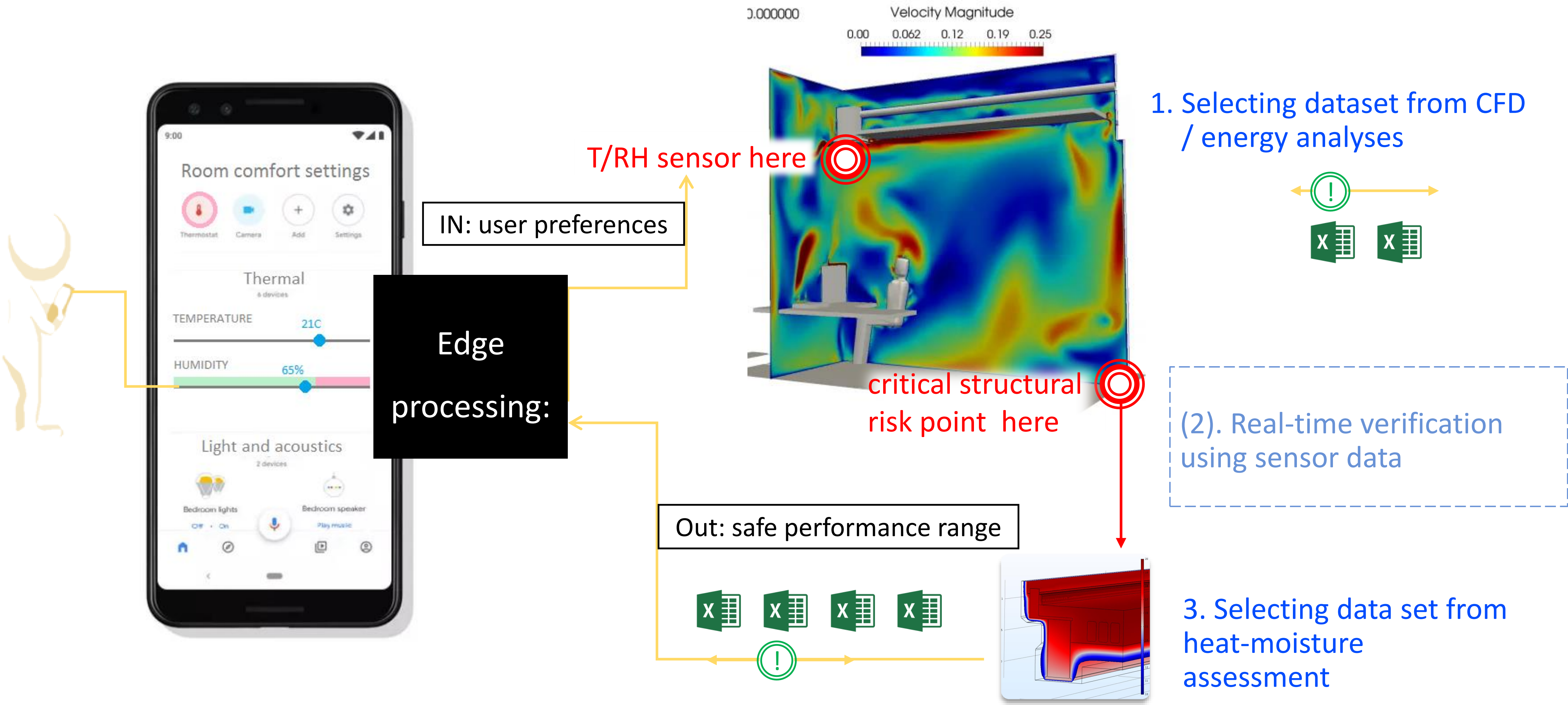


Illustration based on: [RMIT University, Intelligent Asset Management of Buildings]

STRUCTURAL KINESTHESIA:

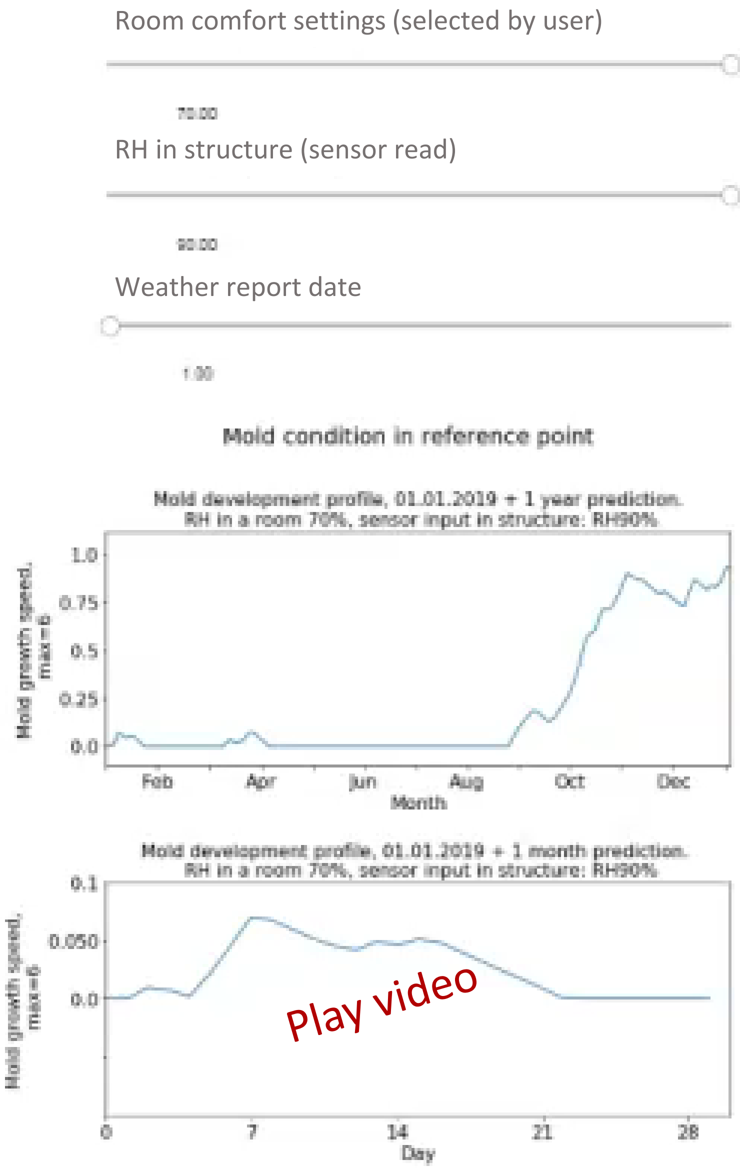
- Building ”is aware”, how its structures react to changing environment impact
- It optimizes its functional accordingly
- It is able to communicate its knowledge to reduce the owner’s risks

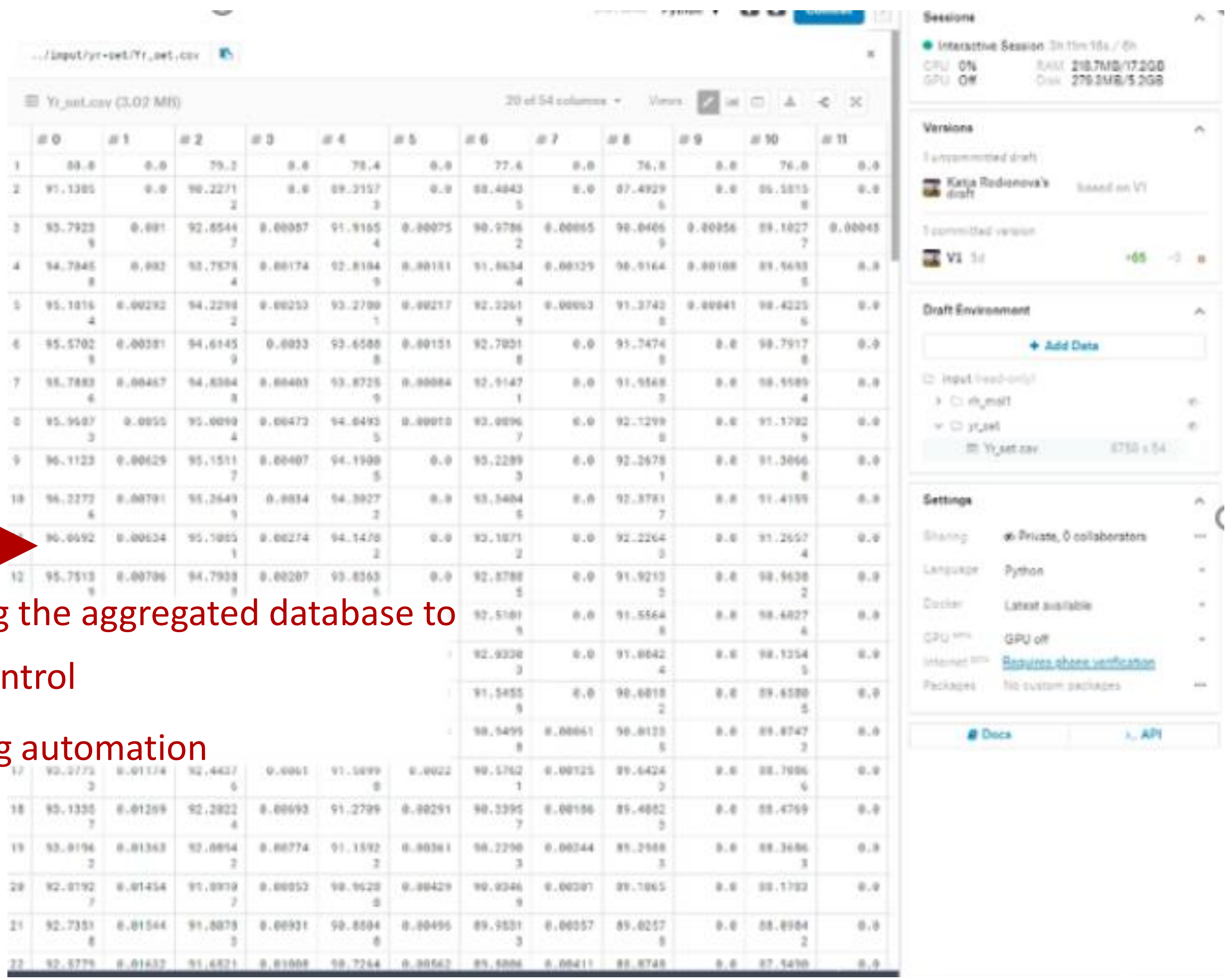
Story: cold bridge safeguarding



Story: behind the scene

Comfort & performance data analytics and visualization





Connecting the aggregated database to

- user control
- building automation

Aihejako 4.6.2019

Rakennesimulointi

Rakennesimulointi tarkoittaa esimerkiksi lämmön, kosteuden, ja mekaanisten ilmiöiden mallinnusta, jonka tuloksena saadaan massan tai energian jakaumat rakenteessa. Analyysin tuloksia käytetään mm. rakennesuunnittelijan päätöksenteon tukena vaativissa tapauksissa.

