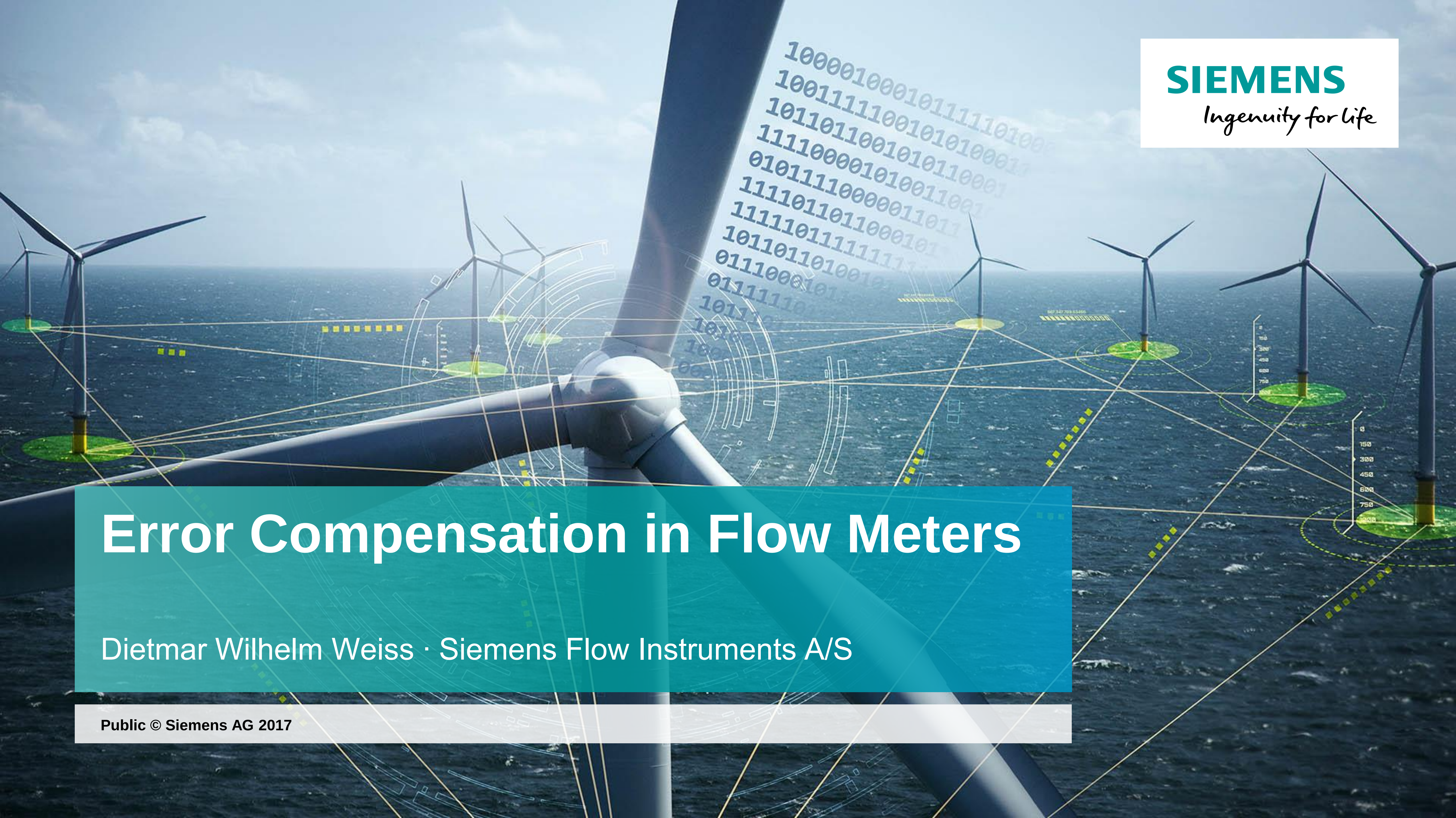


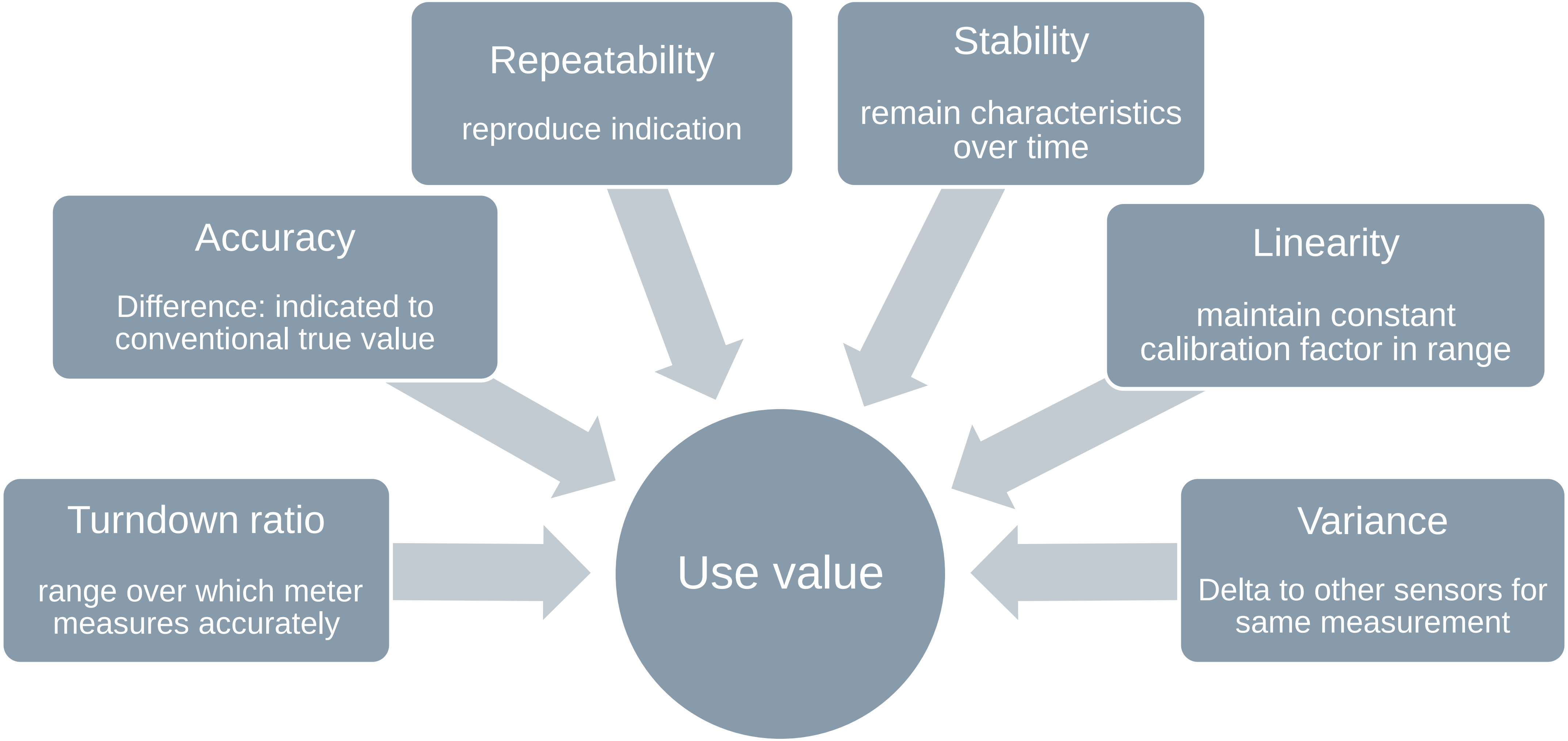
Error Compensation in Flow Meters

Dietmar Wilhelm Weiss · Siemens Flow Instruments A/S

Objective

- View on competitiveness of flow meters
- Process control versus custody transfer
- Limits of turn-down-ratio
- Complementation of Sensorfront model with empirical model

Use Value Definition



Exchange Value

Dual character

Instrument satisfying a technical need

Product traded in a market

Technology:

Sensor solves technical problem

- Process control
- Custody transfer

Economy:

Production of commodities by means of commodities

Economic value = max { price in free market }

Observation

- Growing necessity to minimize overall production costs
- Potential demand from multi-sensor data fusion:
    - less costly sensors
    - compensated by higher numbers of sensors

Indication

Customer's wish

1) Buy it - for LOWEST price with acceptable performance/service
(buyers are not necessarily control folk)
2) Install it
3) Commission it
4) Forget it

Compromising certain product requirements

- Base accuracy of high performance mass flow meters ≈ 0.1% (liquids)
- ≈ 70% of mass flow meter market can tolerate base accuracy of 1%
- Control applications focus often on time derivatives instead of absolute values

Cost reduction in

- Software ?
- Hardware ?
- Mechanics

Lower Design Requirements on Sensors
& Error Compensation in Software

Objective of Error Compensation

Minimize:

