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IEBB THEMA 2
DATAGEDREVEN OPTIMALISATIE VAN RENOVATIECONCEPTEN
IEBB Theme 2

TRANSACT

Buildings as Sustainable Energy Systems (edX)

TU Delft

Models for Digitized Operation & Assessment of BESs

Prof. Dr. L.C.M. Itard

Chair Building Energy Epidemiology

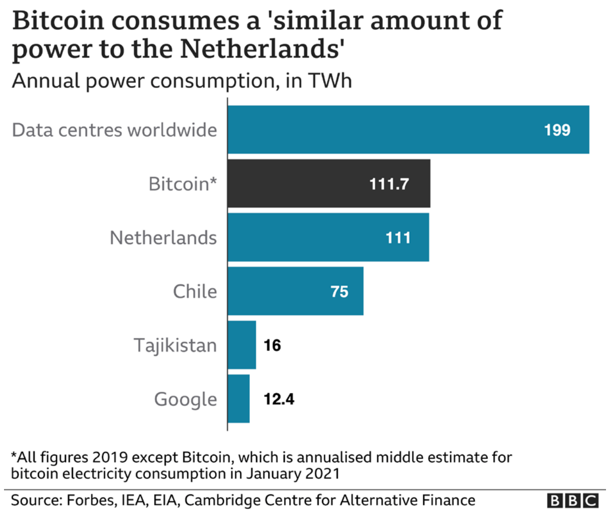
13 Januari 2022

https://www.goodfreephotos.com/netherlands/the-hague/full-cityscape-view-of-the-hague-netherlands.jpg.php

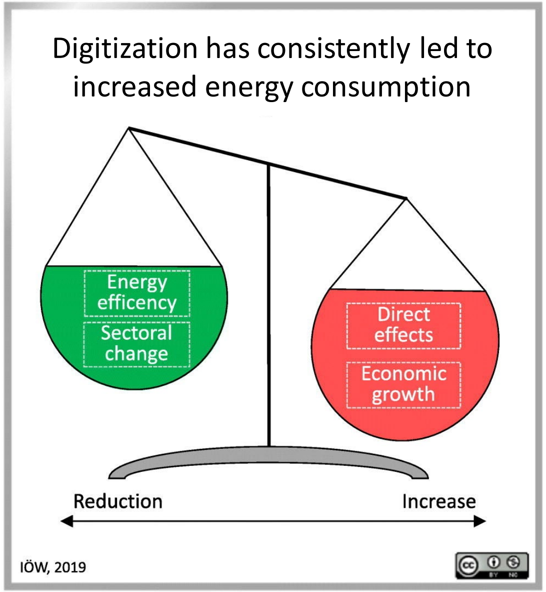
Will Digitization Help Energy Transition?

Energy Transition

- Renewable sources
- Emission free
- **Reduced demand**



https://www.bbc.com/news/science-environment-56215787



Digitalization and energy consumption. Does ICT reduce energy demand?
S. Lange, J. Pohl,T. Santarius (TU Berlin; Humbolt-U, Inst. Ecological Economy Research) *Ecological Economics, Volume 176, October 2020*

Big data on energy use: to understand rebound effect & steer on actual effectiveness of energy efficiency measures

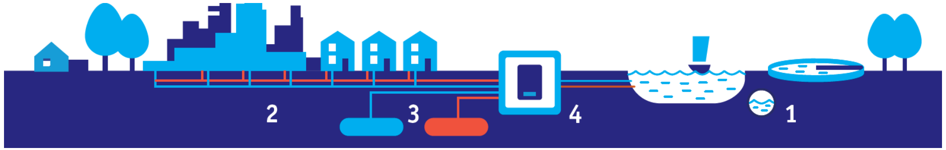
Energy Transition

- **Renewable sources**
- **Emission free**
- Reduced demand

Will Digitization Help Energy Transition?

Heating

- Mix of H2, aquathermy & geothermal with seasonal/daily storage & heat pumps, PVT
- Network of heat sources and heat delivery



Bron: CE Delft; https://cedelft.eu/publications/aquathermy-configurations-an-assessment-framework/

Electricity

- Central & distributed sources (wind/solar/geothermal etc..)