Tekodata, ”artificial data”

Koneoppiminen ja datakäsittely

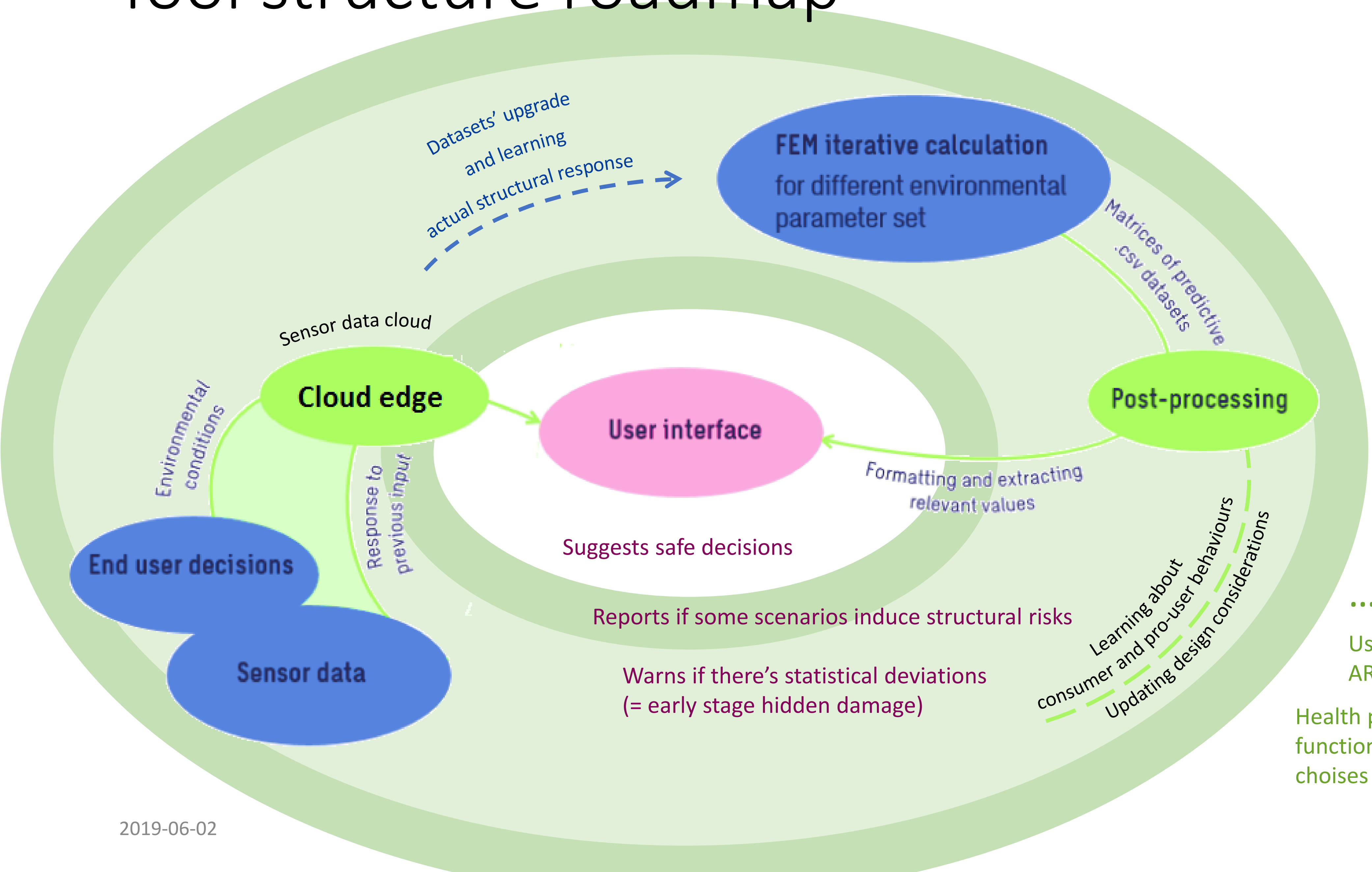
Simulointidatan ja IoT-mittausdatan käsittelyn ja koneoppimisen menetelmät mahdollistavat esimerkiksi simulointituloksista saatavan datan tehokkaampaa käyttöä laadunvarmistuksen työkaluna kohteen elinkaaren aikana.

Sensoridata

IoT eli esineiden internet

tarkoittaa järjestelmiä, jotka perustuvat teknisten laitteiden suorittamaan automaattiseen tiedonsiirtoon sekä kyseisten laitteiden etäseurantaan ja -ohjaukseen internet-verkon kautta

Tool structure roadmap



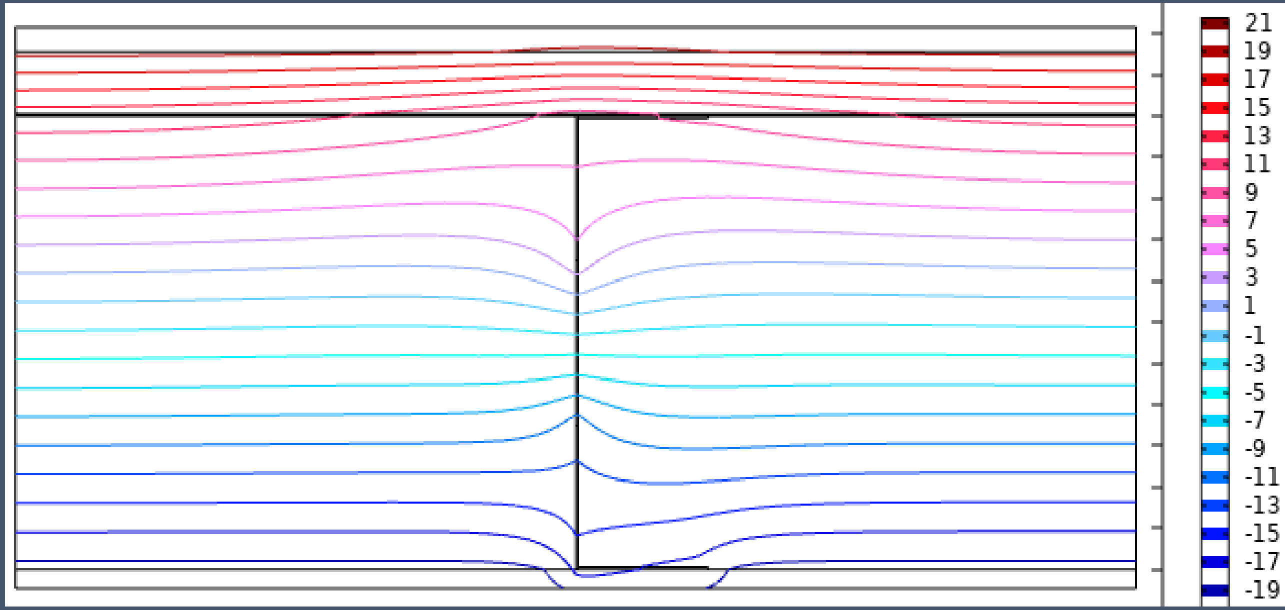
...

User behavior as a function of ARK planning

Health parameters as a function of material choises

Part 1:

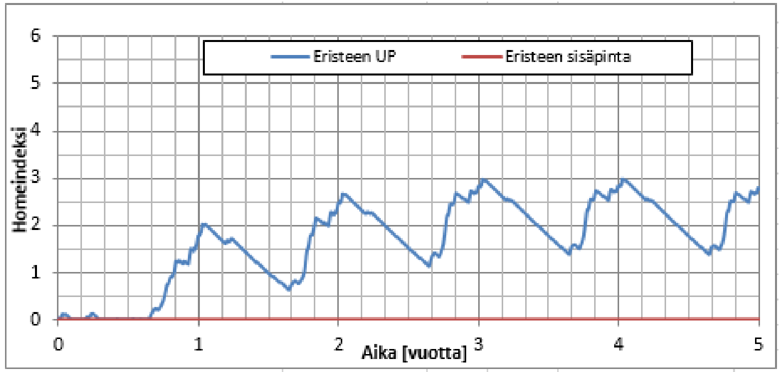
PREDICTIVE ANALYSES



”ARTIFICIAL DATA”
USING SIMULATION SOFTWARE

Heat and moisture in structures

mold models postprocessing
TUT/Fraunhofer

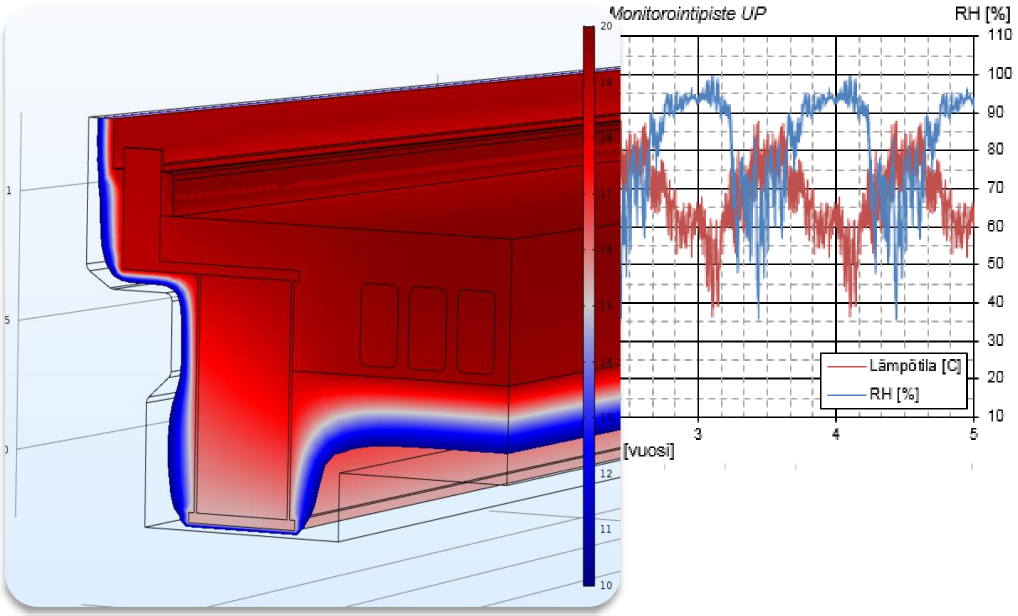


Boundary conditions and material values: Python, IDA ICE

FEM simulations: Comsol/WUFI

Parametric datasets: Comsol app builder

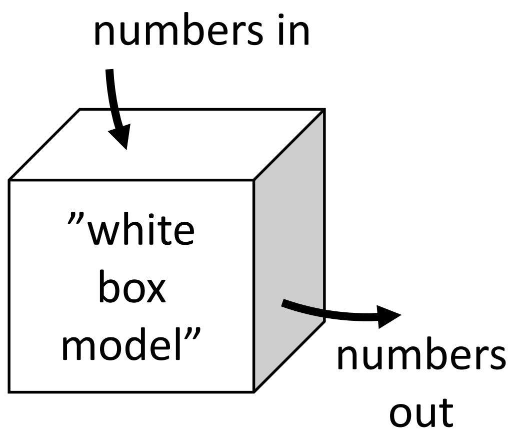
DIGITIZED ASSESSMENTS



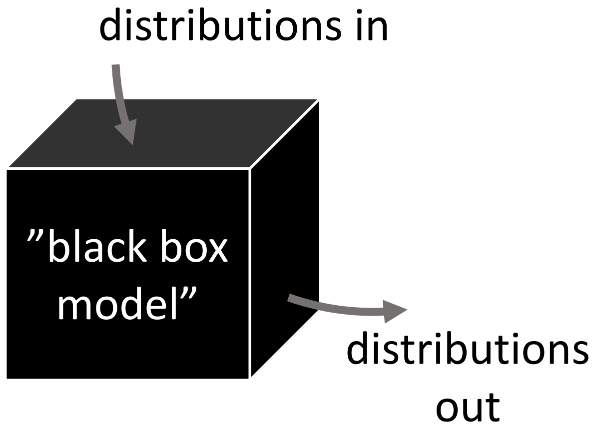
Building physics

- Quality assurance
- Moisture control
- Design and detailing

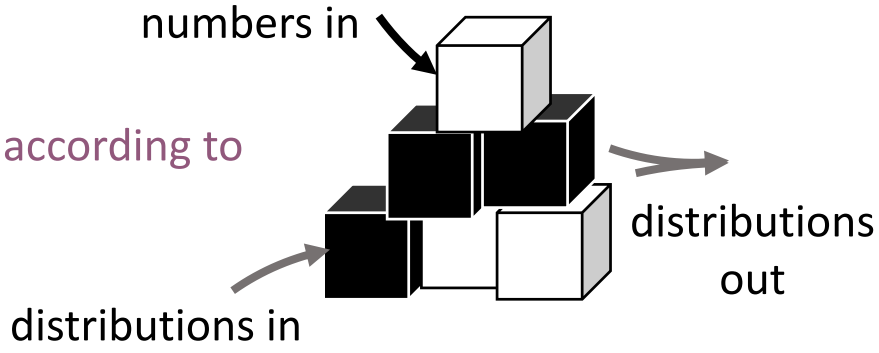
Input data



Deterministic model:
- the material properties are well known, i.e. deterministic. none of them is random
- the applied loads are also deterministic (at least 10%)