1) Dependency of absolute error on

- Flow rate
- Fluid temperature
- Fluid pressure, etc

2) Dependency of zero flow rate on

- Fluid temperature
- Fluid pressure
- Mechanical stress situation, etc

Differentiation into: Rate of Change, Absolute Value and Integral Value

Instrument Performance

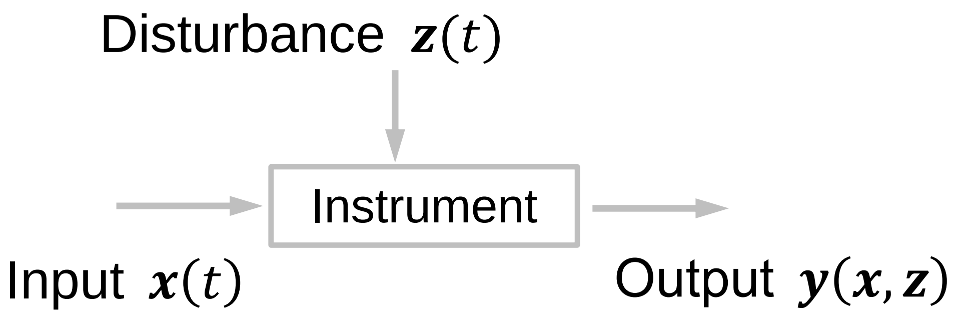
Performance during Verification → **Test Situation** — 'Ideal' reference conditions: $x \neq f(t, p, T), \quad z = const$

Robustness and Accuracy in Real Life → **Process Control** — Temporal changes:

Derivative: $\frac{dy}{dx(t)}$

Absolute: $y(x(t))$

Robustness and Accuracy in Real Life → **Custody Transfer** — Time integral of absolute values: $\int y(x)\ dt$



Mass Flow Meter: Input x, Output y, Disturbance z

Continuous input:

$$x(t) = \{\dot{m}\}$$ true flow rate

Absolute continuous values:

$$y(t) = \begin{Bmatrix} \dot{m} \\ \rho_{FLUID} \\ (T, p) \end{Bmatrix}$$

indicated flow rate
fluid density

Main disturbance:

$$z(t) = \begin{Bmatrix} T_{FLUID} \\ p_{FLUID} \\ T_{AMBIENT} \end{Bmatrix}$$

fluid temperature
fluid pressure
ambient temperature

Time integral over transfer period: $t_1 \rightarrow t_2$

$$y_{12} = \int_{t_1}^{t_2} \dot{m}\, dt$$ transferred mass

A Competitive Product has Low Minimum Flow Rate

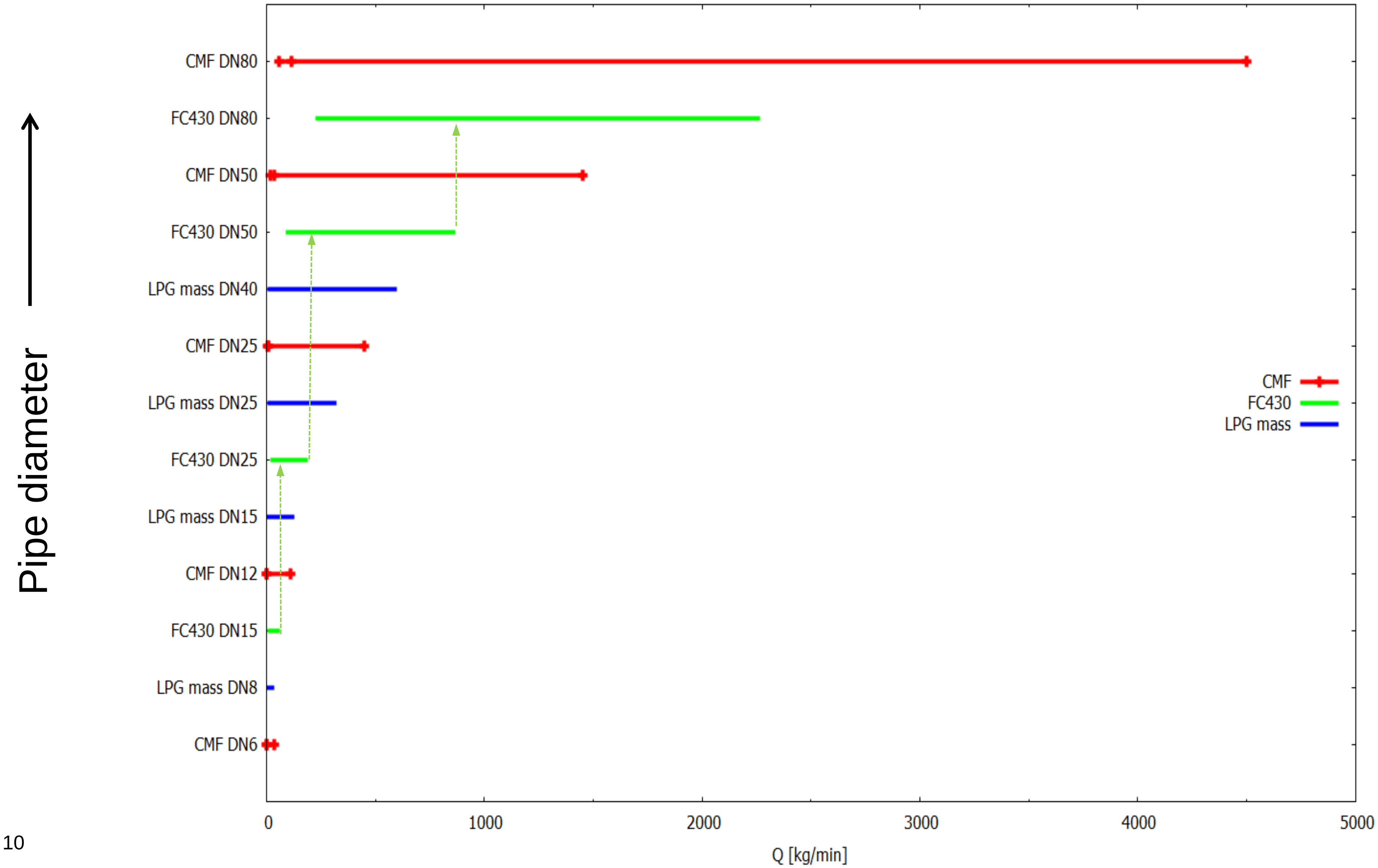
- Great turn-down ratio (max-to-min flow rate)
- Overlapping flow rate ranges of nominal product diameters

Max flow rate is limited by pressure drop → Low minimum flow rate

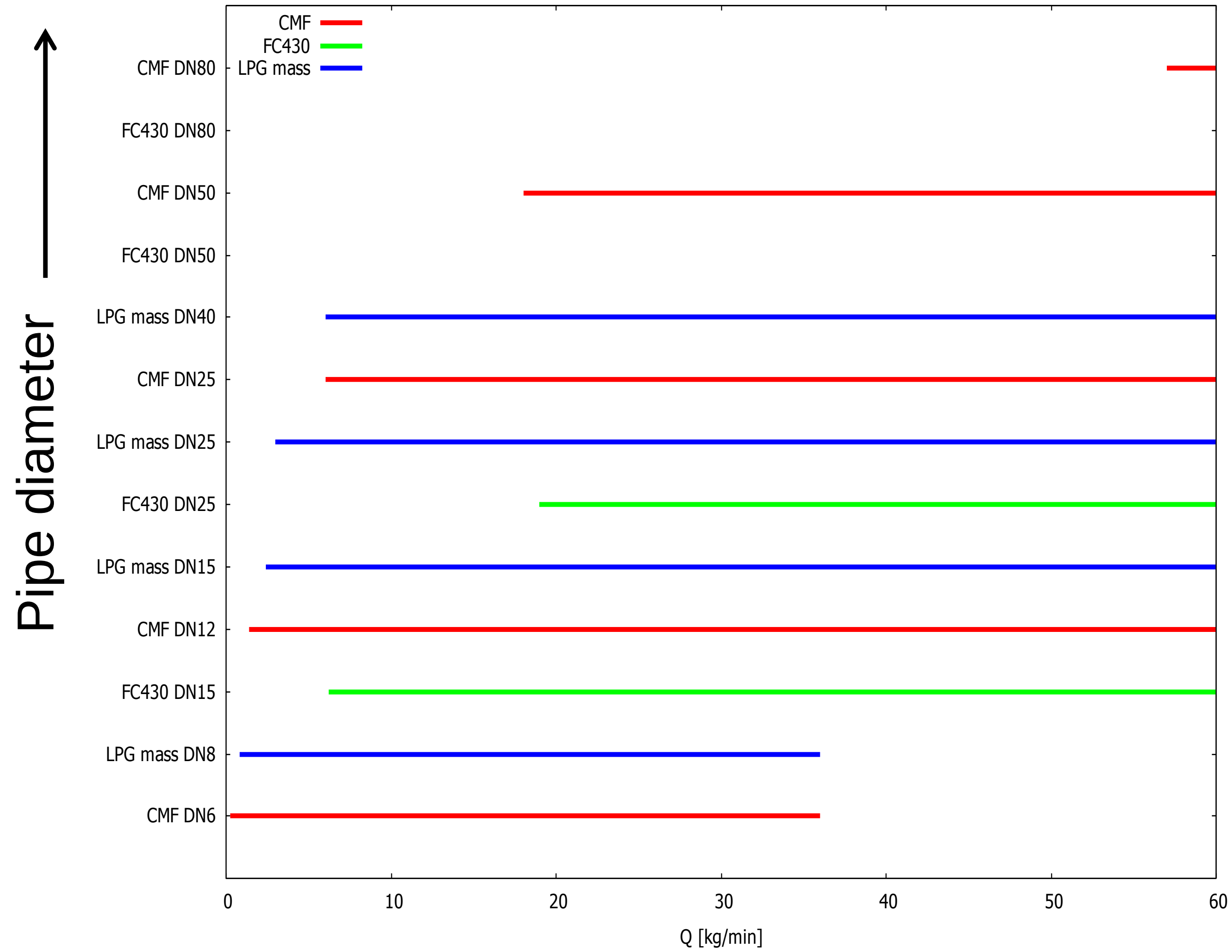
Lower minimum flow rates
ensuring relative errors less than error limits at:

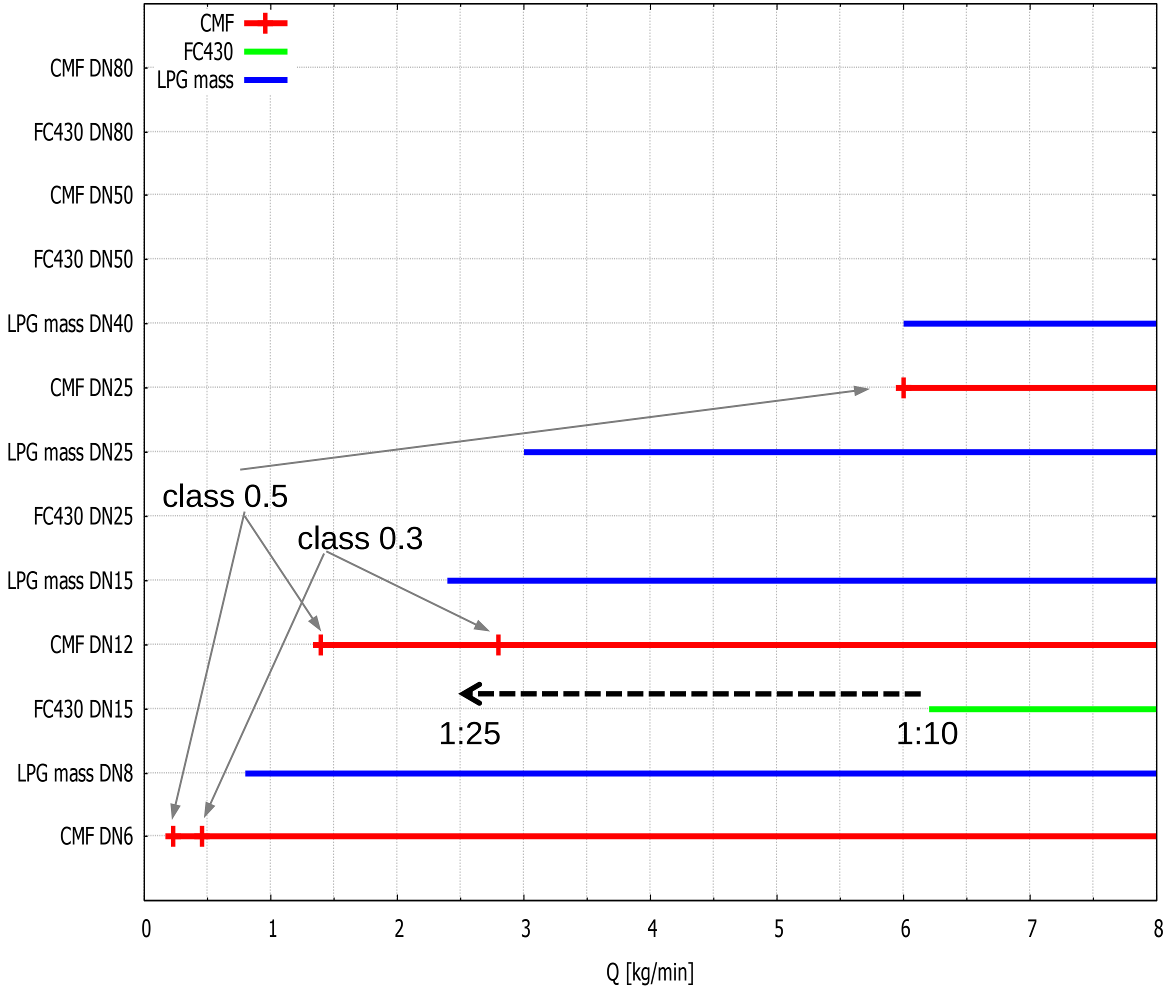
- Variation of fluid temperature in full operational range
- Variation of fluid pressure in full operational range