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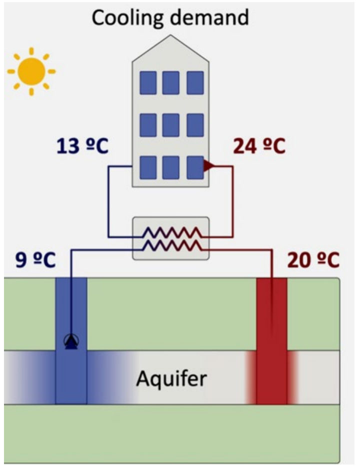
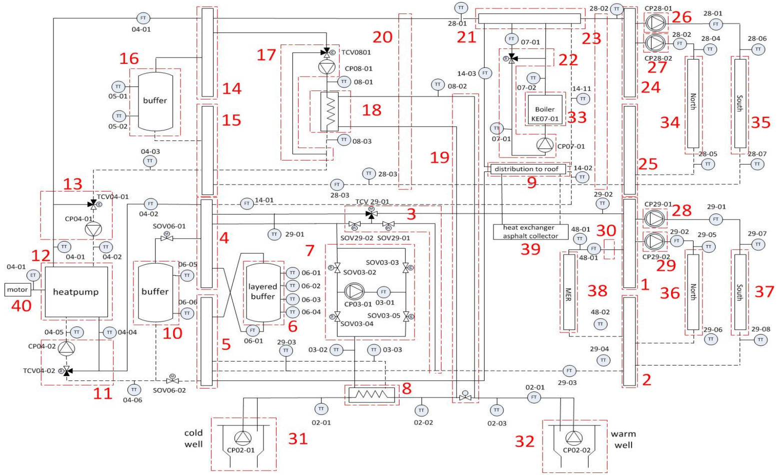
Digitization needed to control and steer

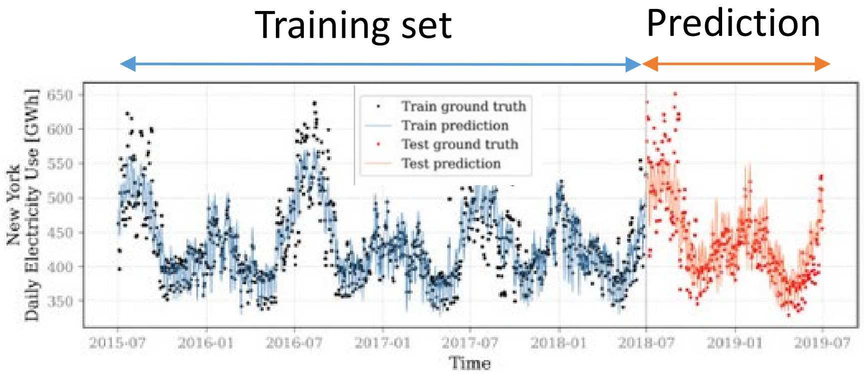
- Optimum charge & discharge of storage
- Optimum use of a heat resources in a network (availability, emissions, price)
    - Steering from/to energy market (forecasts)
- Automatic identification of faults





ML-models to Forecast Electricity Use

- Forecast electricity demand for steering from/to energy market



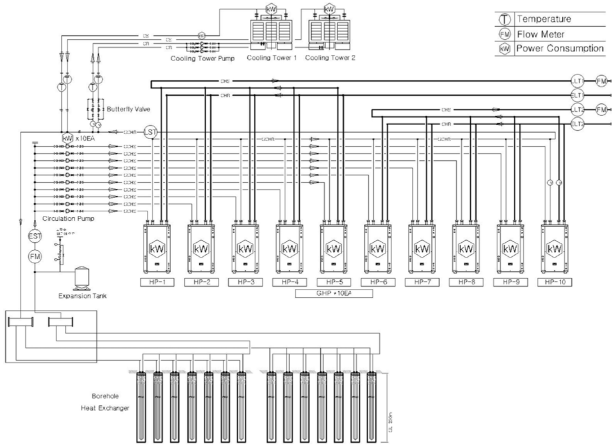
- Multivariate linear regression model
  - Input: Ashrae 5- parameters
- ML models
  - (Fed with time series e.g. month, day, hour)
    - Random Forest
    - Support Vector machine
    - Artificial neural networks
    - Generalized Additive
    - Gradient Boosting Machine

Predicting city-scale daily electricity consumption using data-driven models
Wang, ZheHong, Tianzhen, Li, Han, MaryAnn Piette Lawrence Berkeley national laboratory
Advances in Applied Energy, Volume 2, 26 May 2021