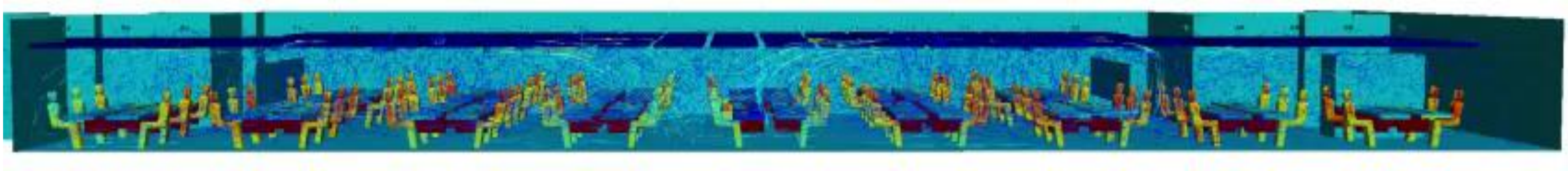


Stochastic model:
- random properties:
  - material property represented by a random variable with uniform distribution
  - or, deterministic definition + “noise”
- especially loads, e.g. air humidity, wind & driving rain, solar gains, excess moisture…



Hybrid model:
- some parameter(s) of the deterministic model are randomly defined, according to the experimental observations
- needs to be treated similarly to the stochastic model

Boundary conditions: advanced



Computational fluid dynamics simulations

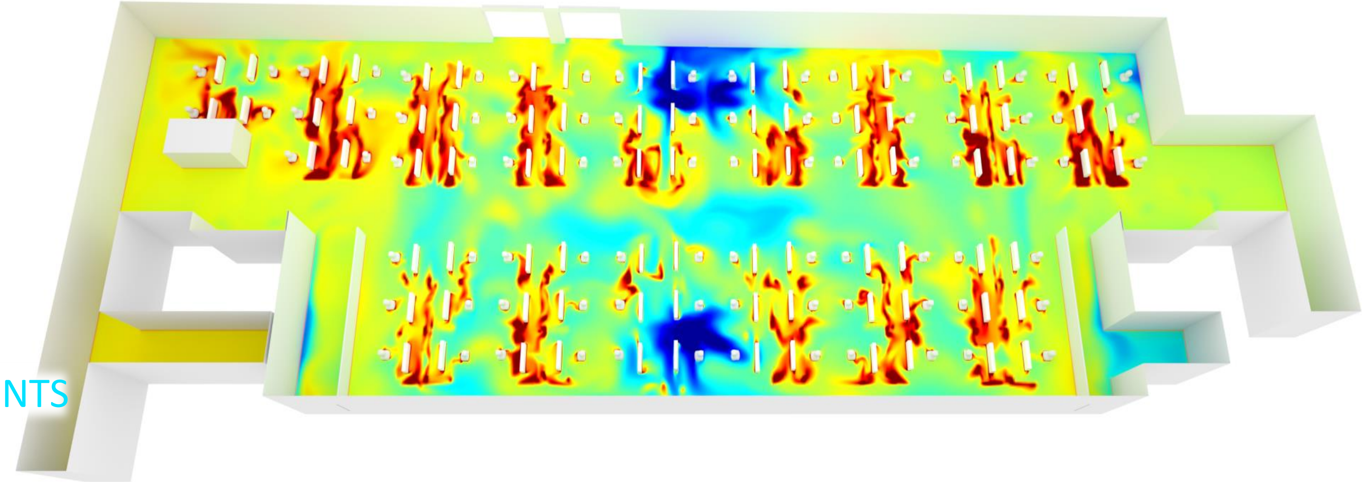
HVAC Design–Temperature Distribution
and Thermal Comfort

TEMPERATURE DISTRIBUTION

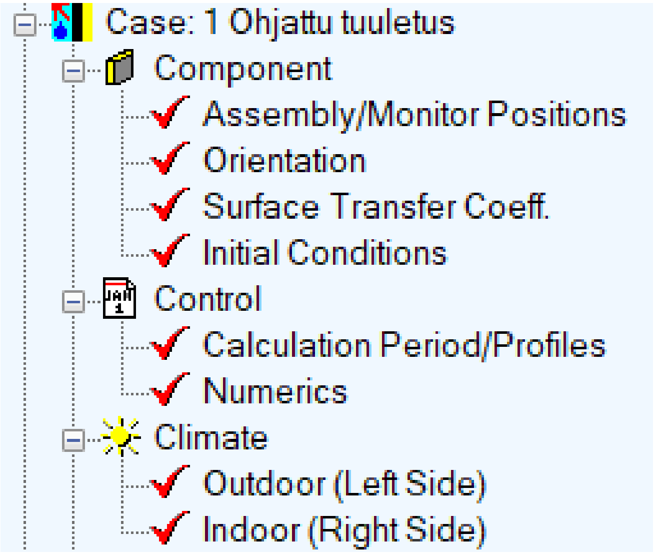
Safe and comfortable environment regardless of the location within the indoor environment.

Accessing structural risk points

DIGITIZED ASSESSMENTS



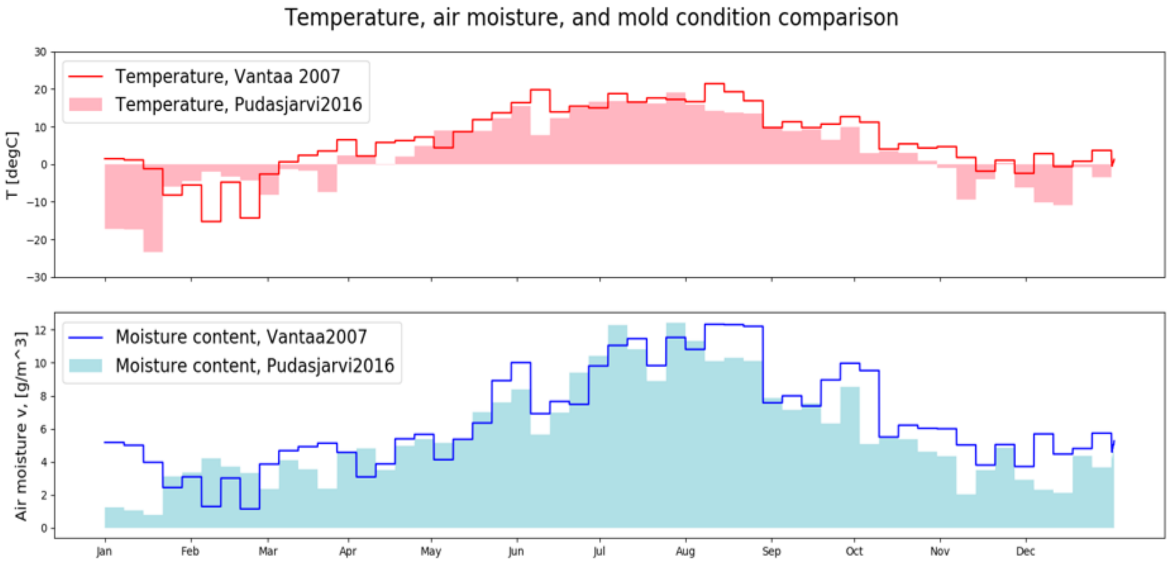
Input data



Deterministic modelling:

- standard material properties
- geometry variability poorly accessed
- orientation, shadowing, wind and rain obstacles
- surface changes (snow, aging…)
- internal ventilation rates
- climate variability
- internal moisture/heat loads approximations

Nonlinearity!



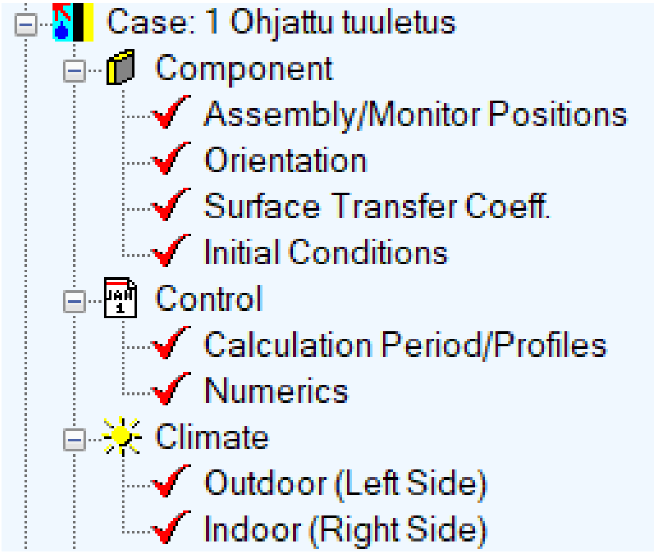
"In deterministic hygrothermal calculations, critical climatic loads and material parameters ensure that the design solution is within the margins of safety. The IEA EBC Annex 24 (Sanders, 1996) has recommended applying a 10% critical level.

(…)

Cornick and Kumaran (2008) compared empirical indoor climate models (ASHRAE 160P, 2009; EN ISO 13788, 2012; Jones, 1993) against data collected from 25 houses (Rousseau et al., 2007) and found that, relative to the data measured, all of the models generally overestimated RH levels."