Ranges of Mass Flow Rates for different diameters: CMF, FC400, LPG mass



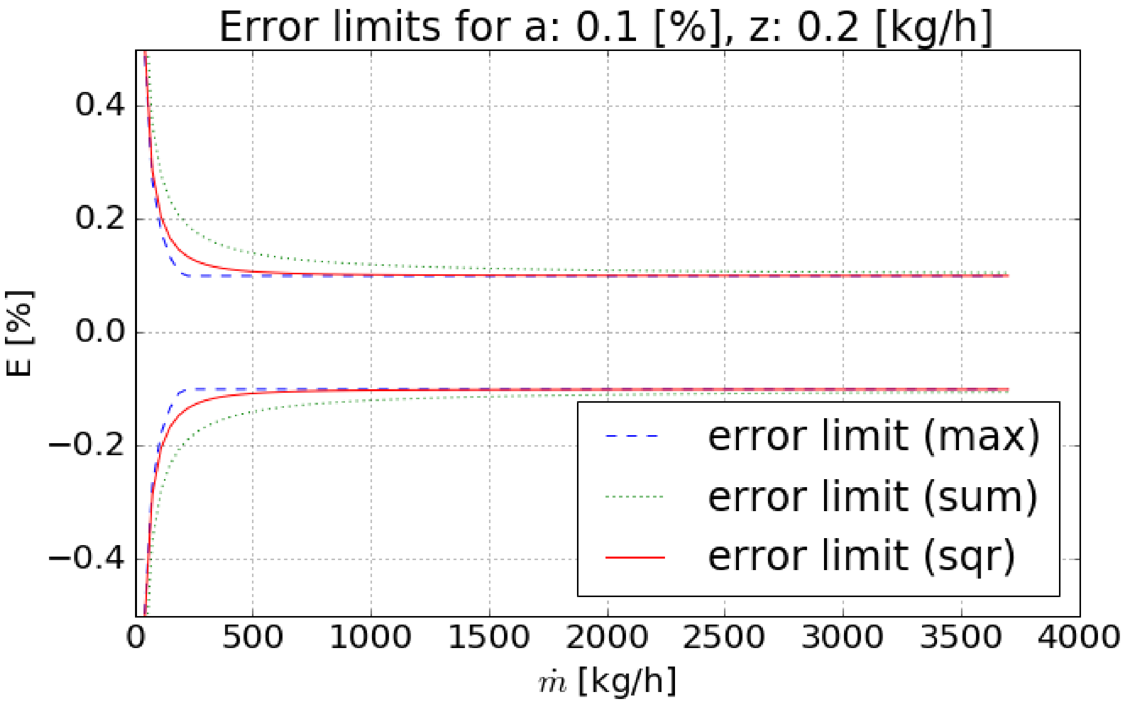
Zoomed: Ranges of Mass Flow Rates: CMF, FC400, LPG mass





What is Limiting the Extension of Turn-down Ratios ?