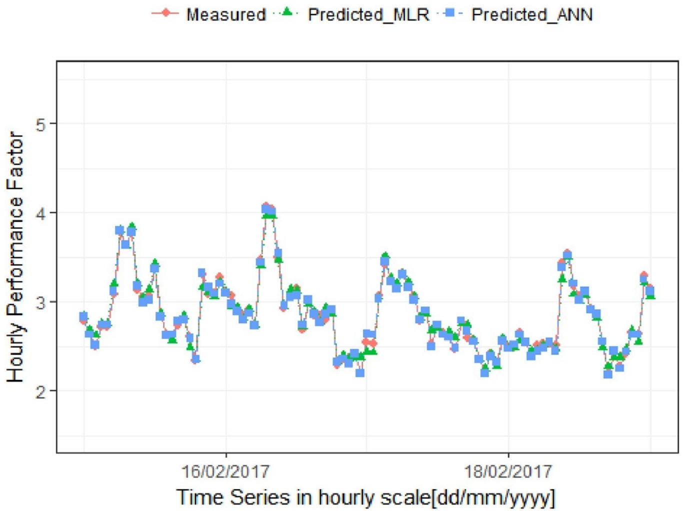
Accuracy of all models > 90%

ML-models to Forecast Heating Use

Hospital Ground source heat pump systems (10 HPs)



(both fed with significant parameters amongst 29 measured ones)



(c) period 3 (February)

Application of a multiple linear regression and an artificial neural network model for the heating performance analysis and hourly prediction of a large-scale ground source heat pump system
Sang KuPar, kHyeun JunMoon, Kyung ChonMin, ChanghaHwang, SudukKim
[(Dankook Univeristy, Korea) Energy and Buildings], [Volume 165, 15 April 2018, Pages 206-215]

Accuracy of both models > 95%

Behavioural ML-Clustering Models

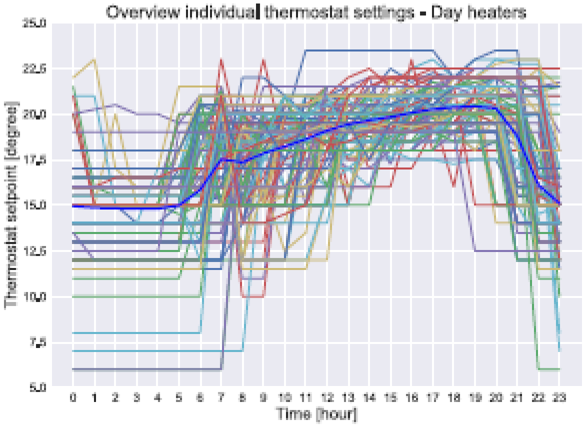


Table 3.9: Spread of users between clusters overview

	Percentage of users in cluster [%]
Day lowering	11
Morning-evening program	18
Adaptable program	19
Day heating	21
Gradient day heating	18
Continues heating	12

The impact of adjusted thermostat practices in the residential sector, T. Vosmeer, master thesis TPM, 2018; data from Toon/Quby

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Statistical / ML-based Models

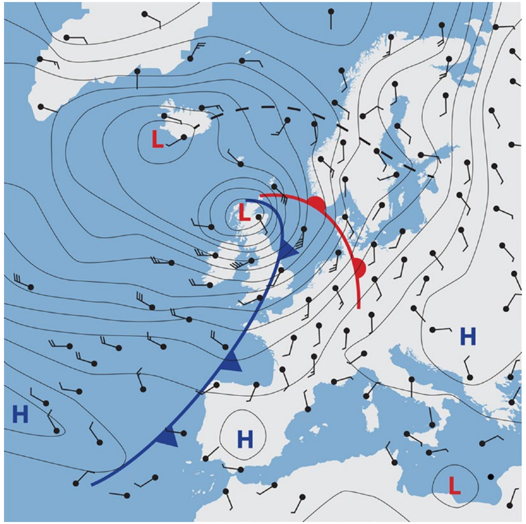
- Very powerful to predict
- Are used e.g. to buy electricity, discover patterns, see trends
- Based on correlations, not causalities
- No a-priori knowledge?

