Module 5.3
Detection of malfunctions

SHaKE – Sharing Heat and Knowledge on Energy Communities
Erasmus+ KA220-HED Cooperation Partnerships in Higher Education
Developing institution: Mines Paris – PSL
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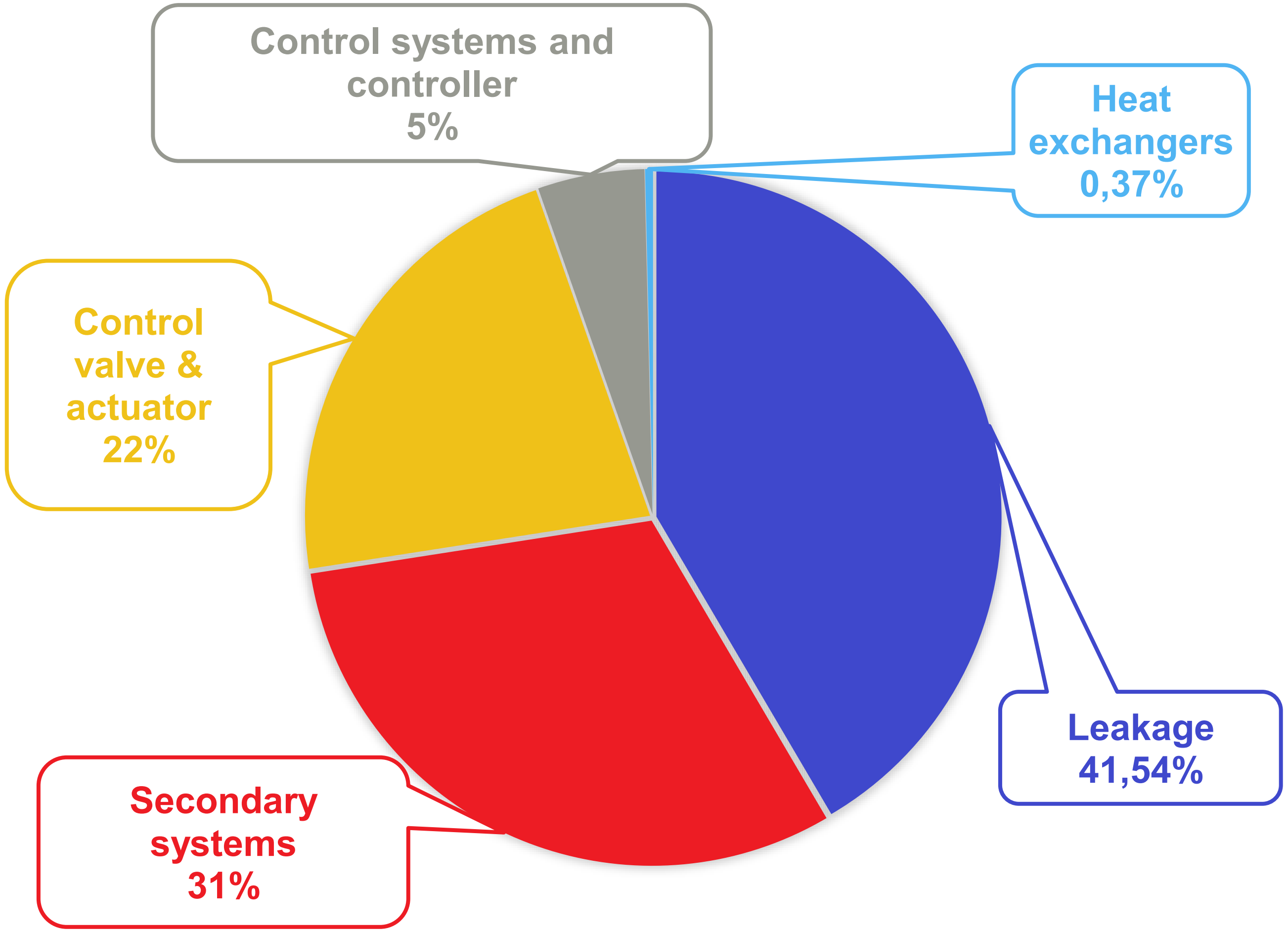
SHaKE
Sharing Knowledge on Energy Communities

1. Introduction



[Mansson & al, 2019]

Only 26 % of the substation works correctly

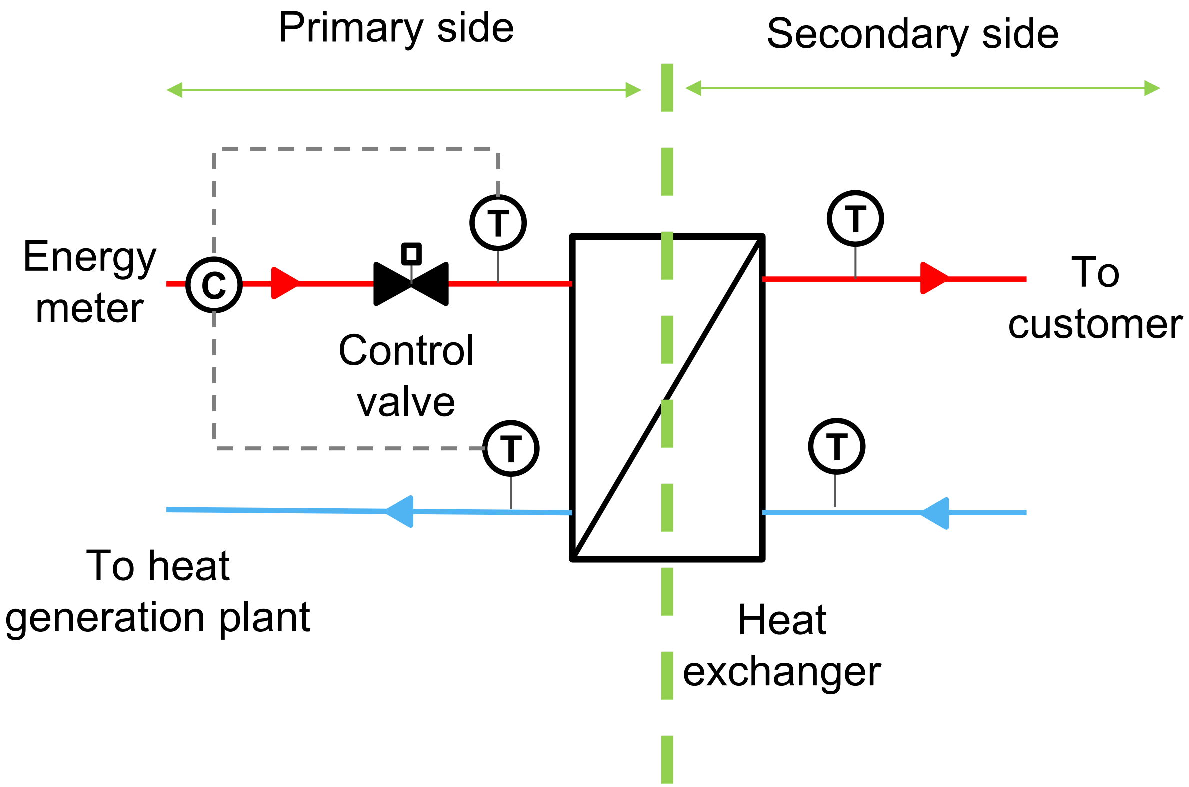
[Gadd et Werner, 2015]

The most impacting malfunctions are:

- Faulty control valves
- Unsuitable secondary network systems
- Unsuitable DHW supply system

[Zinko et Al, 2005]

2. What is a malfunction?



How to detect if there are malfunctions?

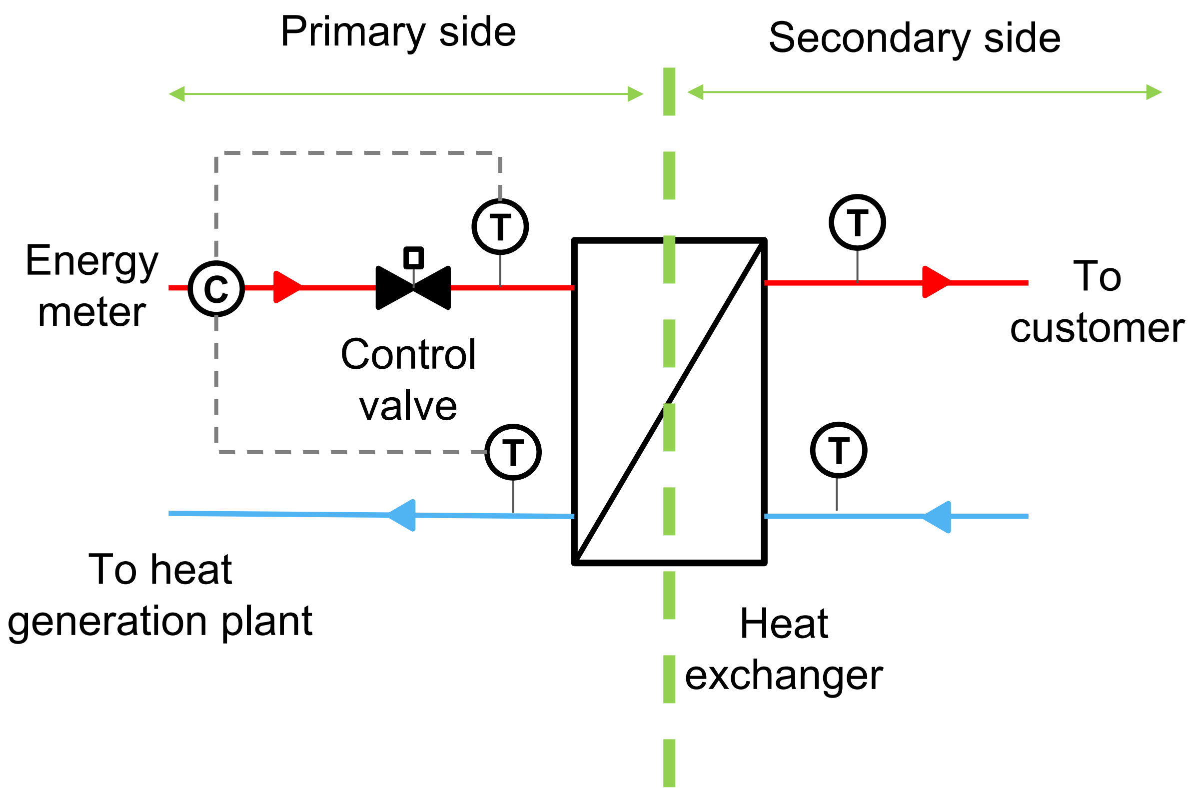
Available data:

Legal:
- Primary supply and return temperature
- Secondary supply temperature
- Primary mass flow rate
- Exchanged power at the substation

Highly needed:
- Secondary return temperature
- Secondary mass flow rate

Useful:
- Return temperature at each emitter

2. What is a malfunction?



Methods of malfunction detections used by operators

- Monthly checks of customer billing data
- Quality index based on the installation performance
- Analysis of return temperature levels
- Analysis of flow rates
- Over-consumption method

2. What is a malfunction?

Anomaly detection

Patterns in data that do not conform to a previously defined notion of expected and « normal » behavior

- Outliers
- Deviations
- Atypical behavior
- Abnormal patterns

Fault detection

Change in a system so that it can no longer operates satisfactorily and meet the requirements of its user

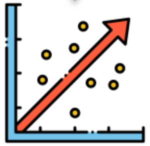
- Need of corrective action
- Finding of the causes

Faults? Inefficient usage? Change in user behavior?

2. What is a malfunction?

Anomaly detection


Classification


Regression


Thresholds

Fault detection


Visualization


Clustering

These methods of anomaly or fault detections can be used separately or in combination

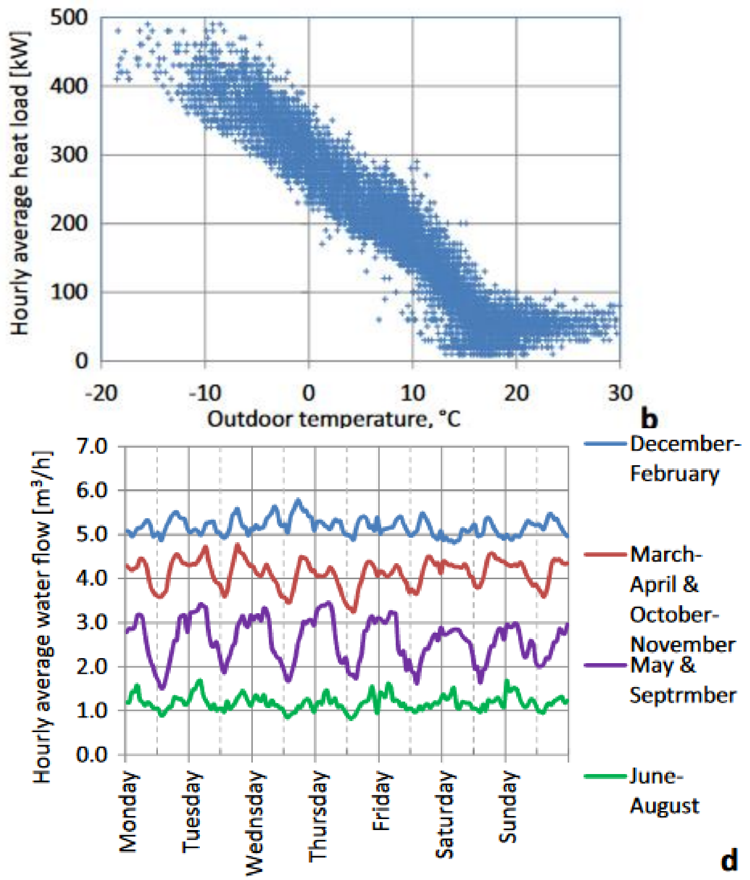
3. Anomaly detection

Visualization & Manual analysis

Human experts examine the substation measurements or derived metrics with the help of visualization → Great flexibility but subjective

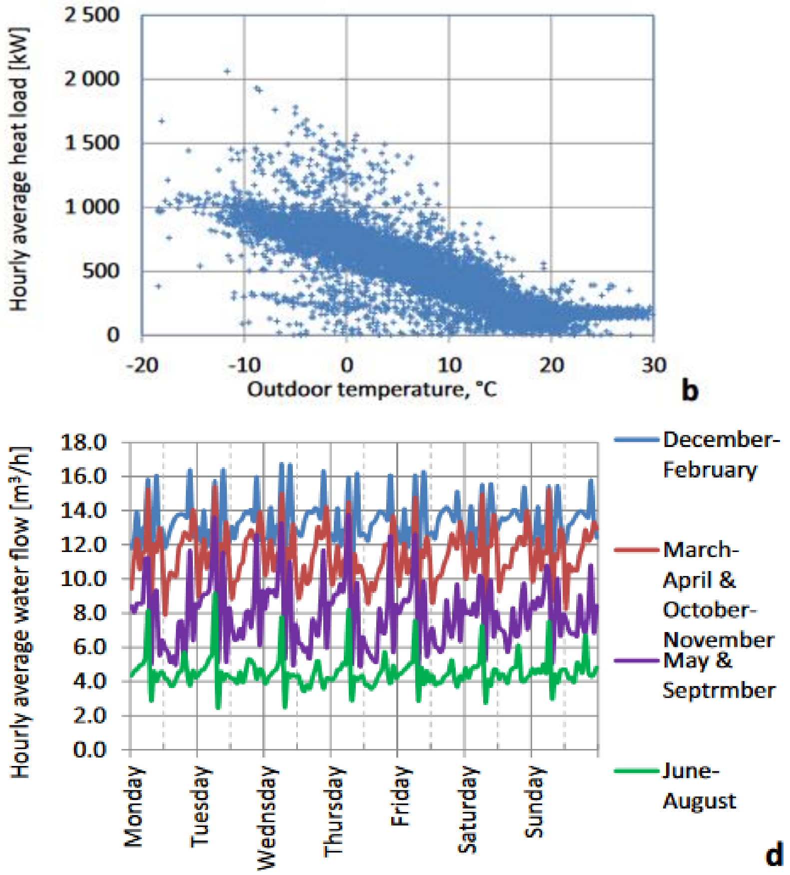
3. Anomaly detection

Correct behavior



Different behaviors of the substation compared to a reference one

Incorrect behavior



[Gadd & Werner, 2015]

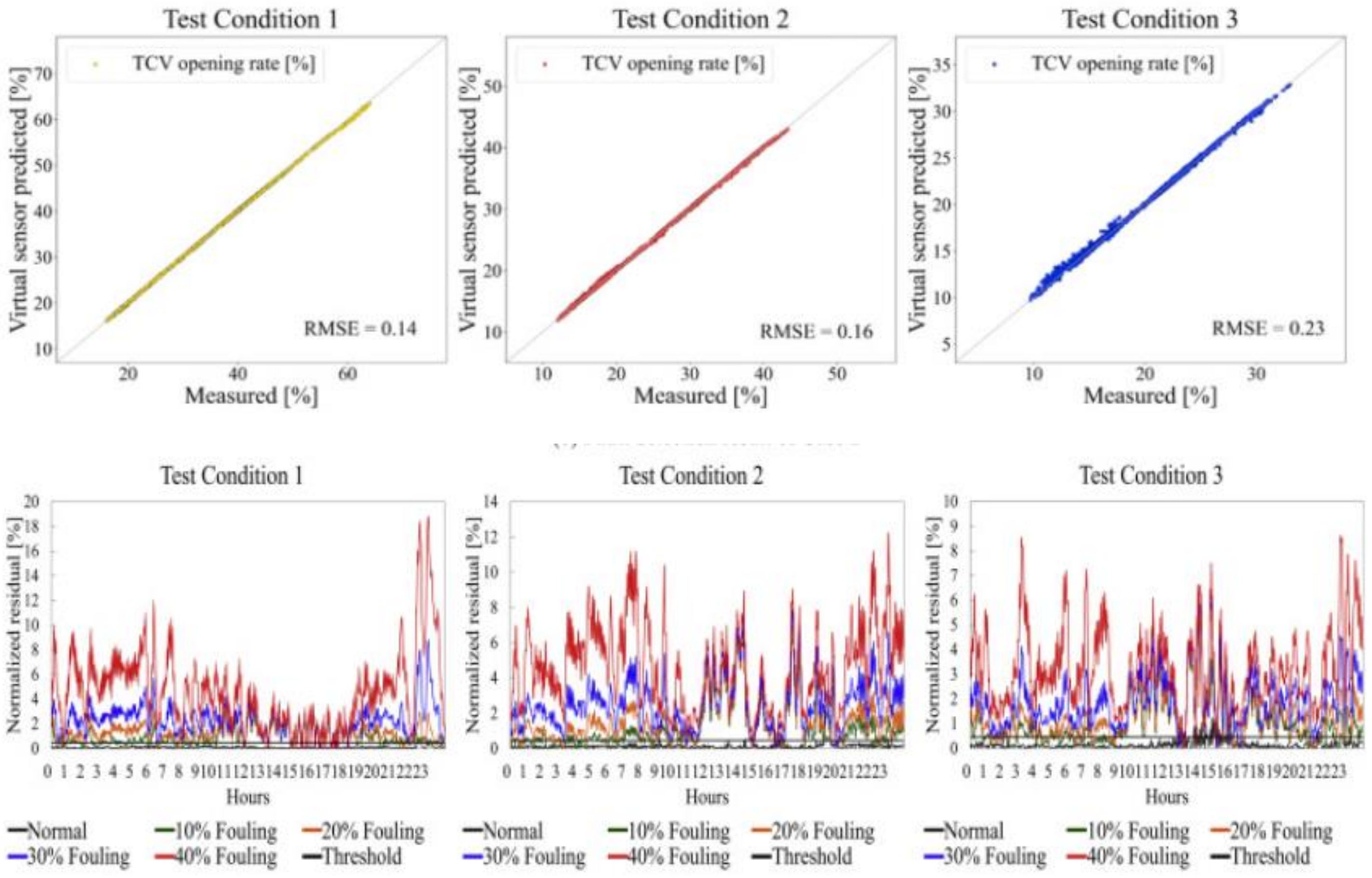
3. Anomaly detection

Thresholds

A threshold is used to decided the state of a substation. Thresholds can be set manually by a human expert according to error rate or statistical analysis