Limits of relative error, isothermal: $z \neq f(T)$



Error limit E_{lim}:

$$E_{\mathrm{lim}} \geq \mathrm{E} = \frac{\dot{m}_{\mathrm{ind}} - \dot{m}_{\mathrm{true}}}{\dot{m}_{\mathrm{true}}}$$

Variants of E_{lim} definition:

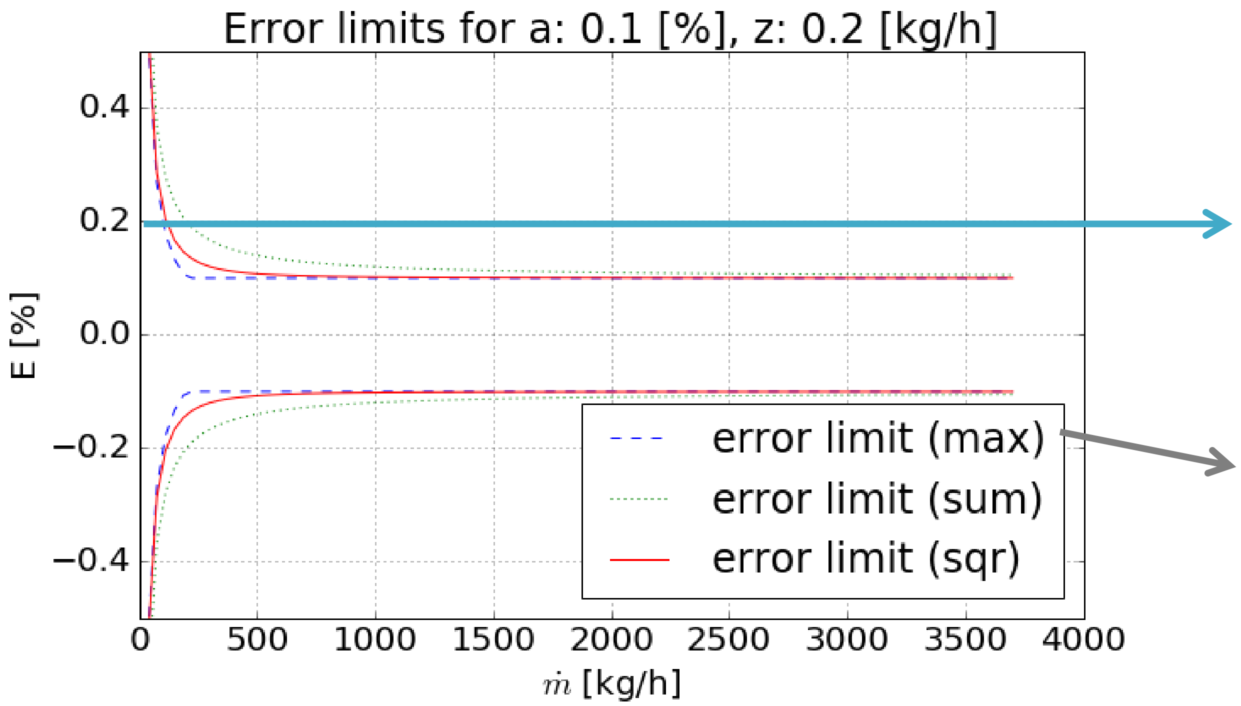
$$E_{\mathrm{max}} = \max\left(a, \frac{z}{\dot{m}}\right)$$

$$E_{\mathrm{sqr}} = \left(a^2 + \left(\frac{z}{\dot{m}}\right)^2\right)^{0.5}$$

$$E_{\mathrm{sum}} = a + \frac{z}{\dot{m}}$$

z .. zero flow error, a .. base accuracy, E .. relative error, $\dot{m}$ .. mass flow rate

Error Limit of Product Specification versus Limit of Standard OIML R117



Error limit of OIML standard R117 (0.2%) **independent** of flow rate

But error limit of product specification: **dependent** on flow rate

OIML Standard R117 : Liquids other than water

The Plan

a) Increase dynamics of given product or
b) Reach same dynamics with cheaper mechanical design