Hidden in parameters of MLR (electricity example)

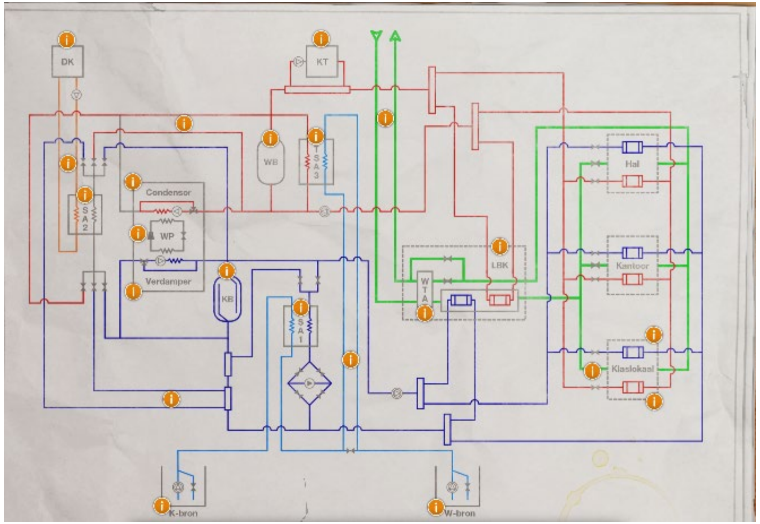
Hidden in choice measurement points (heat example)

- Can't tell us
  - What to do to improve operation
  - On which buttons to turn to steer
  - How to make better designs

Complex Natural versus Engineered Systems



https://www.esa.int/Applications/Observing_the_Earth/FutureEO/Aeolus/Forecasting_weather



We have no influence on it:
ML-based forecast

We conceive & design it

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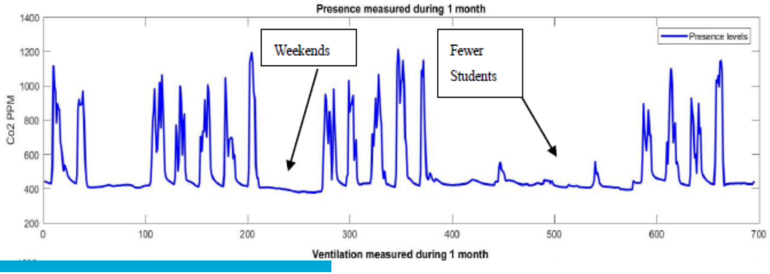
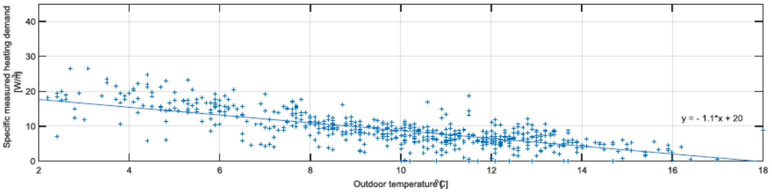
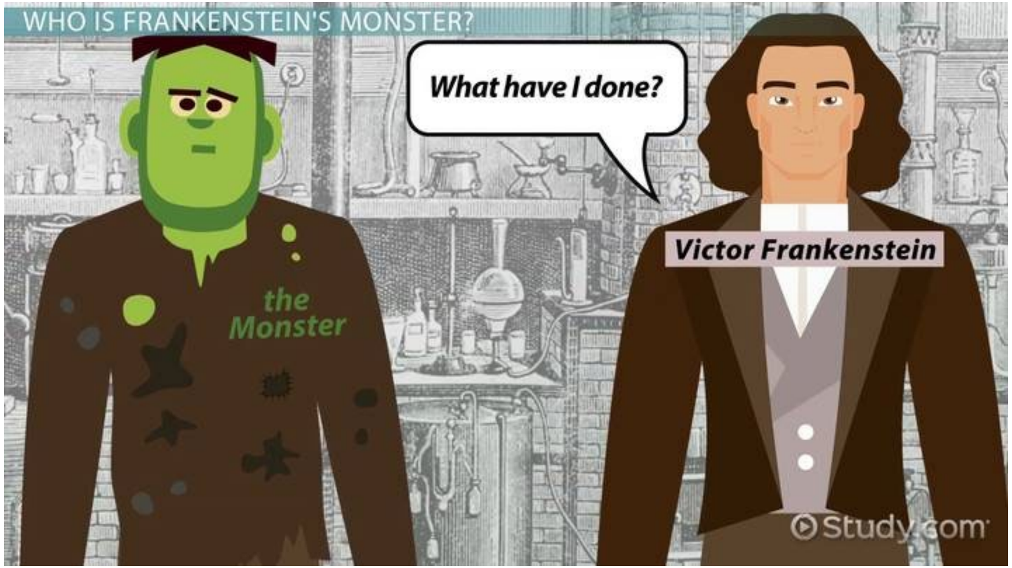
Complex Natural versus Engineered Systems