[Kim & al , 2021]

3. Anomaly detection



Correlation between the control valve opening measured and simulate by a ML model without faults

Calculus of the normalized residual between the simulate valve opening and the measured one for several fouling case

A fouling is detected when the threshold is exceeded

The threshold is based on the false alarm rate (under 3%) for the normal operation

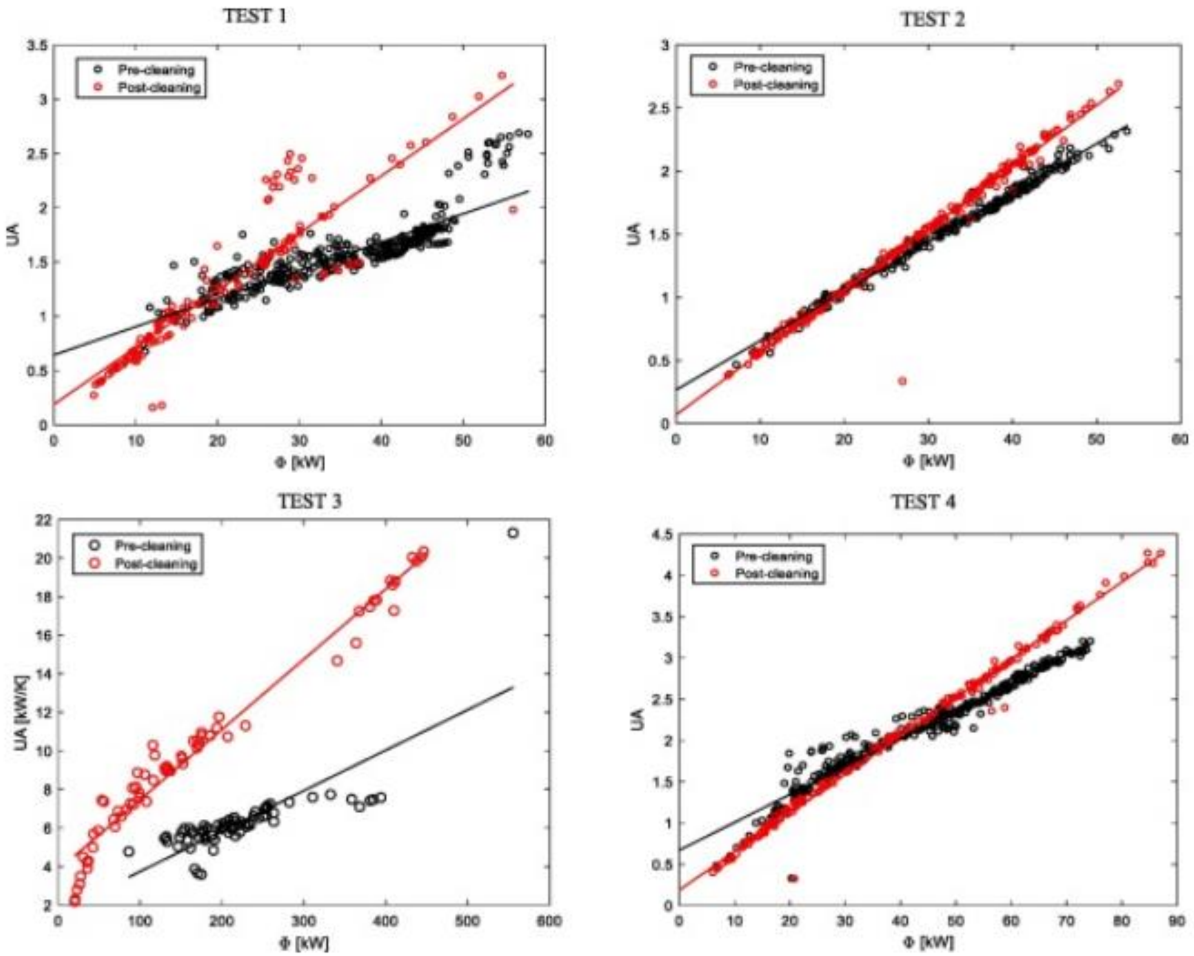
[Kim & al , 2021]

3. Anomaly detection

Regression

Regression aims at estimating the relationship between a dependent variable and one or more independent variables. Regression is typically used to forecast a certain variable and evaluate the deviation between predicted and measured values

3. Anomaly detection



[Guelpa & Verda , 2020]

For a heat exchanger, there is a linear regression between the power exchanged and the global heat transfer coefficient UA

$$UA = \frac{1}{DTLM} * \phi = \mathrm{a} * \phi$$

The fouling of the heat exchanger modifies the slope of the linear curve.

Three thresholds are defined on the slope variation:

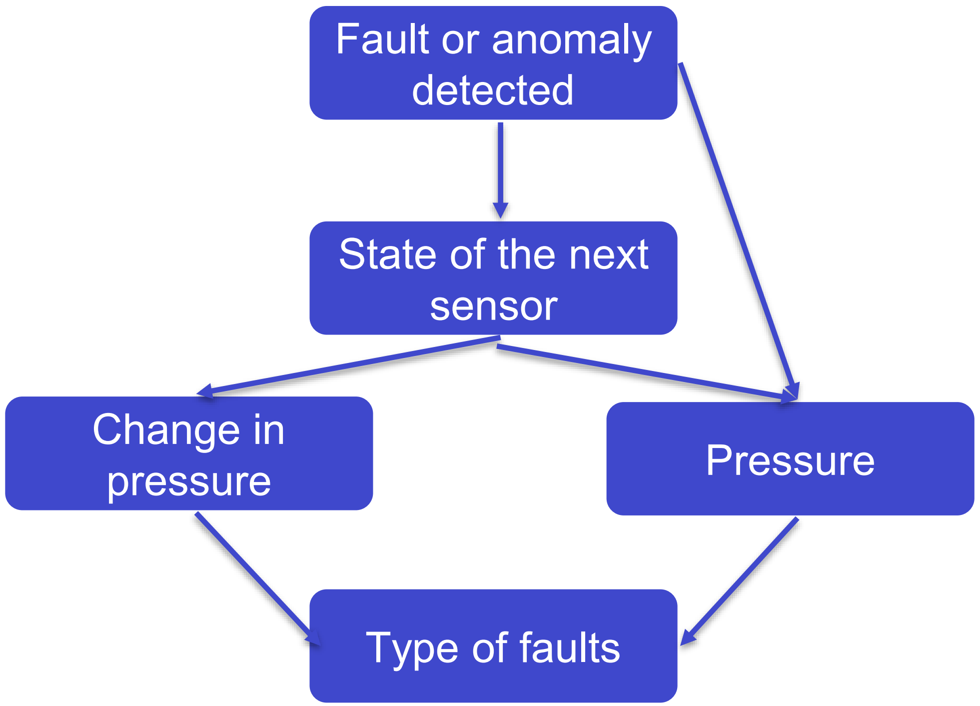
- <15% → Clean conditions
- 15% < x < 25 % → Partially fouled conditions
- >25% → high fouling

3. Anomaly detection

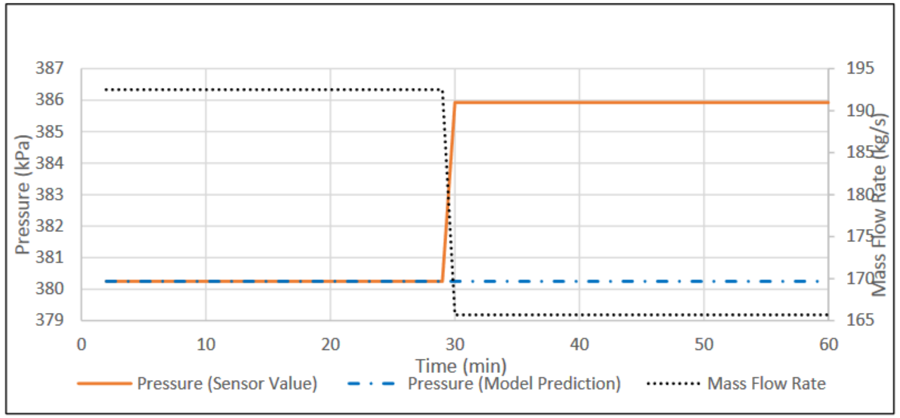
Classification

A machine learning task of assigning an item to one of several given classes (for example normal operation, abnormal operation). Contrary to regression, the result of a classifier is the assignment of an item represented by an integer number