Vinha, J. et.al. *Indoor hygrothermal loads for the deterministic and stochastic design of the building envelope for dwellings in cold climates*

Input data



Stochastic model treated as deterministic (and strategies):

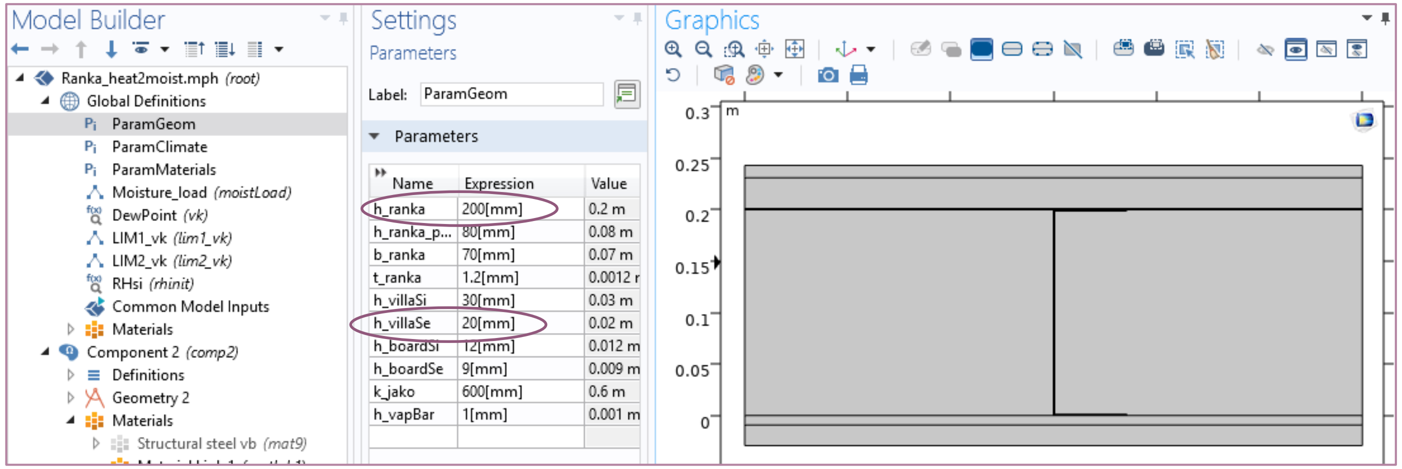
- standard material properties
- geometry variability poorly accessed
- orientation, shadowing, wind and rain obstacles
- surface changes (snow, aging…)
- internal ventilation rates
- climate variability
- internal moisture/heat loads approximations

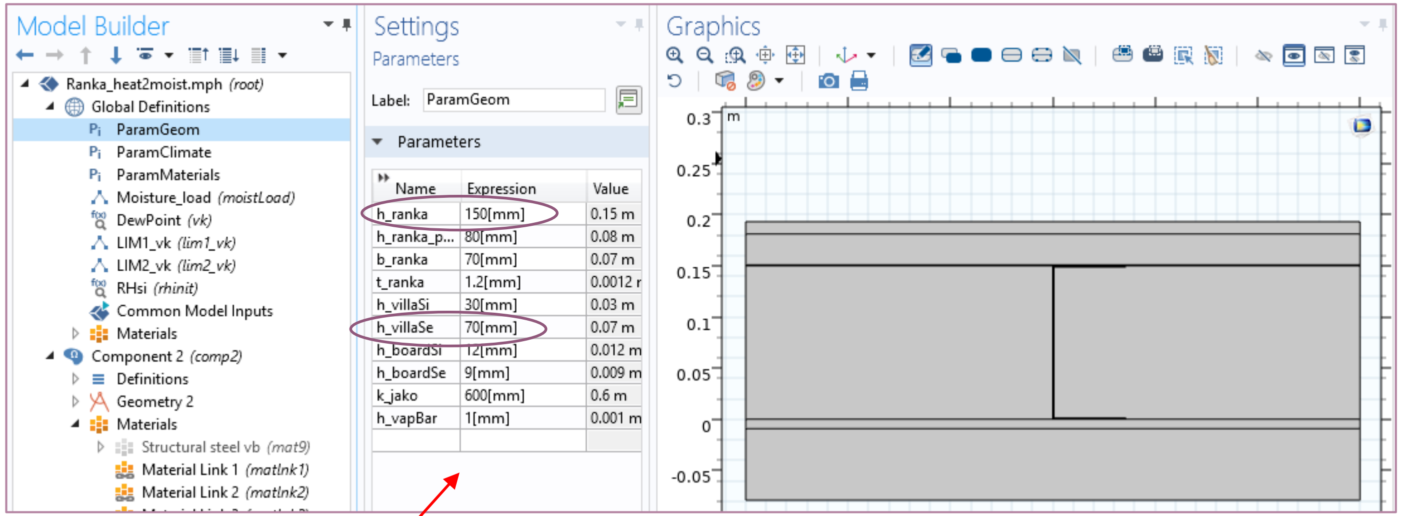
analytically accessible using sensor data

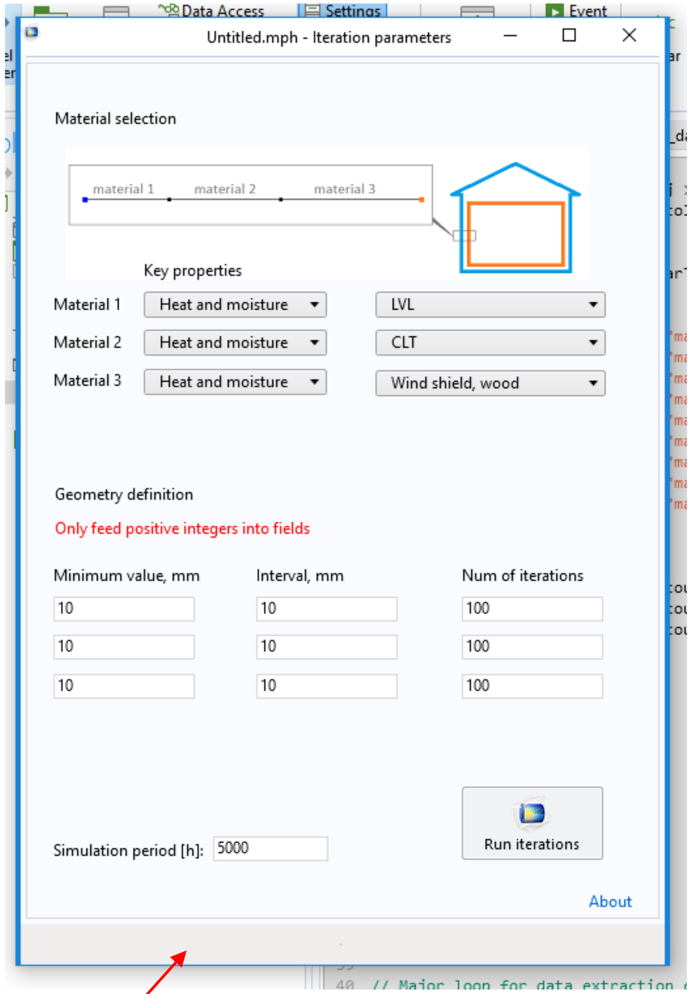
directly accessible using sensor data

directly accessible using parametric input data

Input data: parametric







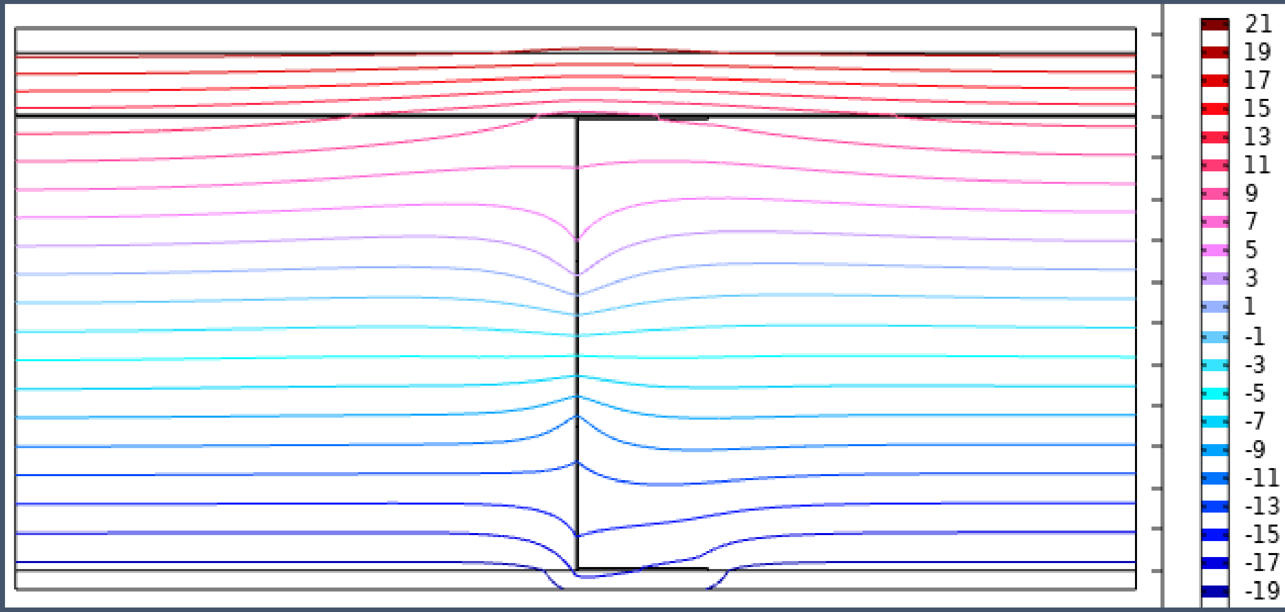
In Comsol, it is much easier to redefine geometry parameters

Using Java AppBuilder interface, can iterate parametrically, preprocess, and automatically save high quality artificial data

SWECO

Part 2:

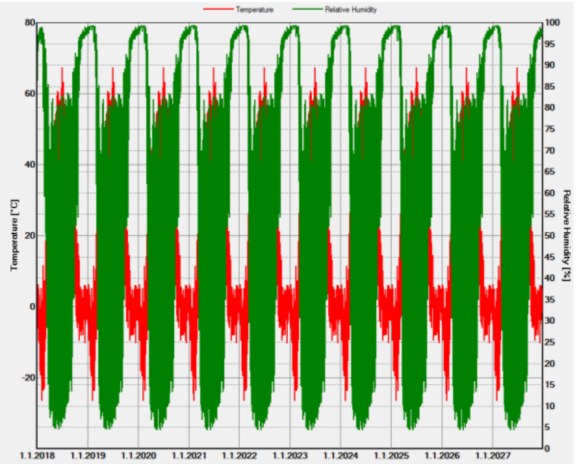
DATA OPTIMIZATION

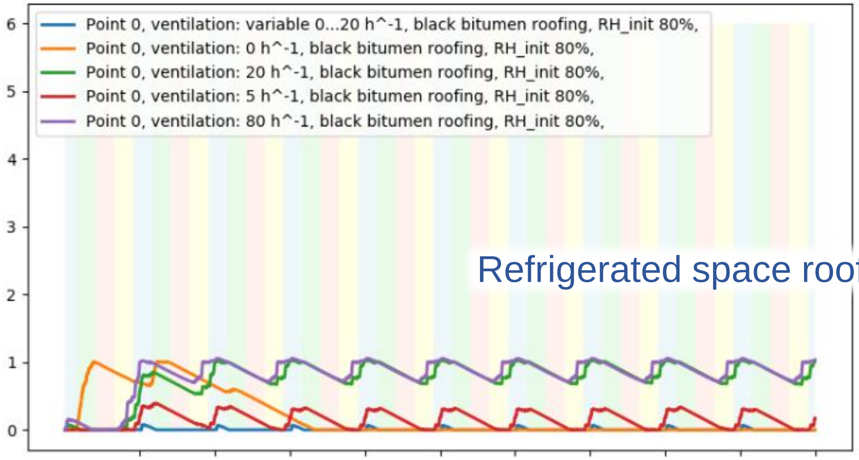


VISUALIZATION
SAFE DATA TRANSFER
MACHINE LEARNING

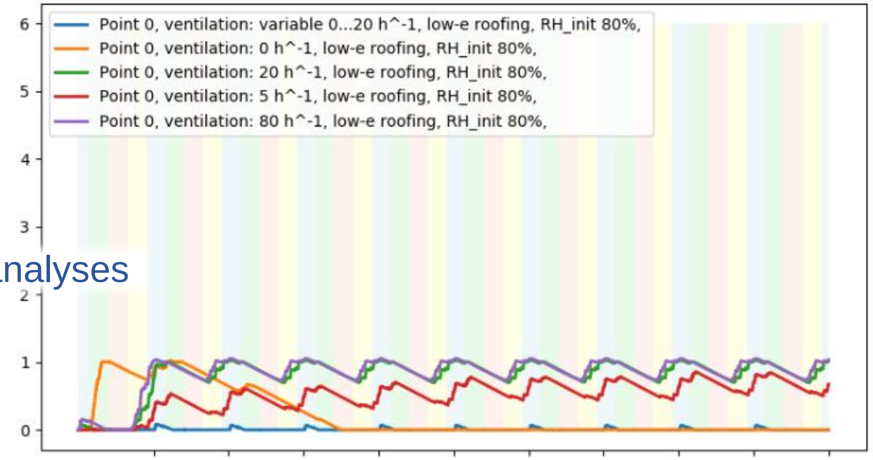
Visualisation and data transfer

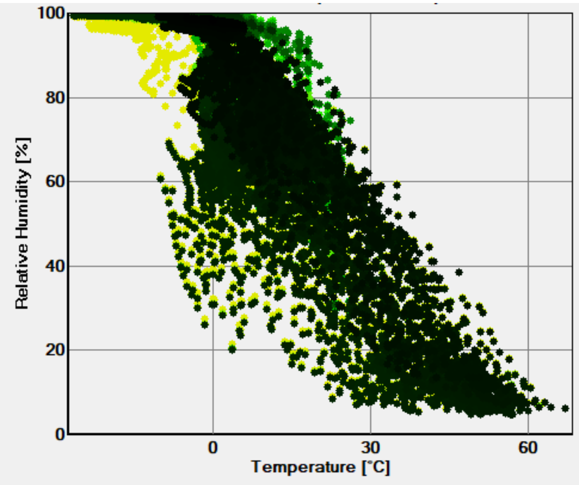
Is there mold? **VS** **What are our choices?**

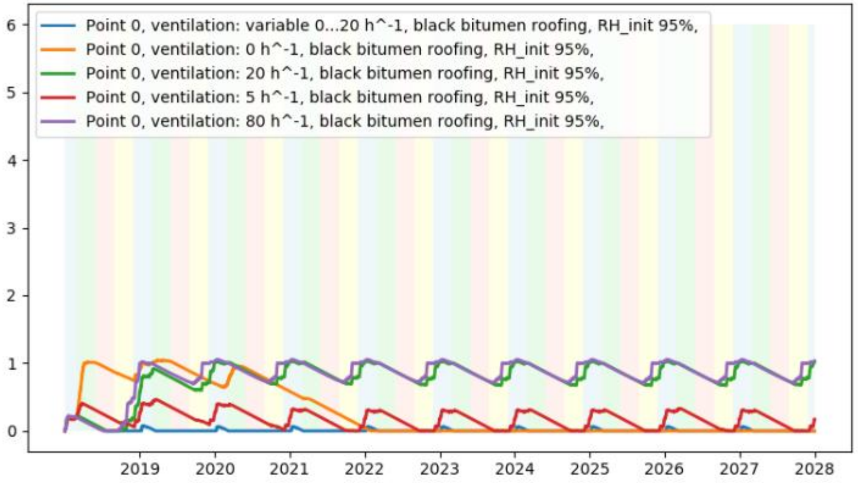


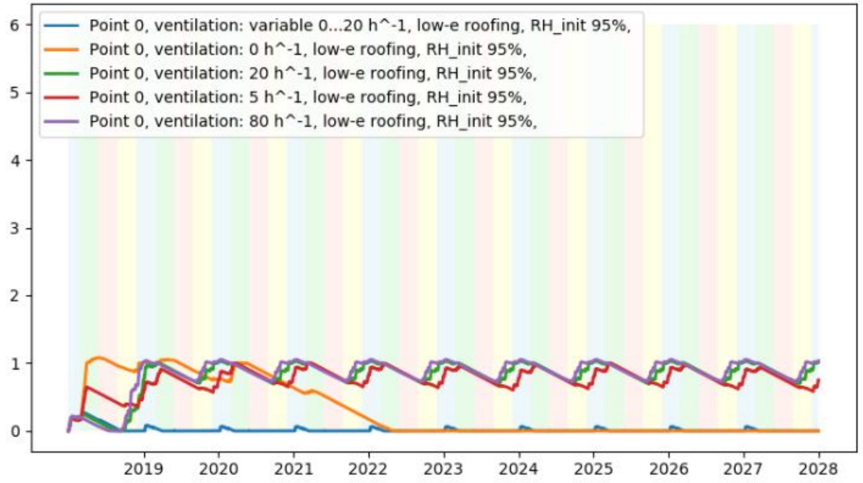


Refrigerated space roof analyses



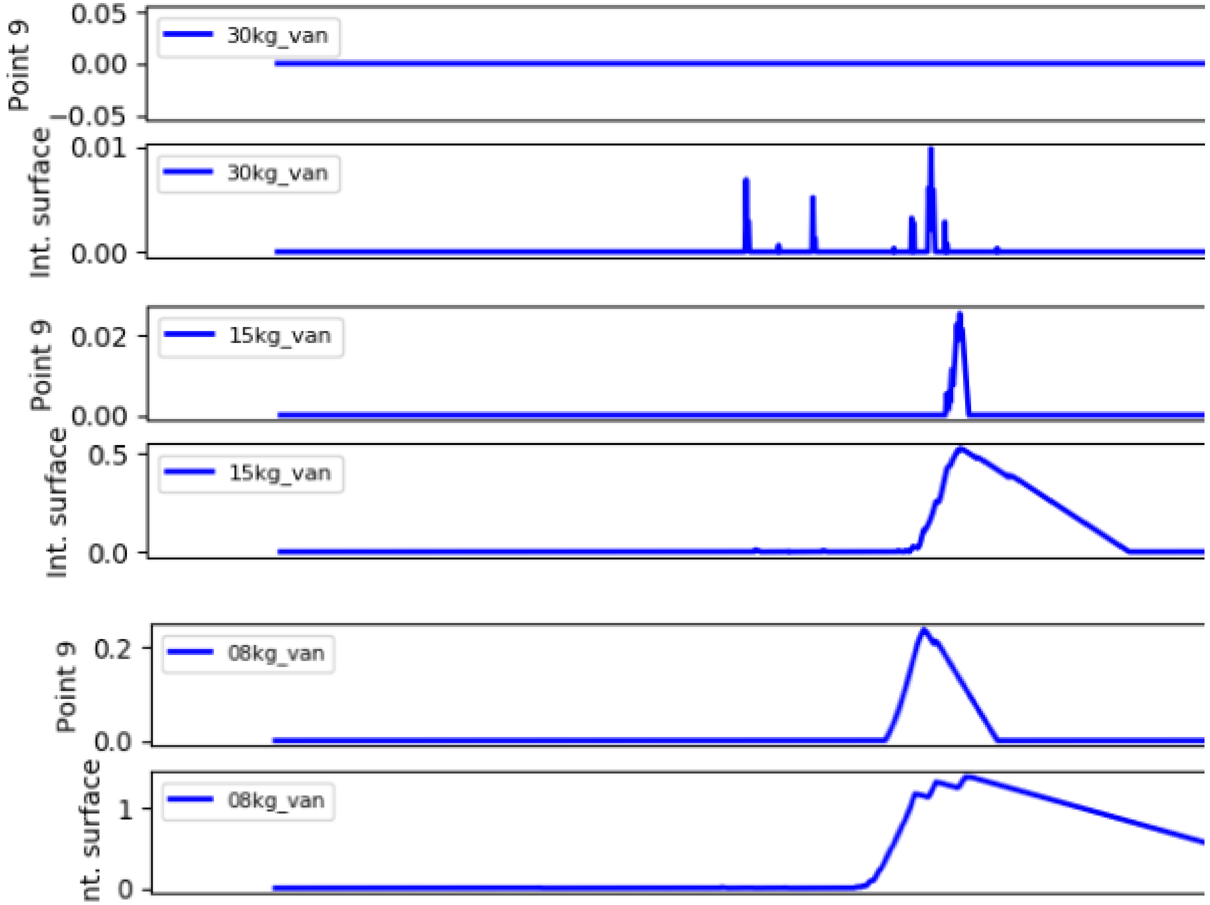






Visualisation and data transfer

Choosing dehumidification capacity



Homeindeksi eri kuivatustehon arvoilla: sisäpinnat

Machine learning: “stupid AI”

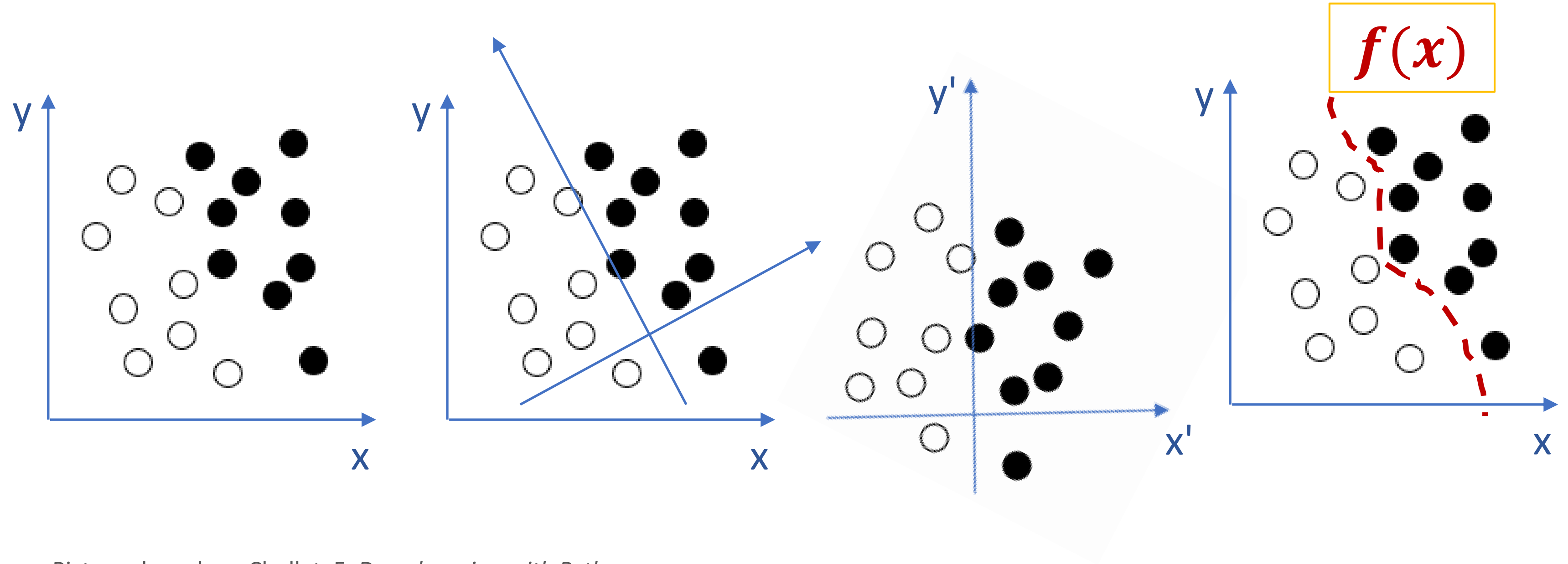
According to a TU Wien & MIT study it only takes 12 neurons to park a car…
We aim to find out in which areas results can be maximized with minimum viable product development.