The Building Energy System

The designer

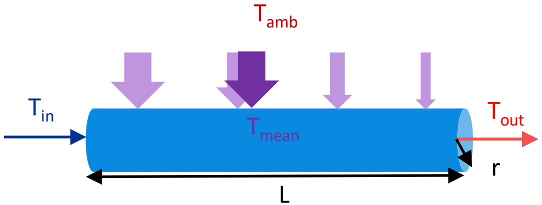


https://study.com/academy/lesson/who-is-the-monster-in-frankenstein-character-traits-analysis.html

Mathematical Models of Physical Processes

To understand/simulate/design real systems based on physical laws

- (e.g. conservation of energy, mass; equations describing heat & mass transport)
- Input, Output and description of the (causal) relationship between input and output



$Q = \rho.V_r.C.(T_{out}-T_{in})$ [W]

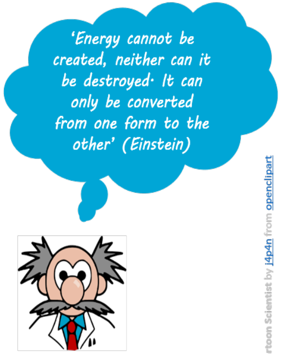
$Q = h.A.(T_{amb}-T_{mean}) = h.A.LMTD$ [W]

With $LMTD = \frac{(T_{amb}-Tin)-(Tamb-Tout)}{Ln|(T_{amb}-Tin)|-Ln|(T_{amb}-Tout)|}$

Very simple steady-state model of a heat exchanger

$E_{in} = E_{stored} + E_{out}$

$$E_{heating} = -(E_{sol} + E_{int} + E_{trans} + E_{vents})$$



Cartoon Scientist by j4p4n from openclipart

Very simple steady-state model of a building

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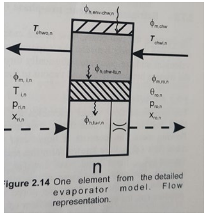
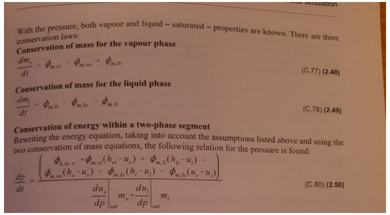
Complex models





With the pressure, both vapour and liquid – saturated – properties are known. There are three conservation laws:

Conservation of mass for the vapour phase

$$\frac{dm_v}{dt} = \phi_{m,vi} - \phi_{m,vo} + \phi_{m,lv} \qquad \text{(C.77) (2.48)}$$

Conservation of mass for the liquid phase

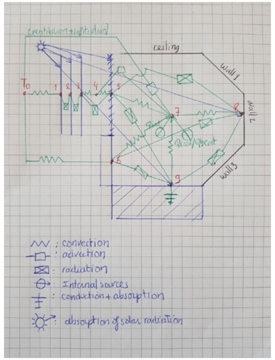
$$\frac{dm_l}{dt} = \phi_{m,li} - \phi_{m,lo} - \phi_{m,lv} \qquad \text{(C.78) (2.49)}$$

Conservation of energy within a two-phase segment

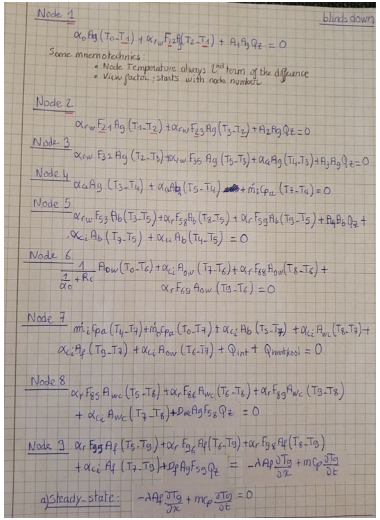
Rewriting the energy equation, taking into account the assumptions listed above and using the two conservation of mass equations, the following relation for the pressure is found:

$$\frac{dp}{dt} = \frac{\begin{pmatrix} \phi_{h,tu-r} + \phi_{m,vi}(h_{vi}-u_v) + \phi_{m,li}(h_{li}-u_l) - \\ \phi_{m,vo}(h_v-u_v) - \phi_{m,lo}(h_l-u_l) - \phi_{m,lv}(u_v-u_l) \end{pmatrix}}{\left.\frac{du_v}{dp}\right|_{sat} m_v + \left.\frac{du_l}{dp}\right|_{sat} m_l} \qquad \text{(C.80) (2.50)}$$