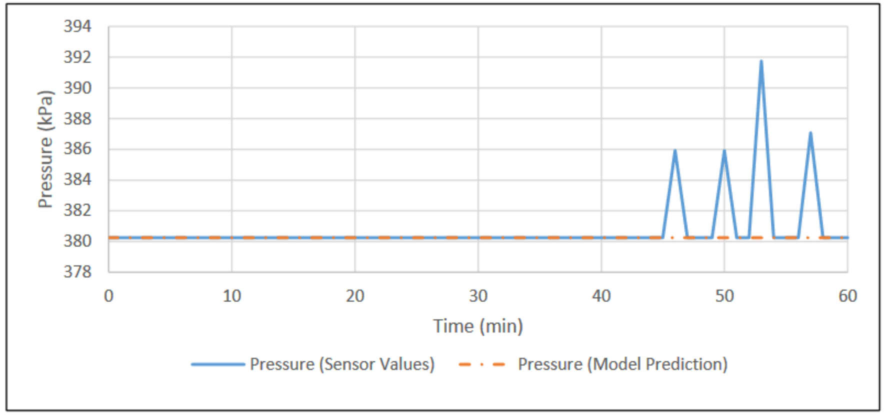
3. Anomaly detection



Leak



Sensor fault



Bayesian networks can be used to probabilistically describe the cause-and-effect relationships of known quantities for automatic detection of fault

Here the comparison of the pressure measurement towards a pipe

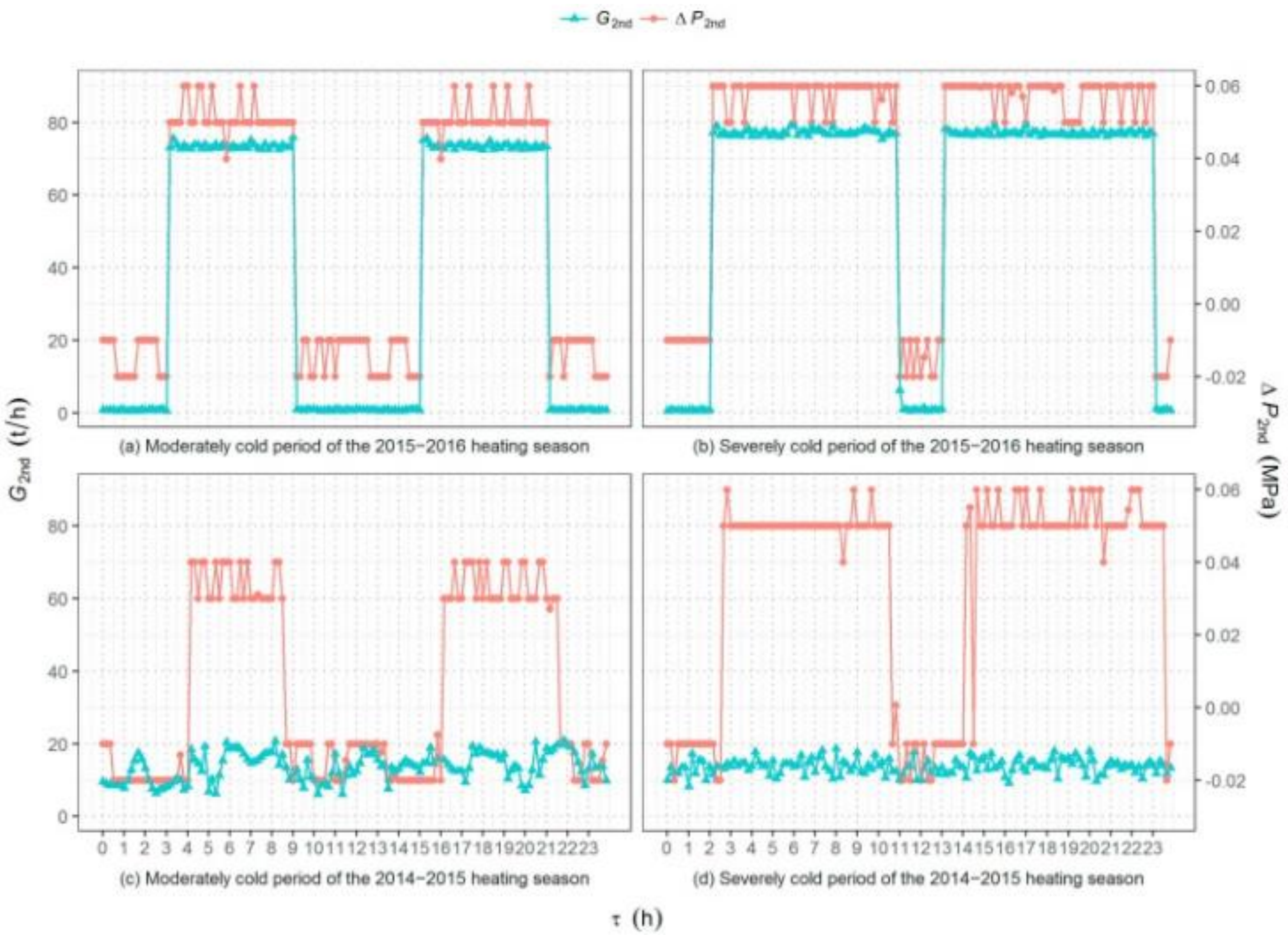
[Zimmerman & al, 2020]

3. Anomaly detection

Clustering

Clustering looks like the classification but instead of learning from annotated examples, clustering organizes the items in a way that they share more similar properties with items in their clusters. Outliers or marginal clusters can be then ne identified and analyzed

3. Anomaly detection



[Xue & al , 2017]

Clustering analysis can identify the seasonal and daily operating patterns

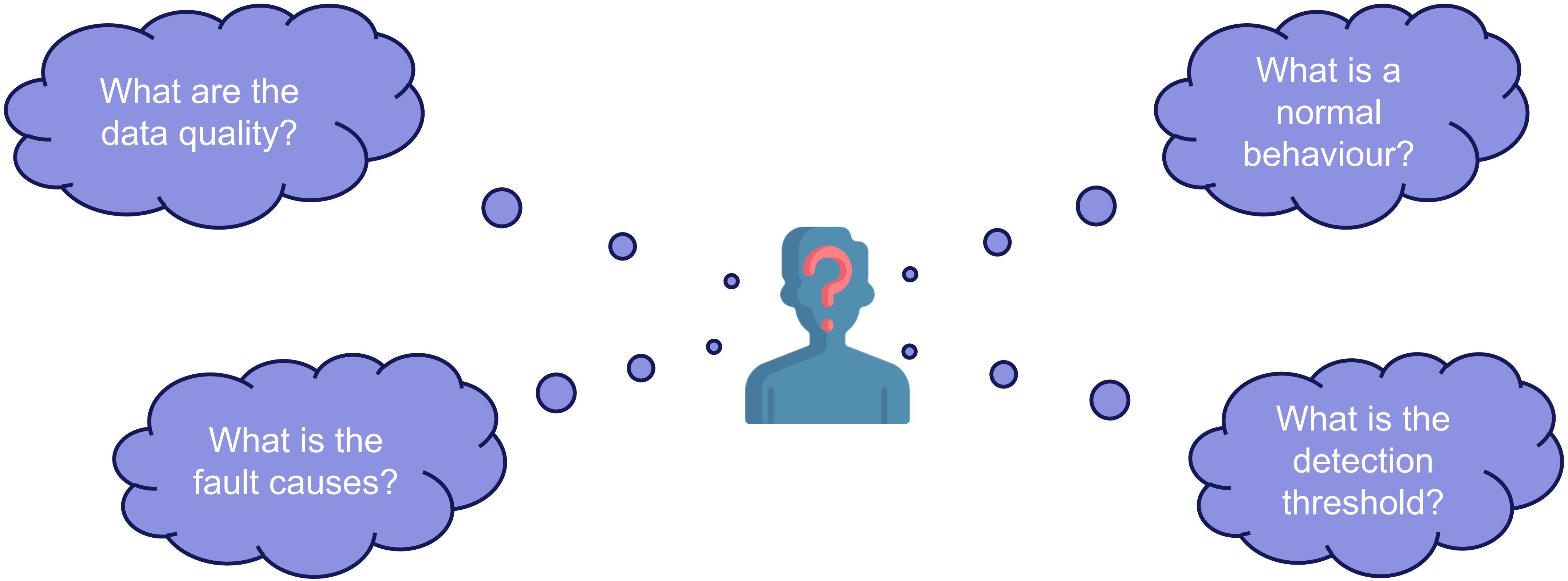
Different regulation strategies are identified:

- Relation between the primary temperature difference and the exchanged heat
- Relation between the secondary mass flow rate and the exchanged heat
- Relation between secondary mass flow rate and secondary pressure difference
- Relation between exchanged heat at primary and secondary side