Building physics:

- A lot of ”free” data available from simulations and sensors
- Clean data
- SLS case, possibility to provide comparatively safe training environment for engineers and officials

which calculation reports are available en masse?

Name	Expression	Value
h_ranka	200[mm]	0.2 m
h_ranka_p...	80[mm]	0.08 m
b_ranka	70[mm]	0.07 m
t_ranka	1.2[mm]	0.0012 r
h_villaSi	30[mm]	0.03 m
h_villaSe	20[mm]	0.02 m
h_boardSi	12[mm]	0.012 m
h_boardSe	9[mm]	0.009 m
k_jako	600[mm]	0.6 m
h_vapBar	1[mm]	0.001 m

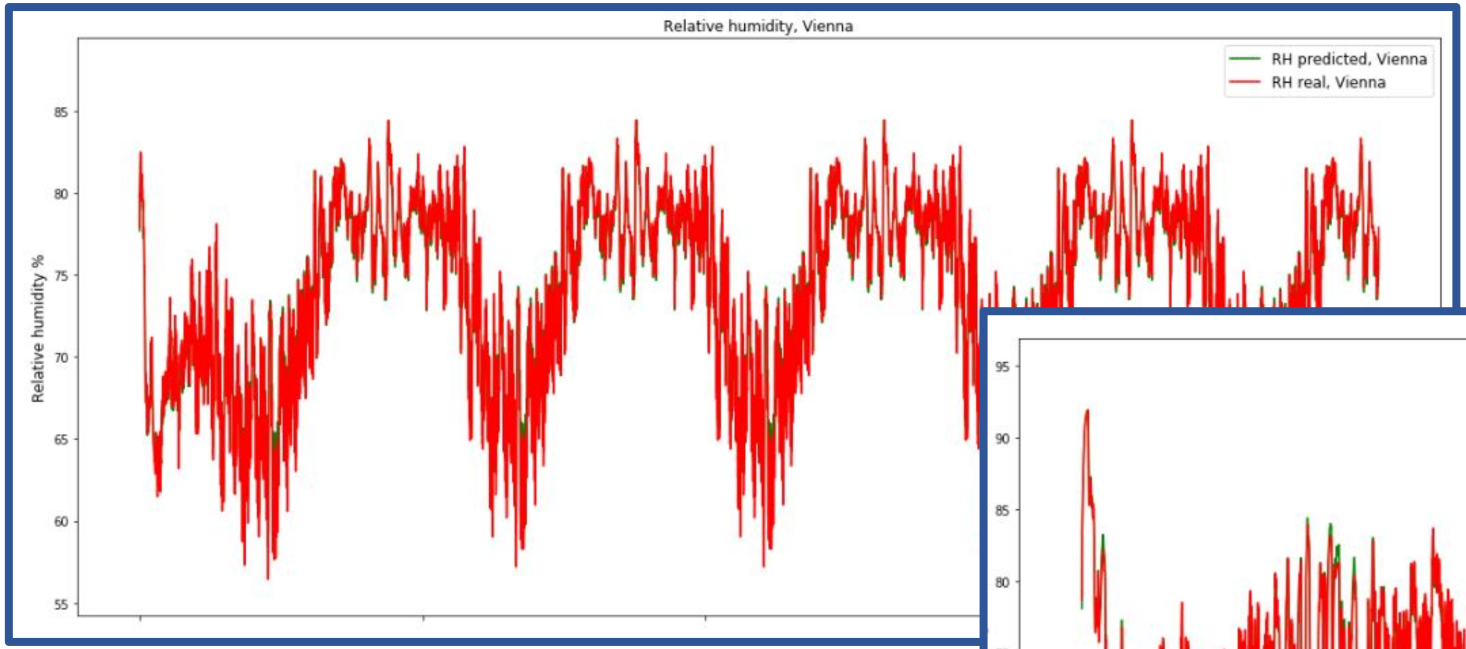


Pictures based on: Chollet, F. *Deep learning with Python*

Machine learning: basic case 1

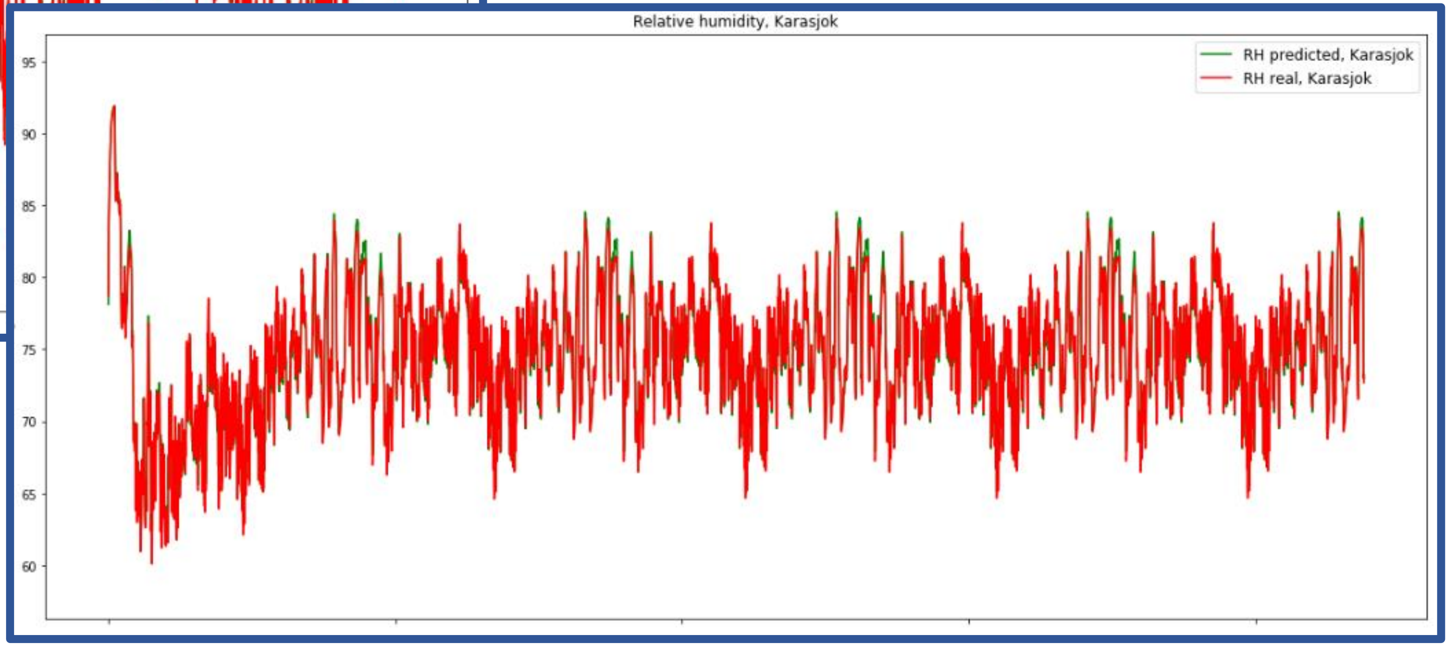
Prototype of moisture/mold risk prediction for given structure in different climates, based on artificial data from WUFI simulation.

- tested RF; 97…99% score for test climates using SVM



Model was trained on a data from simulation based on Vantaa2007 climate.

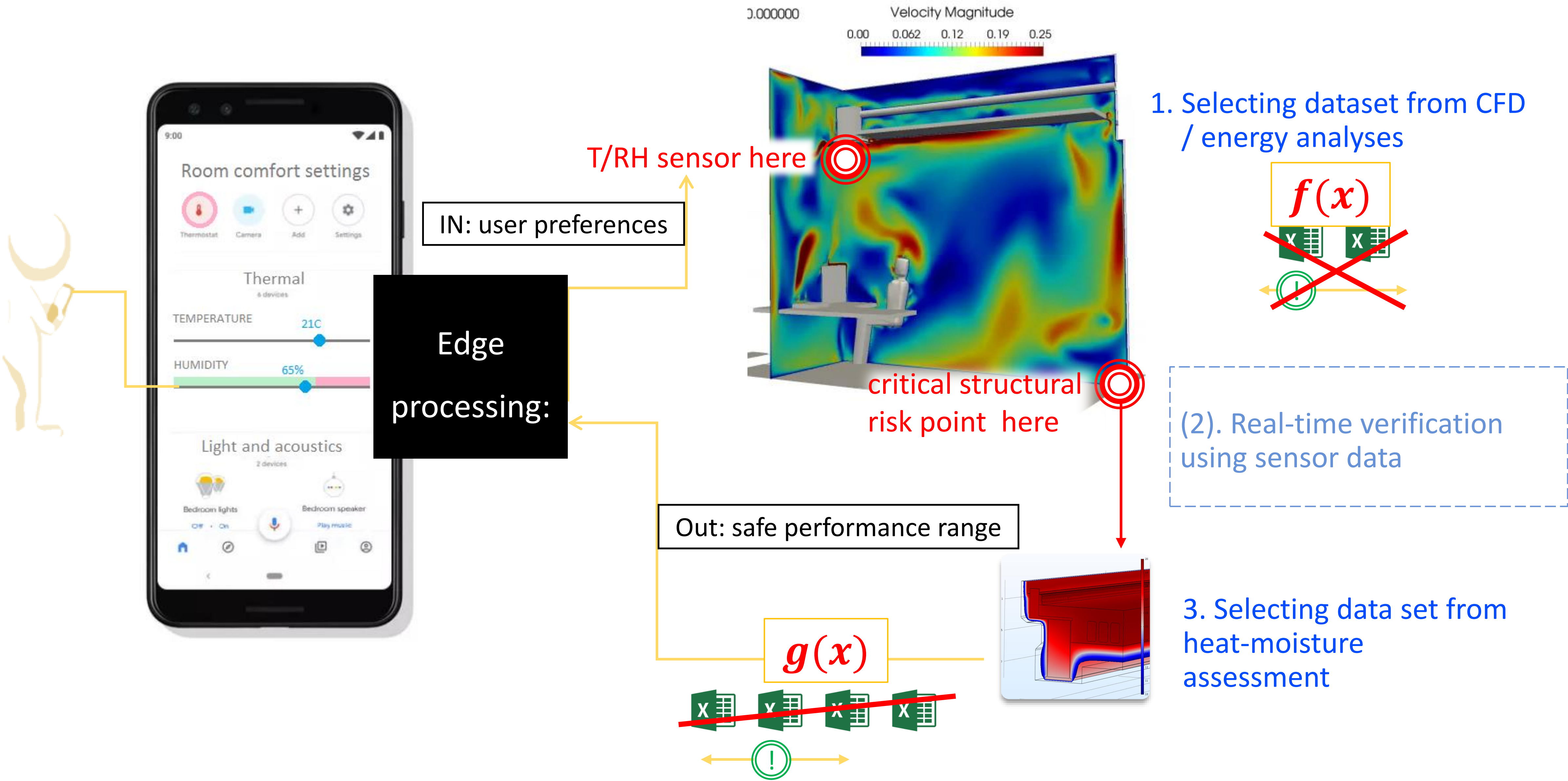
Prediction sequences based on Vienna and Karasjok external climates (e.g. mock-up of a sensor read)