Heat exchanger model:Condition *Monitoring for marine refrigeration plants based on process models,* H. Grimmelius, PhD Thesis 2005, TU Tudelft



Dynamic energy model of a single room



Node 1 — blinds down

$$\alpha_0 A_g (T_0 - T_1) + \alpha_{rw} F_{12} A_g (T_2 - T_1) + A_1 A_g Q_z = 0$$

Some mnemotechnics:

- Node Temperature always 2nd term of the difference
- View factor: starts with node number

Node 2

$$\alpha_{rw} F_{21} A_g (T_1 - T_2) + \alpha_{rw} F_{23} A_g (T_3 - T_2) + A_2 A_g Q_z = 0$$

Node 3

$$\alpha_{rw} F_{32} A_g (T_2 - T_3) + \alpha_{rw} F_{35} A_g (T_5 - T_3) + \alpha_{ic} A_g (T_4 - T_3) + A_3 A_g Q_z = 0$$

Node 4

$$\alpha_{ic} A_g (T_3 - T_4) + \alpha_{ic} A_b (T_5 - T_4) + \dot{m}_i c_{pa} (T_7 - T_4) = 0$$

Node 5

$$\alpha_{rw} F_{53} A_b (T_3 - T_5) + \alpha_r F_{58} A_b (T_8 - T_5) + \alpha_r F_{59} A_b (T_9 - T_5) + A_4 A_b Q_z + \alpha_{ci} A_b (T_7 - T_5) + \alpha_{cc} A_b (T_4 - T_5) = 0$$

Node 6

$$\frac{1}{\frac{1}{\alpha_0} + R_c} A_{ow} (T_0 - T_6) + \alpha_{ci} A_{ow} (T_7 - T_6) + \alpha_r F_{68} A_{ow} (T_8 - T_6) + \alpha_r F_{69} A_{ow} (T_9 - T_6) = 0$$

Node 7

$$\dot{m}_i c_{pa} (T_4 - T_7) + \dot{m}_o c_{pa} (T_0 - T_7) + \alpha_{ci} A_b (T_5 - T_7) + \alpha_{ci} A_{wc} (T_8 - T_7) + \alpha_{ci} A_f (T_9 - T_7) + \alpha_{ci} A_{ow} (T_6 - T_7) + Q_{int} + Q_{heat/cool} = 0$$

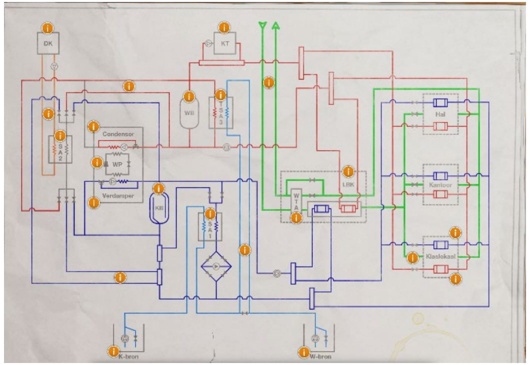
Node 8

$$\alpha_r F_{85} A_{wc} (T_5 - T_8) + \alpha_r F_{86} A_{wc} (T_6 - T_8) + \alpha_r F_{89} A_{wc} (T_9 - T_8) + \alpha_{ci} A_{wc} (T_7 - T_8) + D_{wc} A_g F_{58} Q_z = 0$$

Node 9

$$\alpha_r F_{95} A_f (T_5 - T_9) + \alpha_r F_{96} A_f (T_6 - T_9) + \alpha_r F_{98} A_f (T_8 - T_9) + \alpha_{ci} A_f (T_7 - T_9) + D_f A_g F_{59} Q_z = -\lambda A_f \frac{\partial T_9}{\partial x} + m c_p \frac{\partial T_9}{\partial t}$$