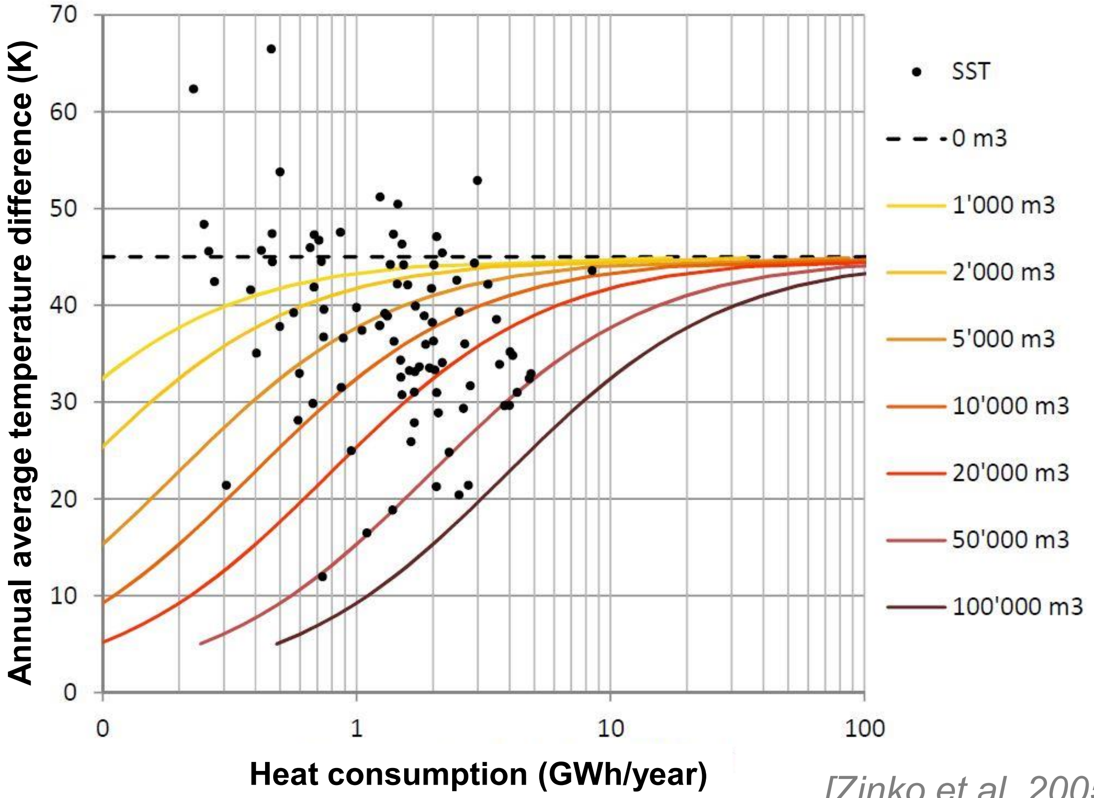
When one of the pattern do not correspond to a cluster a fault is detected

3. Anomaly detection

All these methods are based on the same concept: comparing measured data with reference to a normal operation data to find deviations



3. Anomaly detection



[Zinko et al, 2005]

Few data needed

Prioritize the investigation

Excess flow method

$$V_{excess} = V_{mes} - V_{target}$$

$$V_{excess} = \frac{\dot{Q}_{mes}}{\rho Cp}\left(\frac{1}{T_{sup,mes} - T_{ret,mes}} - \frac{1}{T_{sup,mes} - T_{ret,target}}\right)$$

The more the excess flow is high, the more the substation downgrades the overall performance of the network

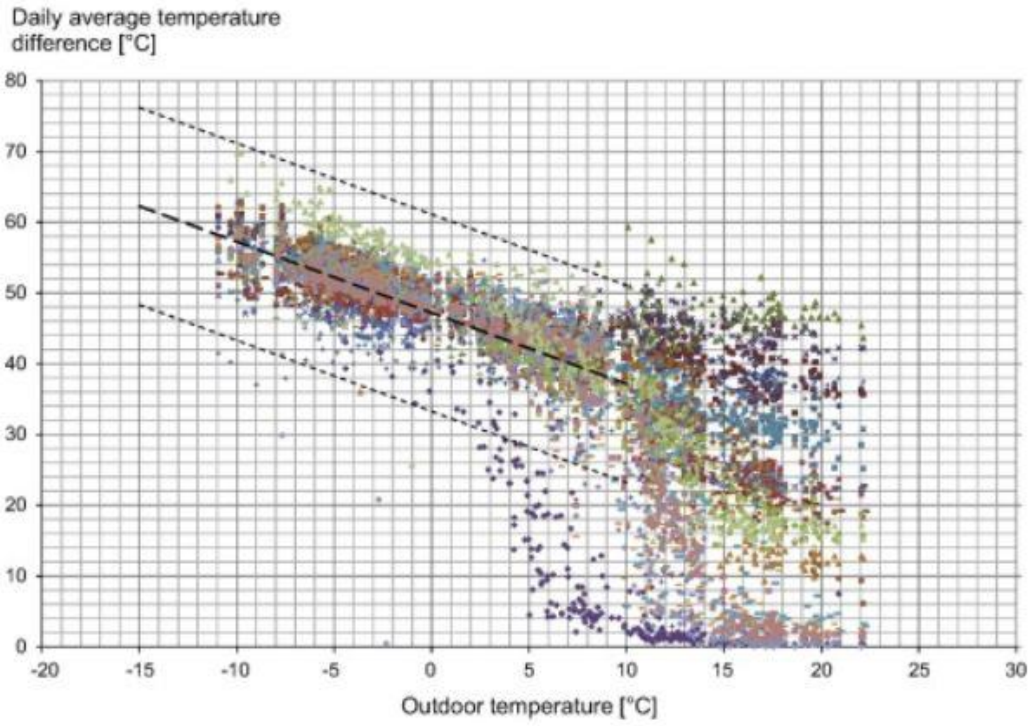
The excess flow method enables to ranked the substations (SST) and so to choose the substation to investigate in priority

How to choose the reference temperature?

Not a daily tool

No clue on the fault origin

3. Anomaly detection



[Gadd et Werner, 2014]

Thermal signature method

Based on measures:

$$\Delta T_{prim,moy} = a\, T_{out} + b$$

$$Threshold_{high} = \Delta T_{prim,moy} = +3\,\sigma$$

$$Threshold_{high} = \Delta T_{prim,moy} = -3\,\sigma$$

When a ΔT_{prim} measured exceed a threshold an anomaly is detected. This indicator does not work if only DHW is supplied by the substation

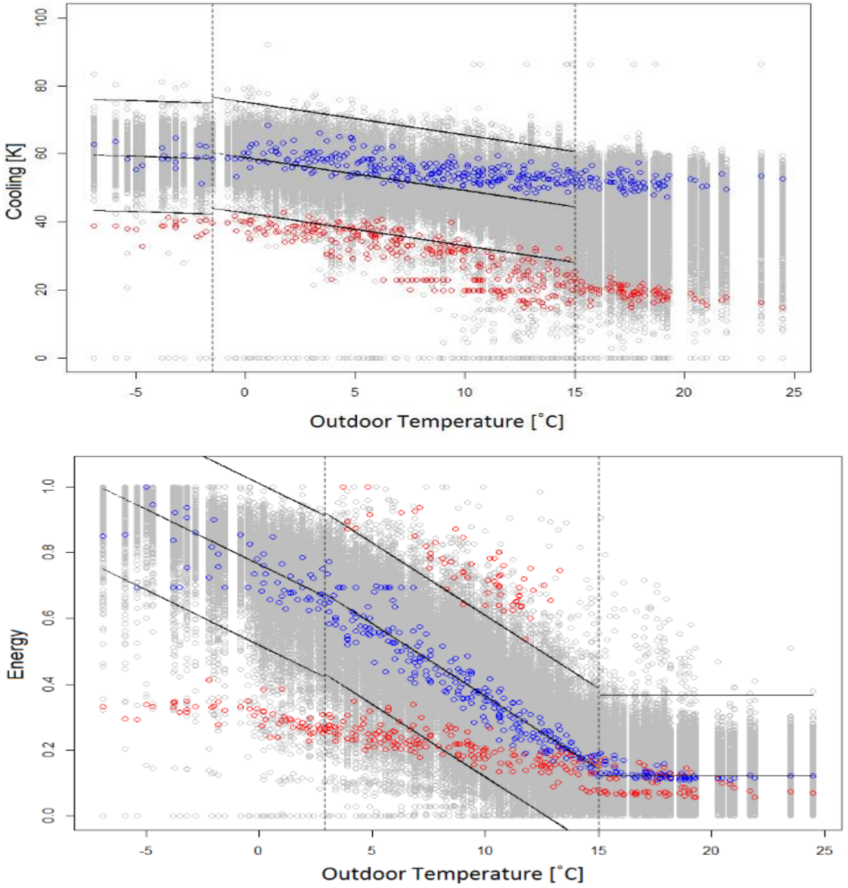
Few data needed

Fast anomaly detection

How to choose the reference behavior?