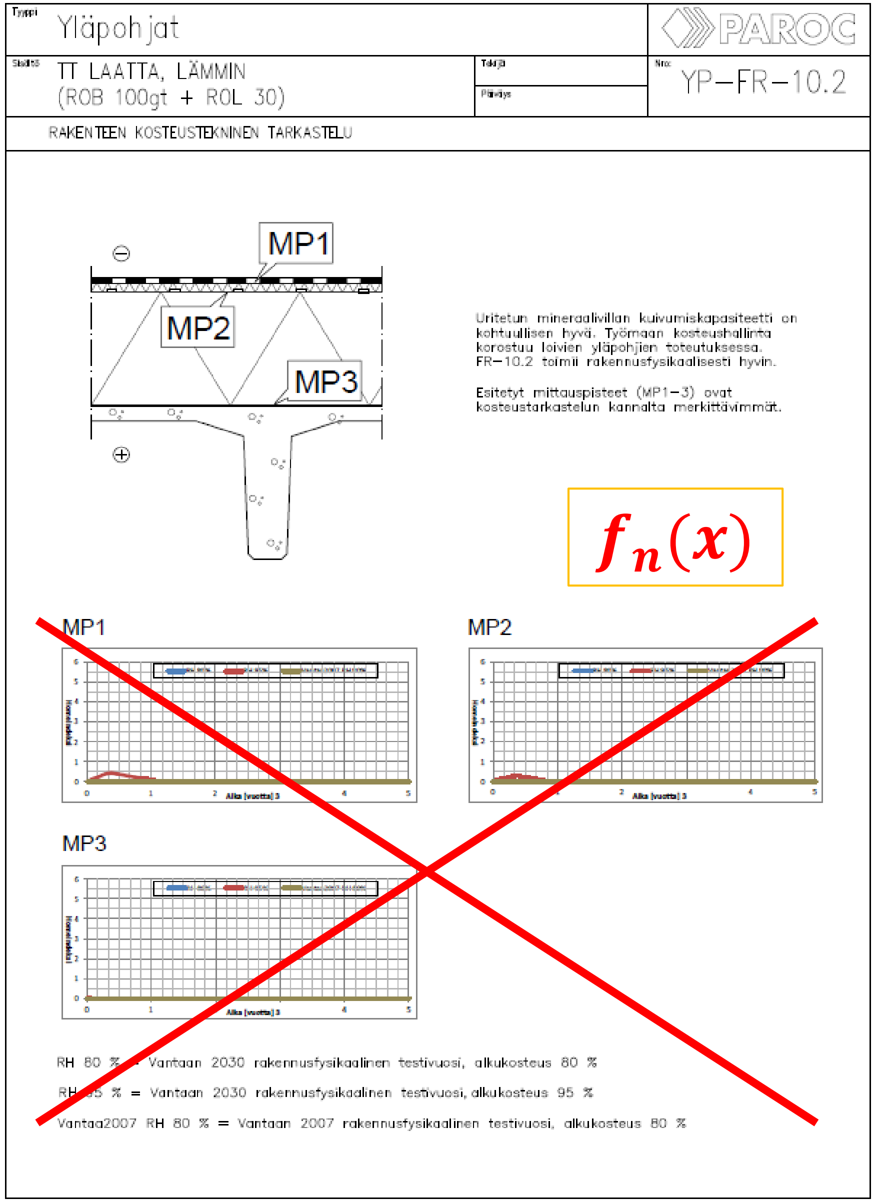
Prediction deviation is seen as difference between red and green

Deviation can potentially pile up if there's no regulating sensor input

Story: cold bridge safeguarding with ML



Potential



Digital passports for structural types:

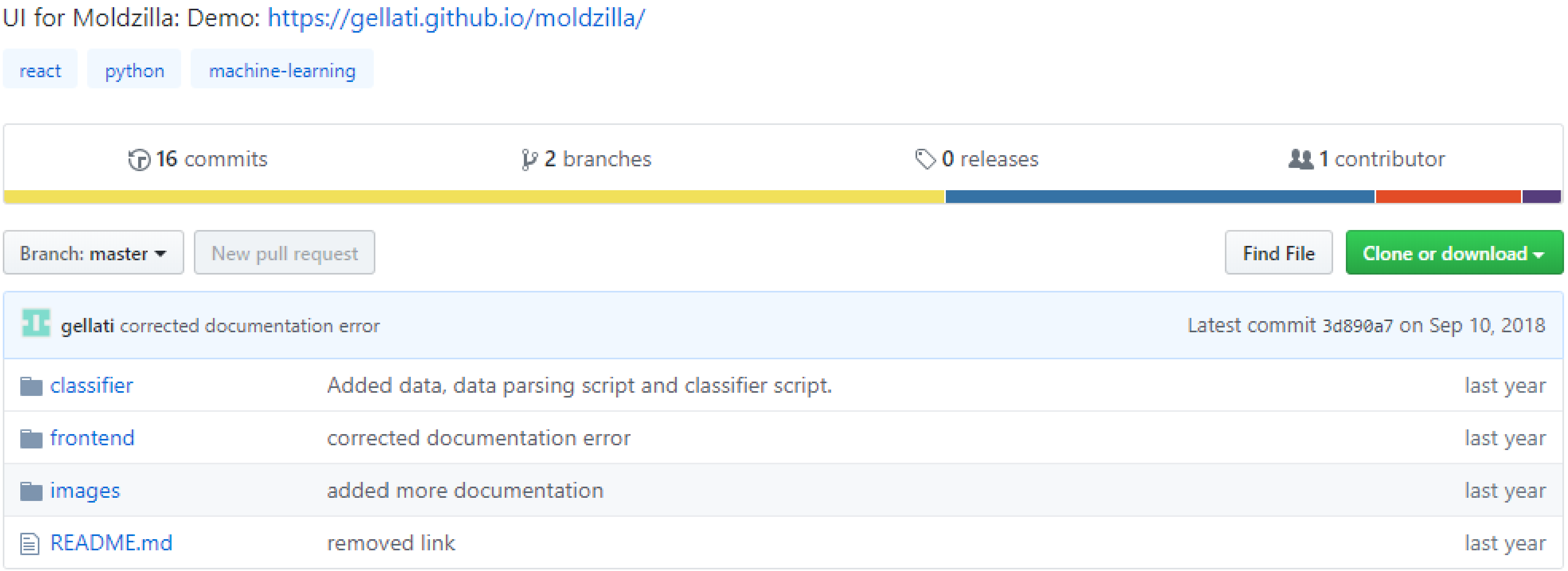
- ML-model covers climate variability
- critical points assessed during energy calculation or BIM process using project UDA-defined climate conditions
- ”digital twin”-readiness

Machine learning: basic case 2

Predicting mold risk of arbitrary structural type under given climate condition. Can be used for scanning BIM model for risk spots preliminary detection w recall score as metrics.

- SVM, Random Forest, NN tested w grid search, >70% accuracy on small sample using RF (mold condition as classification).

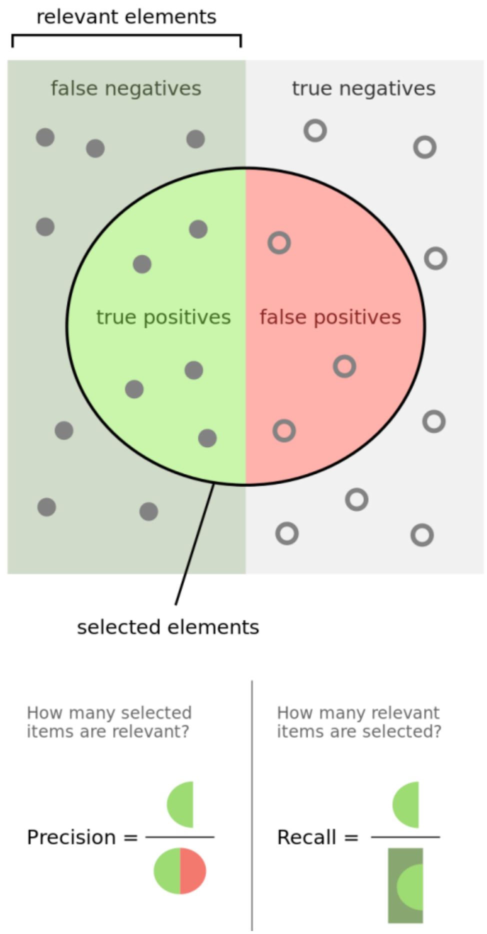
https://github.com/gellati/moldzilla



Machine learning: choosing metrics

In day-to-day project, what is the possibility of a mistake (human mistake, software mistake…)? For ML models, we can have an idea how much and in which way our algorithm is going to fail.