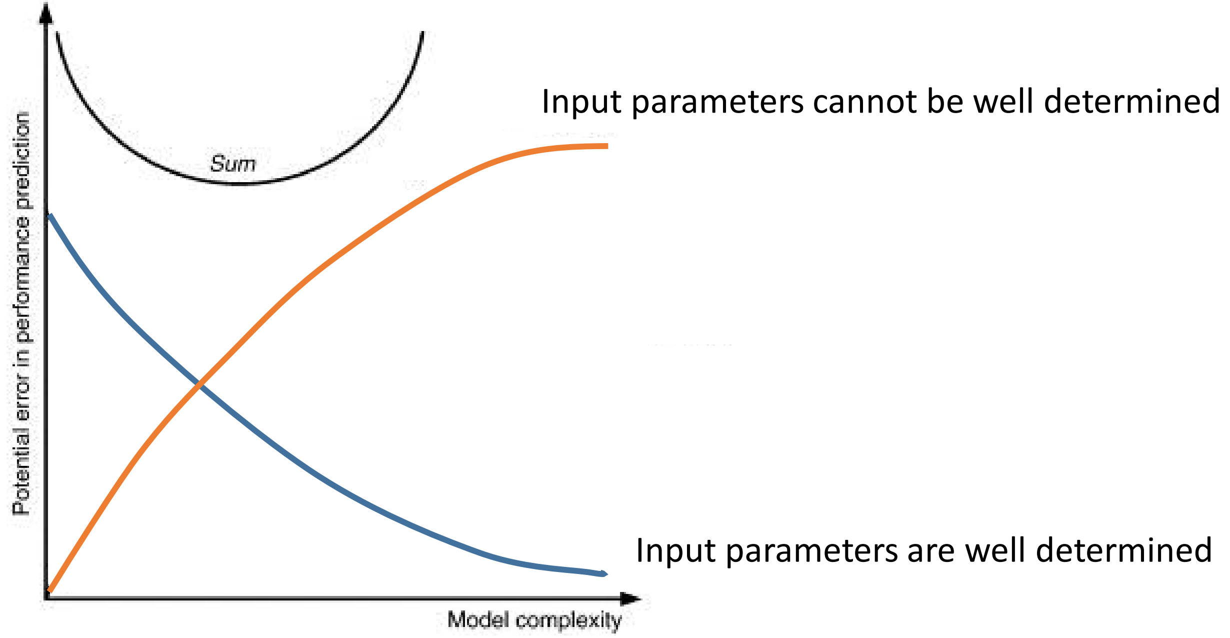
a) Steady-state: $-\lambda A_f \frac{\partial T_9}{\partial x} + m c_p \frac{\partial T_9}{\partial t} = 0$



Model of a HVAC system

Complexity & Accuracy

Complexity: more input parameters, more equations



Adapted from M. Trčka and J. L. M. Hensen, ‘Overview of HVAC system simulation’, *Autom. Constr.*, vol. 19, no. 2, pp. 93–99, Mar. 2010.

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The Art is to:

- Find the right model complexity to **steer, control, improve**
- Improve input data accuracy using ML
- Use ML to complement models with missing parts (e.g. user behaviour, weather forecast etc…)
- Use data analytics to automatically check against engineering knowledge

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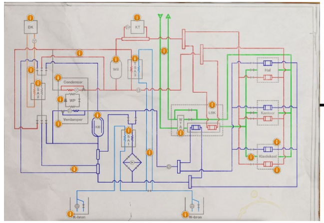
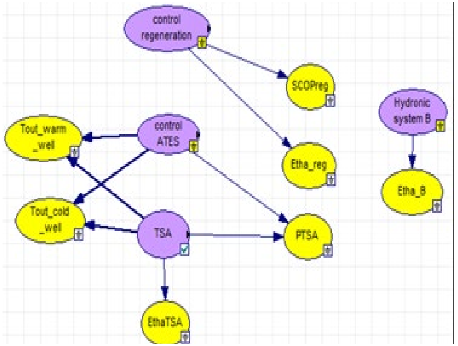
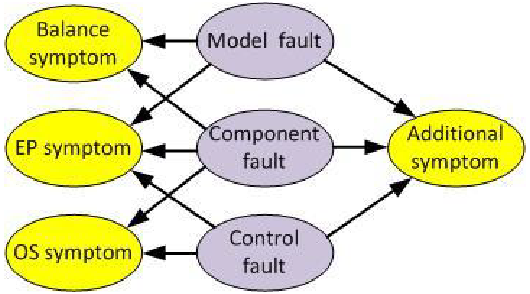
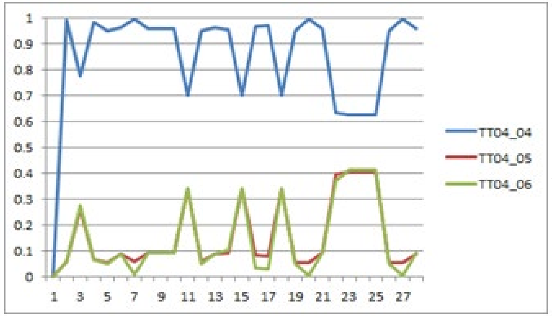
Feed models with data to automate faults finding