No clue on the fault origin

3. Anomaly detection



[Manson & al, 2018]

Improvement of the thermal signature method:

- Different linear regression according to the outdoor temperature
- Same threshold based on the standard deviation
- New data used (Energy exchange and return temperature)

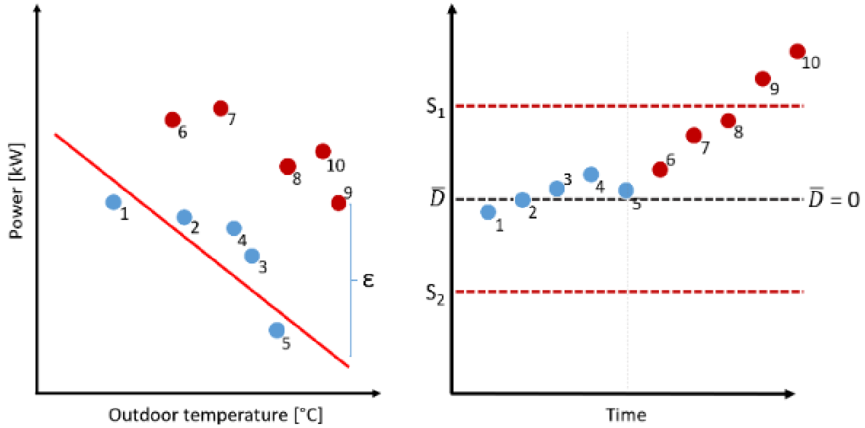
Few data needed

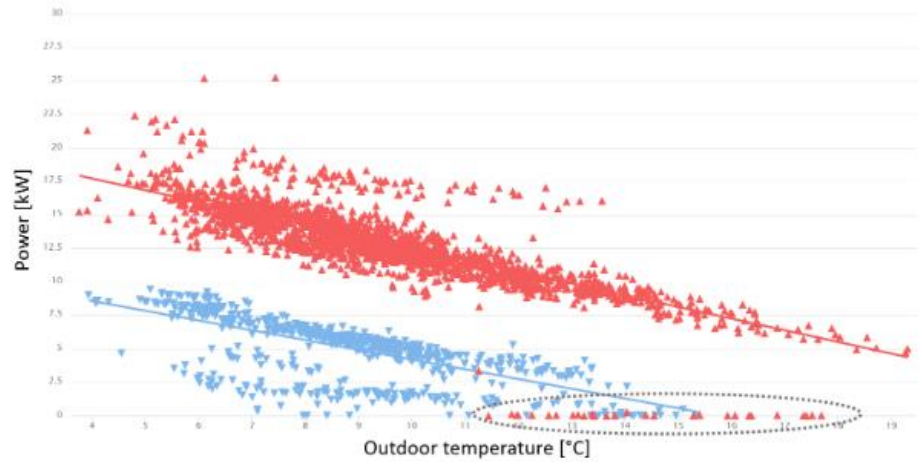
Fast anomaly detection

How to choose the reference behavior?

No clue on the fault origin

3. Anomaly detection





[Theusch & al, 2021]

Improvement of the thermal signature method:

- Clustering of the different heat load patterns (different types of end-users)
- Different linear regressions according to the outdoor temperature
- Adaptative threshold based on the cluster

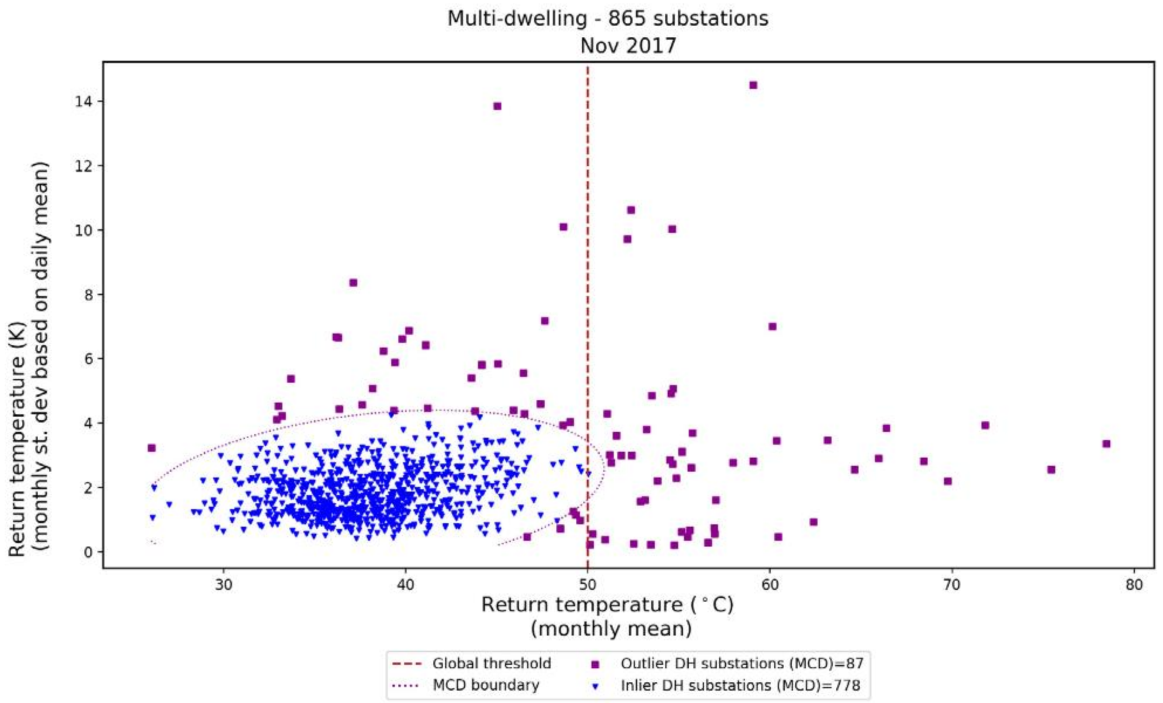
Few data needed

Fast anomaly detection

Need of quality data and knowledge on the end-users

No clue on the fault origin

3. Anomaly detection



Improvement of the thermal signature method:

- Clustering of the different heat load patterns (different types of end-users)
- Adaptative threshold based on the cluster

[Farouq & al, 2020]

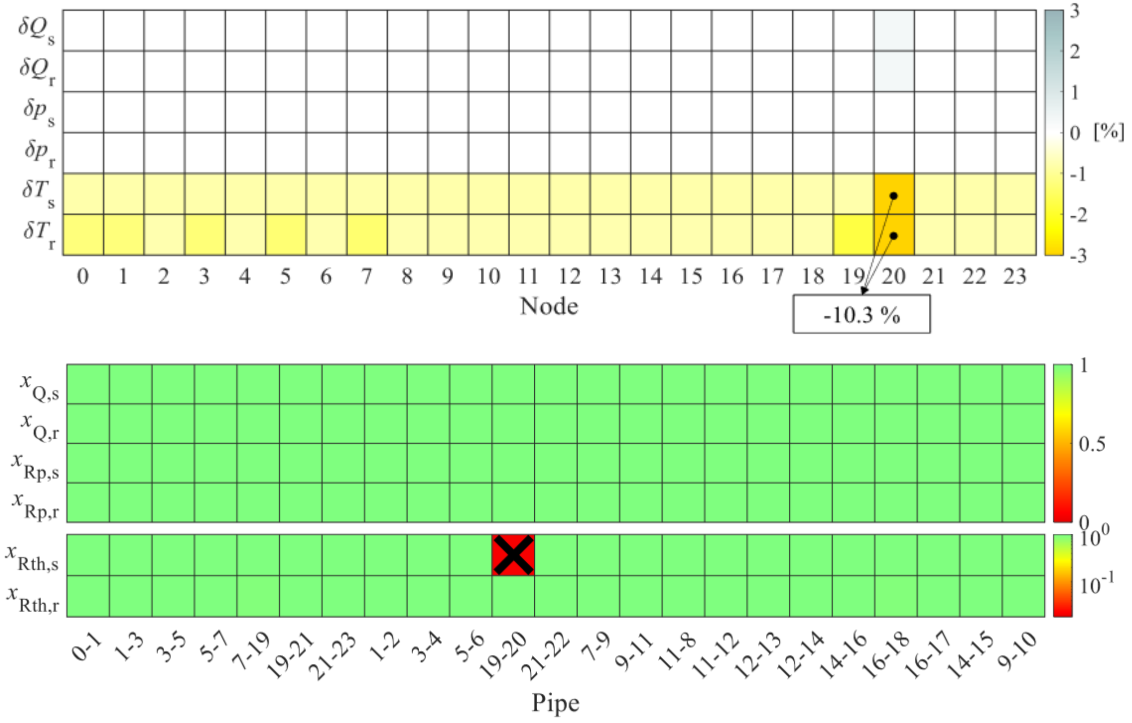
Few data needed

Fast anomaly detection

Need of quality data and knowledge on the end-users

No clue on the fault origin

4. Fault detection



[Bahlawan & al, 2022]

Comparison between measured data and data from a simulation.

A fault is detected through the relative difference between the measured and the simulated data

$$\delta T_s = \frac{T_{s,mes} - T_{s,simu}}{T_{s,simu}}$$

The diagnostic is made through health indices calculated thanks to an optimization algorithm

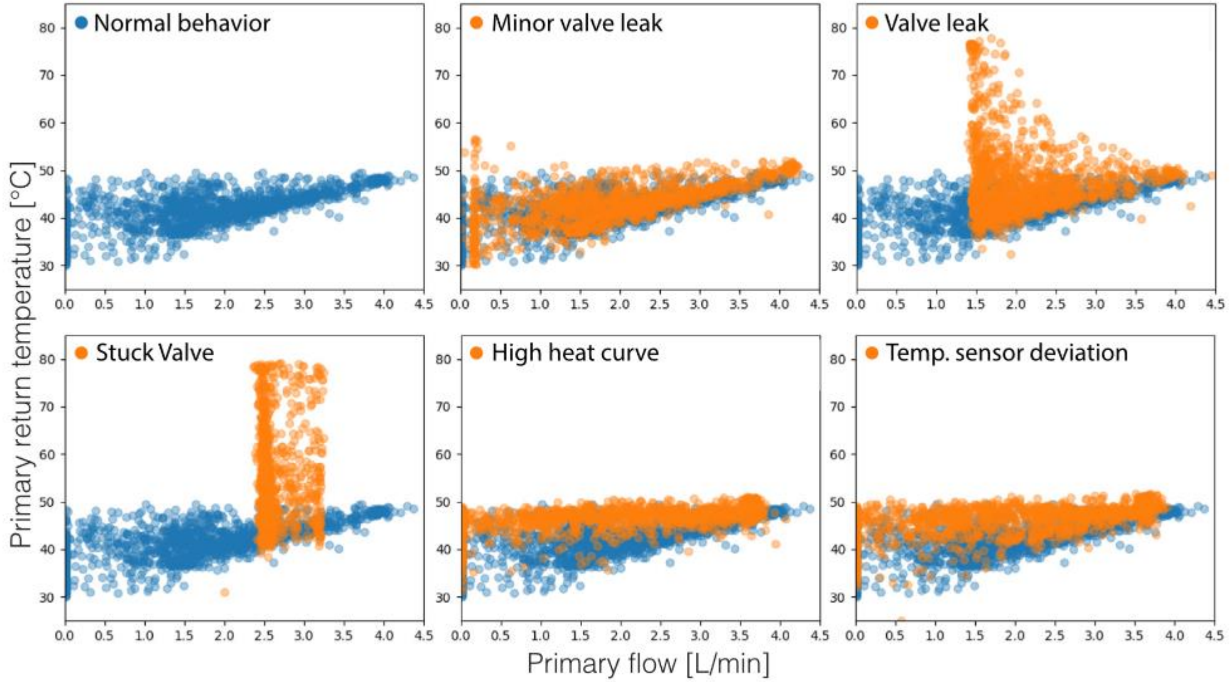
Fast anomaly detection

Diagnostic of the anomaly

Need of quality data

Need of a digital twin of the network

4. Fault detection



A ML algorithm is used to:

- Learn the normal operation behavior (laboratory experimental data)
- Learn the specific signature of several fault (Pattern and statistical value)

[Van Dreven & al, 2024]

Fast anomaly detection

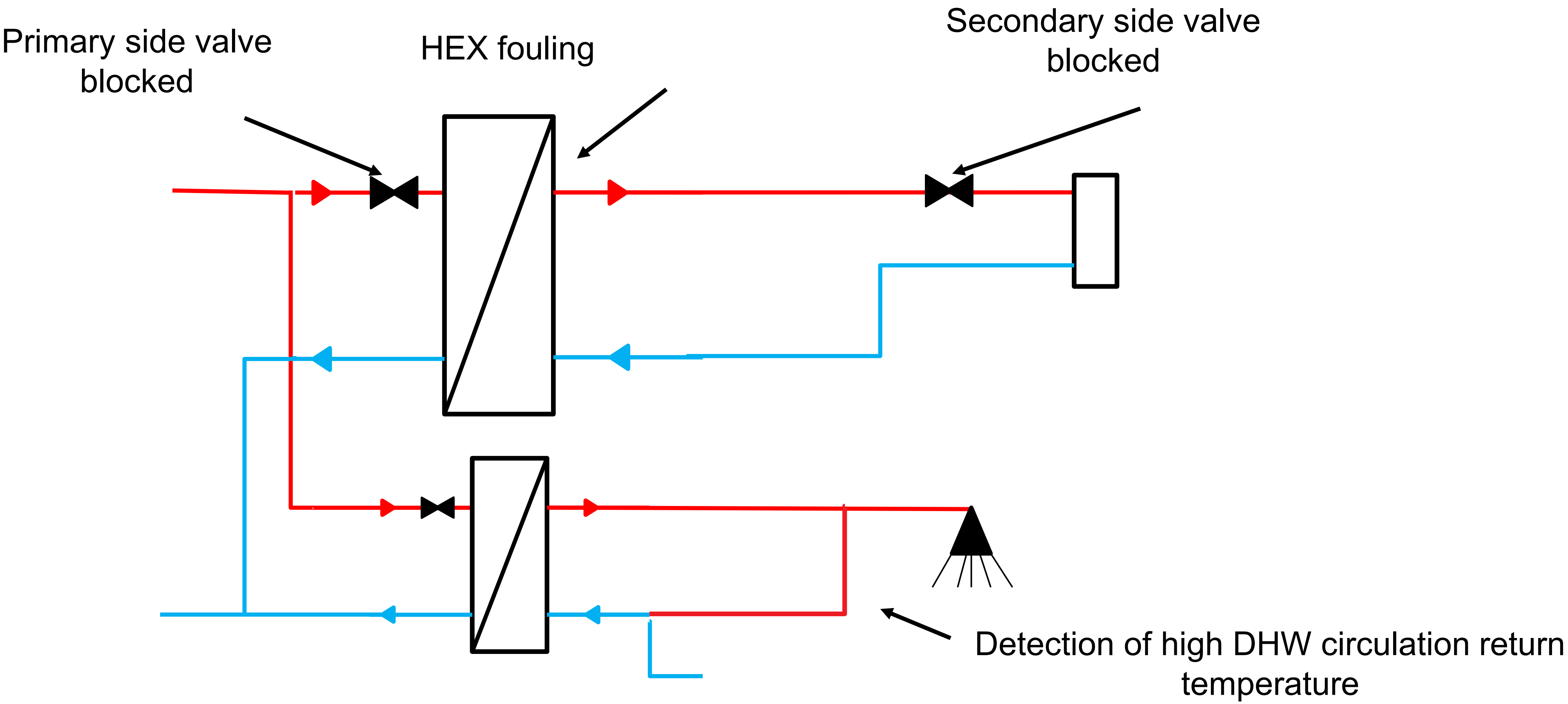
Diagnostic of the anomaly

Need of quality data

Need of a labelled data about fault

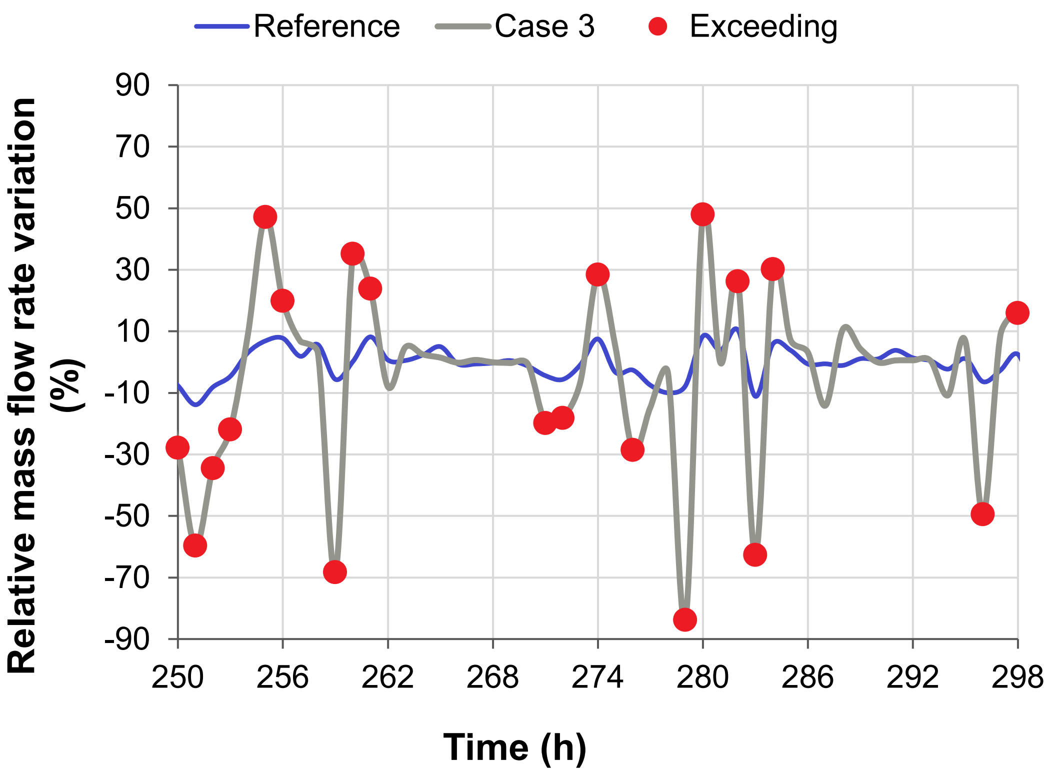
4. Fault detection

Studied malfunctions:



4. Fault detection

Primary side valve blocked



Observation: an instability of the mass flow rate

Proposed indicator:

Calculation of the mass flow rate variation

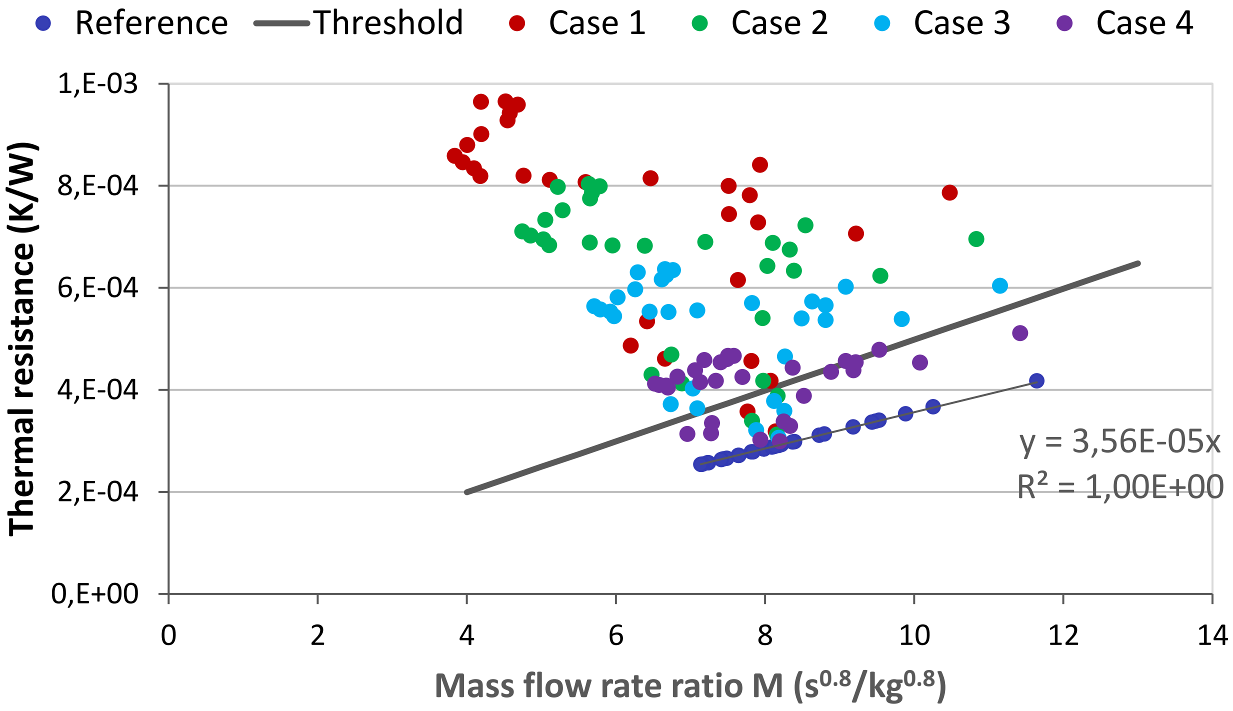
$$D_m = \frac{\dot{m}_{t+\Delta t} - \dot{m}_t}{\dot{m}_{t+\Delta t}}$$