Accuracy is a ratio of correct prediction to all answers. But also…

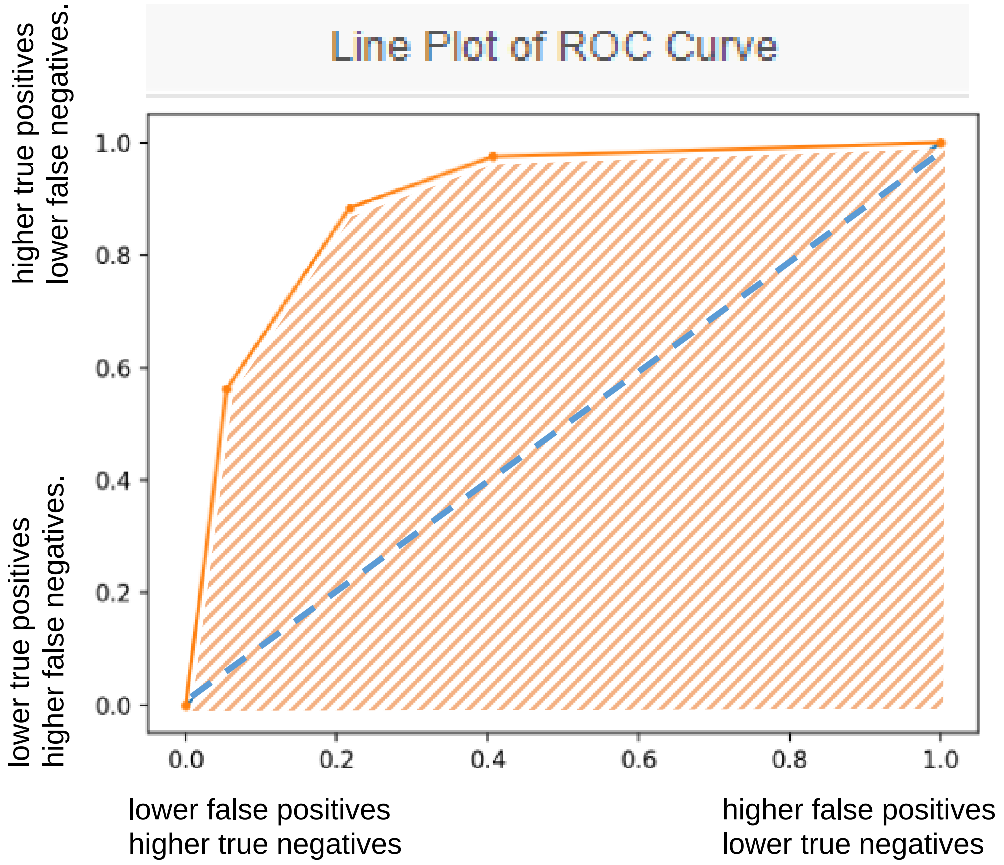


File:Precisionrecall.svg

From Wikimedia Commons, the free media repository

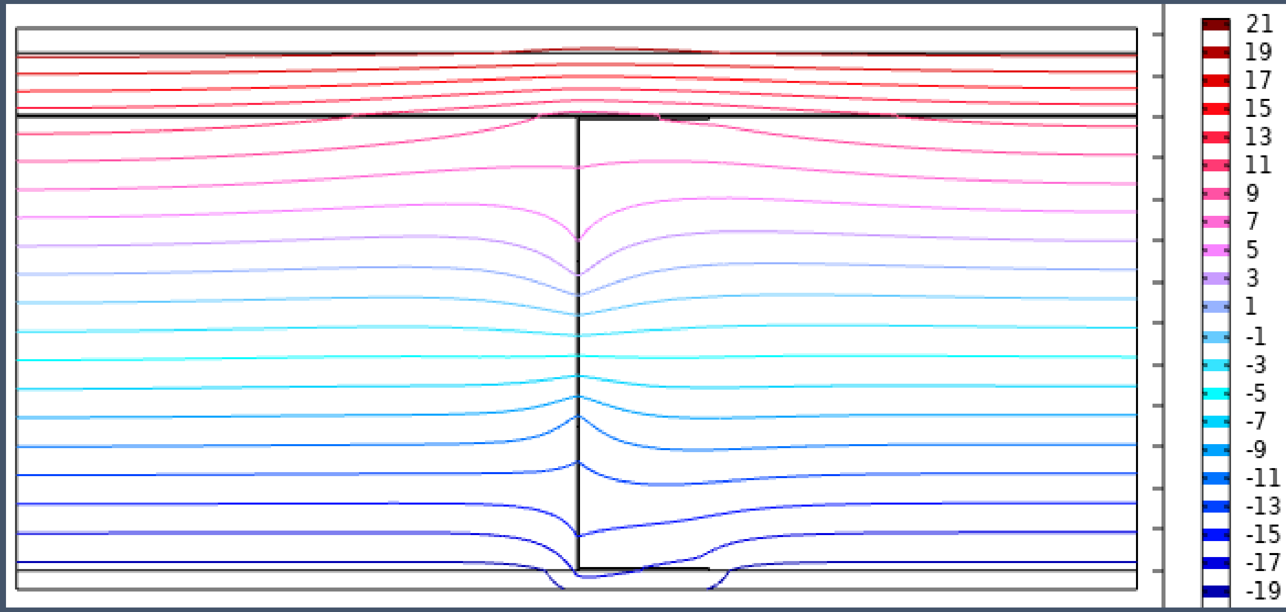
- **ROC Curves** summarize the trade-off between the true positive rate and false positive rate for a predictive model using different probability thresholds.

- **Precision-Recall** curves summarize the trade-off between the true positive rate and the positive predictive value for a predictive model using different probability thresholds.



Part 3:

IoT



HARDWARE & CLOUD SERVICE CASES
DEVELOPMENT POSSIBILITIES

Hardware and cloud service cases

Langattomat anturit + pilvipalvelu (case RF SensIT)

- voidaan asentaa elementtiin jo tehtaalla
- valvotaan mm. kuljetuksen ja asennuksen olosuhteet
- tulokset luettavissa pilvipalvelusta
- takuuehtojen mukainen toimintajakso 10 vuotta, 15 realistinen tavoite

Langalliset anturit + pilvipalvelu (case Siemens Mindsphere)

- nykyään lähinnä taloteknisen järjestelmien seuranta (rakenteisiin asennettaessa sähköasennusten hinta piisaa)
- ilman päättäväistä suunnittelua projektivaiheessa, saatavilla oleva data ei-uniforminen (vaikeahko saada relevantit tulokset ML keinoin)
- tulokset luettavissa pilvipalvelusta,
- tavoitteena avoin platformi kaikenlaisille UI kehityksille, tämän rajoitteena todellisten rakennusten BIM-mallien ja datan ”avoimuus”

RFID-anturit

- passiivinen datasiirto: langaton ja pitkäkestoisempi vaihtoehto
- datan kerääminen jaksoittainen, lukupää on tuottava anturin viereen

Preliminary use regime definitions

- Lifetime predictive definitions using e.g. hand input, AI, marker sensor data such as CO_2 levels

suure	arvo	lähde
Hallin ilmavolyymi (suuruusluokka)	25000m^3	Arkkitehtiluonnokset
IV-A: ilmanvaihto tapahtumien aikana, kesällä jaksottaisen kuivatuksen aikana 2h/vrk (ulkoilma 100%)	4200 [l/s] 0.6 [1/h]	TaTe suunnittelijan arvio
IV-B: ilmanvaihto normaalikäytön aikana (3600 [l/s] niistä ulkoilmaa 40%)	1440 [l/s] 0.21 [1/h]	
IV-C: tehostettu ilmanvaihto kesällä, tapahtuma-aikana	1[1/h]	
IV-D: ilmanvaihto kesällä, ei käytössä (max 1 hlö, ei muita kosteuslähteitä)	0[1/h]	
Lämpötila 1.5m korkeudella jääkauden aikana	8 C	
Lämpötila kattopinnan vieressä	10-12C	
Lämpötila 1.5m korkeudella kun viilennys pois päältä	ulkolämpötila +1C	
Lämpötila kattopinnan vieressä	ulkolämpötila +3C	
Kuivatuksen käynnistymisen yläraja	RH 60%	

Taulukko 2. Sisäilmaston määrittelyn lähtötiedot.

tapaus	arvo
Kosteuslisä kesän tapahtumien aikana, kuormitus 500hlö	1.7 [g/m^3]
Kosteuslisä talven tapahtumien aikana, kuormitus 300hlö	0.9 [g/m^3]
Kosteuslisä talven harjoitusten aikana, kuormitus 30hlö	0.3 [g/m^3]
Kosteuslisä kun halli ei ole käytössä (talvella max. 10hlö, kesällä max 1 hlö)	0.1 [g/m^3]

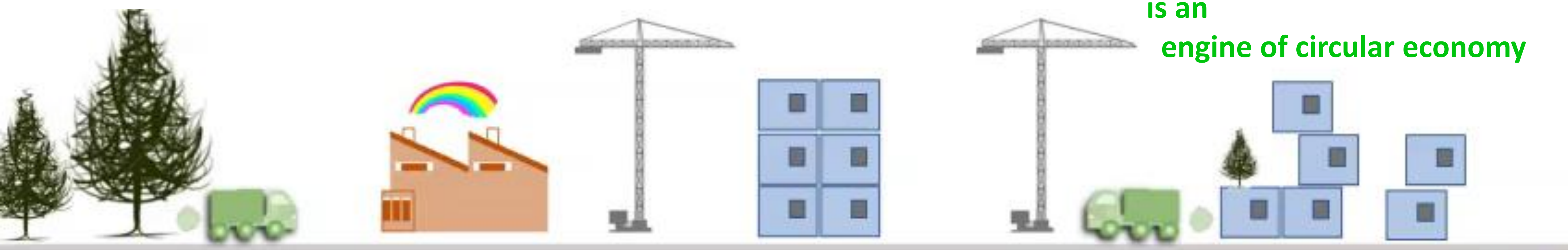
klo	jääsesonki, vk 0-18 ja 36-52		jäähdytys pois päältä, vk 18-36		
	viikoittain		viikko1	viikko2	
	Ma-Pe	La-Su	Ma-Su	Ma-Pe	La-Su
02	0.1	0.1	Ma		0.1
04	0.1	0.1	0.1		0.1
06	0.1	0.1	0.1		0.1
08	0.1	0.1	0.1		0.1
10	0.1	0.1	0.1		0.1
12	0.3	0.3	0.1		1.7
14	0.3	0.3	0.1		1.7
16	0.3	0.3	0.1		1.7
18	0.3	0.6	0.1		1.7
20	0.3	0.6	0.1		1.7
22	0.1	0.6	0.1		1.7
24	0.1	0.1	0.1	0.1	0.1

Taulukko 4. Kosteuslisän (numeroina) ja IV-luvun (värikoodina) valinta sisäilmaston määrittelyssä.

Excess moisture values are provided according to planned use regime

Lifecycle services: IoT roadmap

Sensor cloud service is an engine of circular economy



Design stage	**Construction stage**	**Lifecycle stage**	**~~Demolition~~ upcycle stage**
Analyses	Cloud quality control	Automated building inventory data	Quality assessment for parts' recyclability
Datasets	Dry chain control	Data for test-based design values to part producers	Recommissioning quality control
Sweco Smart Drawings	Automated site mgt		
Sweco BIMVision	VR	Digitized user interface	Knowledge gathering

Ote *Kiertotalous ja siirrettävät rakennukset* – esityksestä

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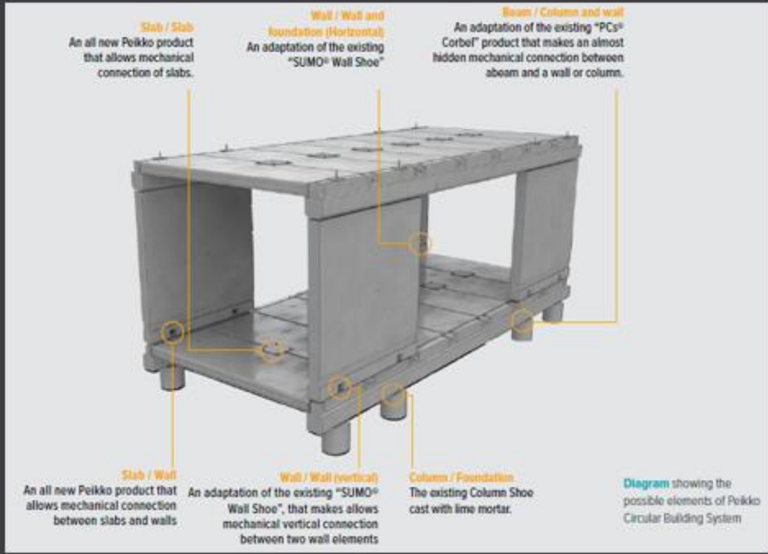
SWECO

TARPEEN MUKAAN JOUSTAVA KIINTEISTÖMASSA

RAKENTAMINEN KESKEN KAAVOITUSPROSESSIN

RAKENNUS = TUOTEOSAVARASTO

PIENEMPI RISKI KIINTEISTÖN VAJAAKÄYTÖSTÄ



PAREMPI PURKU~~JÄTTEEN~~OSIEN JÄÄNNÖSARVO

VÄHÄISEMPI RAAKA-AINEIDEN TARVE

TUOTTEIDEN PIDEMPI ELINKAARI

VEROHELPOTUKSET, PÄÄSTÖKAUPPA ??

Part 4:

TRUST

Let’s work together and fight the global problems!

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“While we can’t get inside a Neanderthal mind to understand how they thought, we have indirect evidence of the limits to their cognition compared with their Sapiens rivals. Archaeologists excavating 30,000-year-old Sapiens sites in the European heartland occasionally find seashells from the Mediterranean and Atlantic coasts. In all likelihood, these shells got to the continental interior through long-distance trade between different Sapiens bands. Neanderthal sites lack any evidence of such trade. Each group manufactured its own tools from local materials …

“The fact is that no animal other than Sapiens engages in trade, and all the Sapiens trade networks about which we have detailed evidence were based on fictions. Trade cannot exist without trust, and it is very difficult to trust strangers. The global trade network of today is based on our trust in such fiction entities as the dollar, the Federal Reserve Bank and the totemic trademarks of corporations. When two strangers in a tribal society want to trade, they will often establish trust by appealing to a common god, mythical ancestor or totem animal. If archaic Sapiens believing in such fictions traded shells, it stands to reason that they could also have traded information, thus creating a much denser and wider knowledge network than the one that served Neanderthals and other archaic humans.”

from Y.N.Harari, *Sapiens*