(4S3F method & Bayesian statistics)

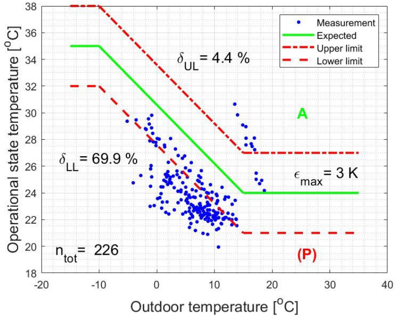






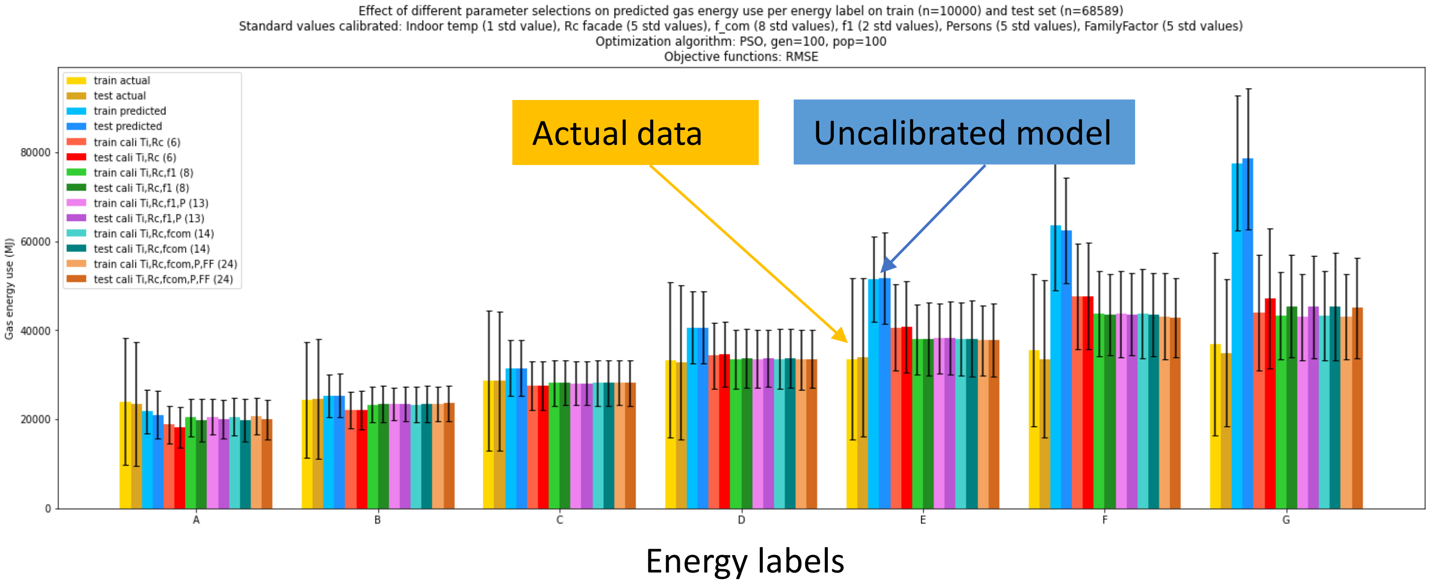


Fault probability of TT04 sensors



Physical Model Calibration (Training)

'EPBD' model calibration fed by data on 100.000 dwellings (similar results with Genetic Algorithm, Simulated Annealing and Particle Swarm Optimization)



Optimization based calibration of building energy simulation models on building stock level: *Application to the Dutch energy label model,* Samuel Smets, thesis TUDelft, 2021, Paula vd Brom

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Conclusions & Future

- Digitization can support energy transition, but cannot replace making the right choices
- We need to mitigate the adverse energy effects of digitization
- ‘Pure’ ML is suitable for prediction and clustering but not for control and optimization
- Combining ML with knowledge on physical processes is powerful for control and optimization

Future

- Identify optimum control set-points (energy flexibility, MPC)
- Add knowledge/data layers to determine better relevant inputs to the model
- Add ML models (e.g. behaviour, weather predictions) to physical ones

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