Criteria : if $D_m > 15\%$ more than 4 times a day, there is a regulation issue

[Fabre, 2020]

4. Fault detection

Fouling of the heat exchanger



Observation: An increase of the thermal resistance according to a mass flow rate ratio

Calculation of the thermal resistance after a cleaning:

$$R_{HEX,without\ fouling} = DTLM/\dot{Q}$$

$$R_{HEX,without\ fouling} = \mathrm{A}\,\dot{M} + \mathrm{B}$$

$$\dot{M} = \frac{\dot{m}_p^{0,8} + \dot{m}_s^{0,8}}{\dot{m}_p^{0,8}\dot{m}_s^{0,8}}$$

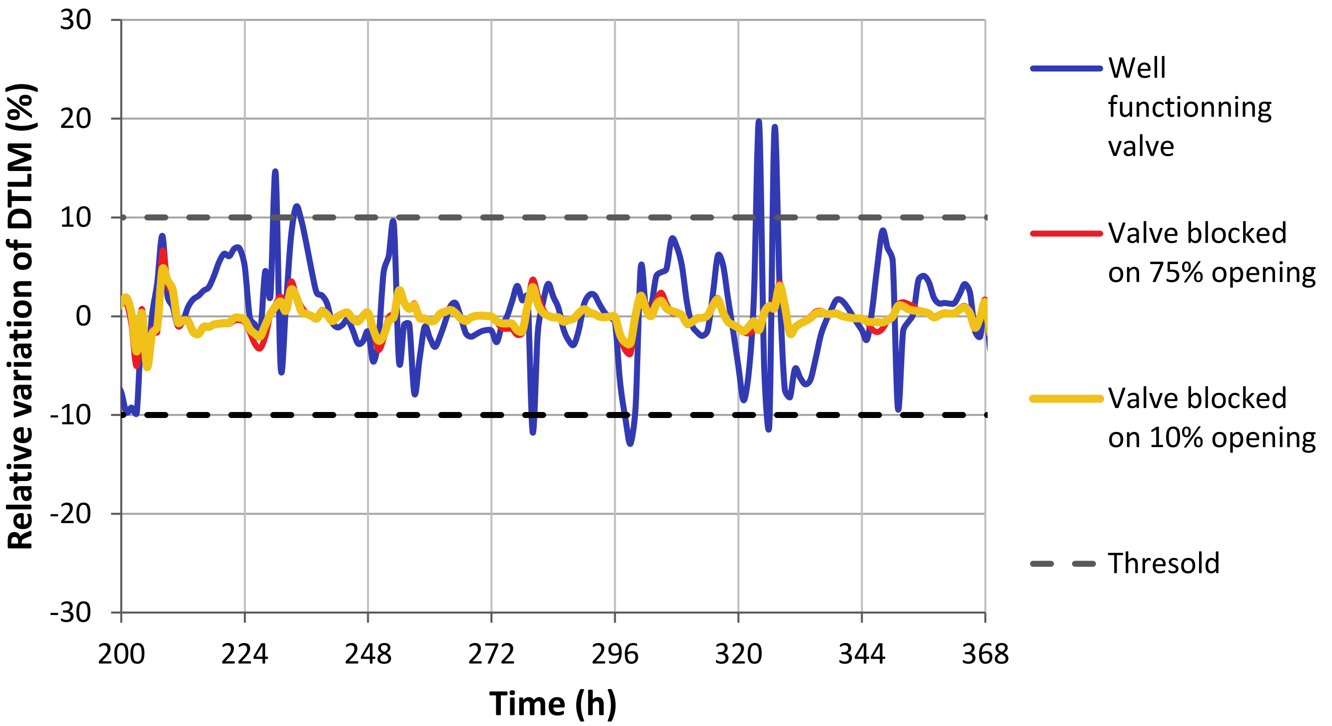
Criteria: for a given $\dot{M}$ if

$$R_{HEX} > 1{,}4\ R_{HEX,without\ fouling}$$

[Fabre, 2020]

4. Fault detection

Secondary side valve blocked



Calculation of the radiator DTLM:

$$\mathrm{DTLM} = \ln\left(\frac{T_{in} - T_{int}}{T_{out} - T_{int}}\right)$$

Criteria:

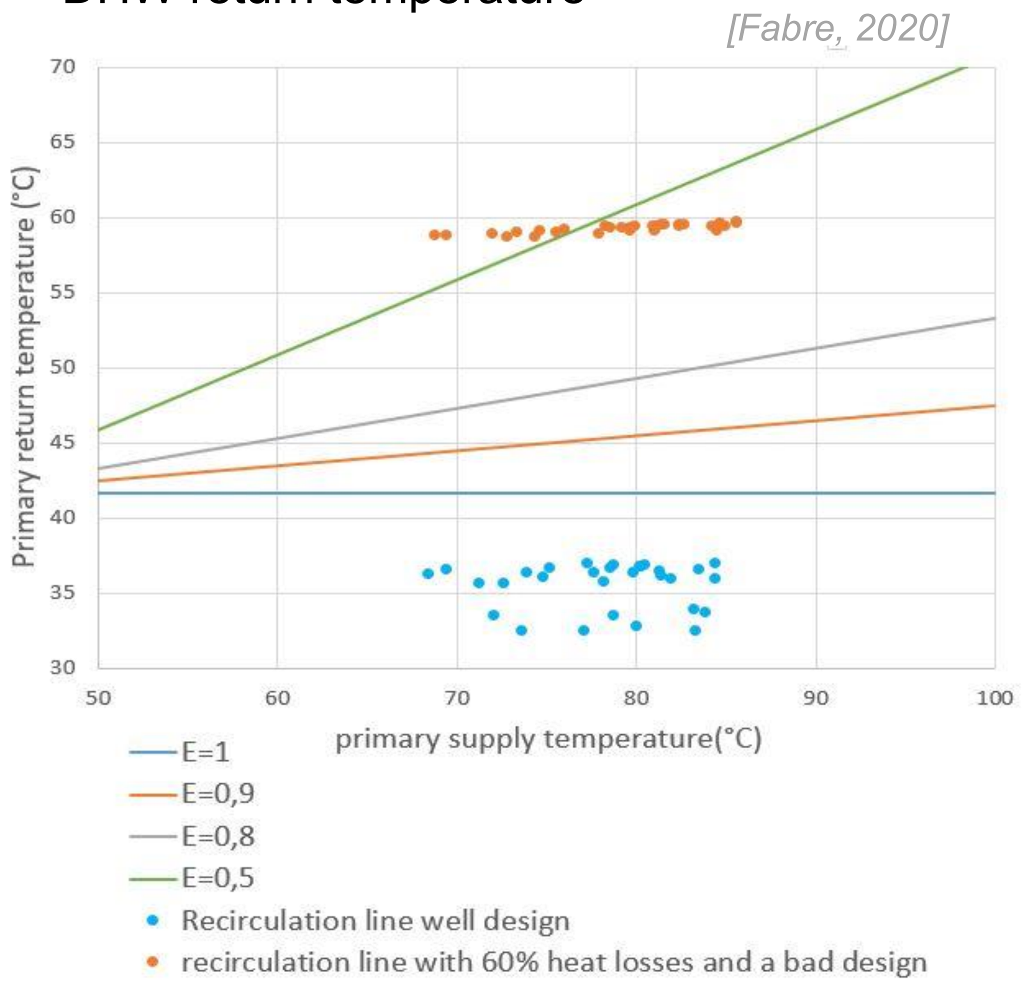
if the relative variation of DTLM < 10%

Observation : the radiator DTLM variations are smoothed

[Fabre, 2020]

4. Fault detection

- DHW return temperature



Observation: the return temperature at the primary side of the DHW HEX is high

Assumption:

$$T_{recirc} = 55°C$$

$$Designed\ F = \dot{m}_{recirc} / \dot{m}_{demand}$$

Calculation:

$$T_{p,out} = (1 - E)\ T_{p,in} + \frac{E}{1+F}\ (T_{recirc}\ F + T_{CW})$$

Criteria: Plot the measure of both primary side temperatures. Check if the plots are upper than the grey line of an effectiveness E=0.8 for instance

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Thank you!

Module 5.4 – Detection of malfunctions

SHaKE – Sharing Heat and Knowledge on Energy Communities

https://www.shakeproject-dhc.eu/

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