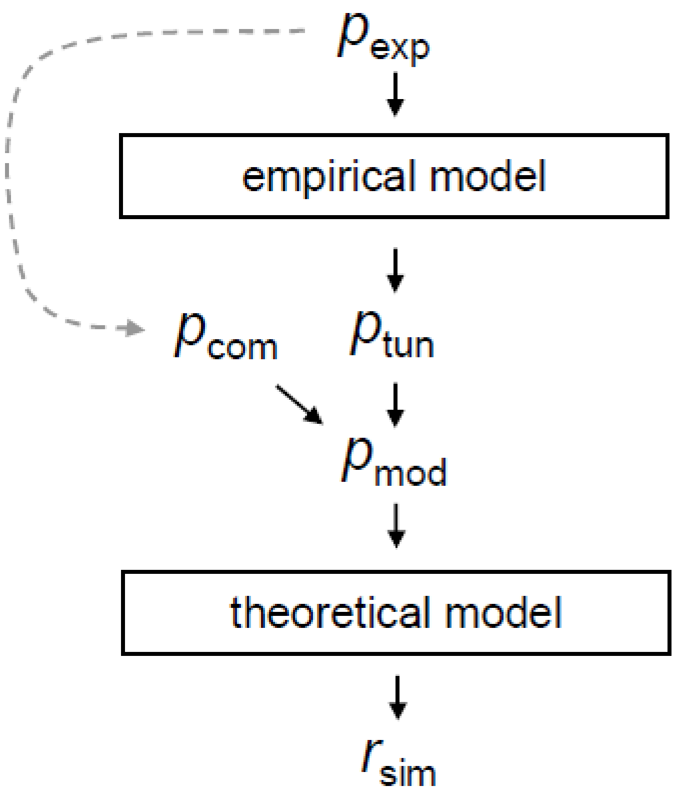
Improving concept of classic calibration

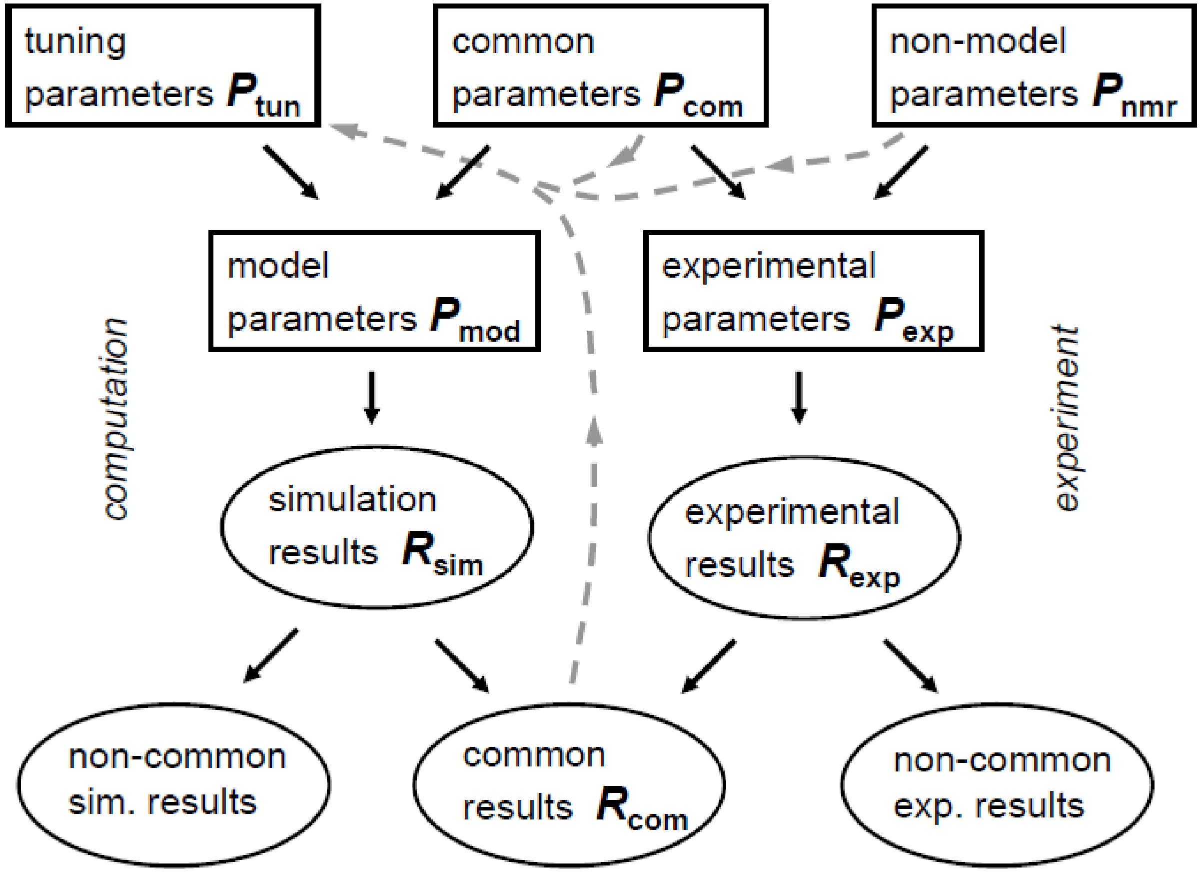
- Offset
- Gain, etc

If repeatability is ensured:

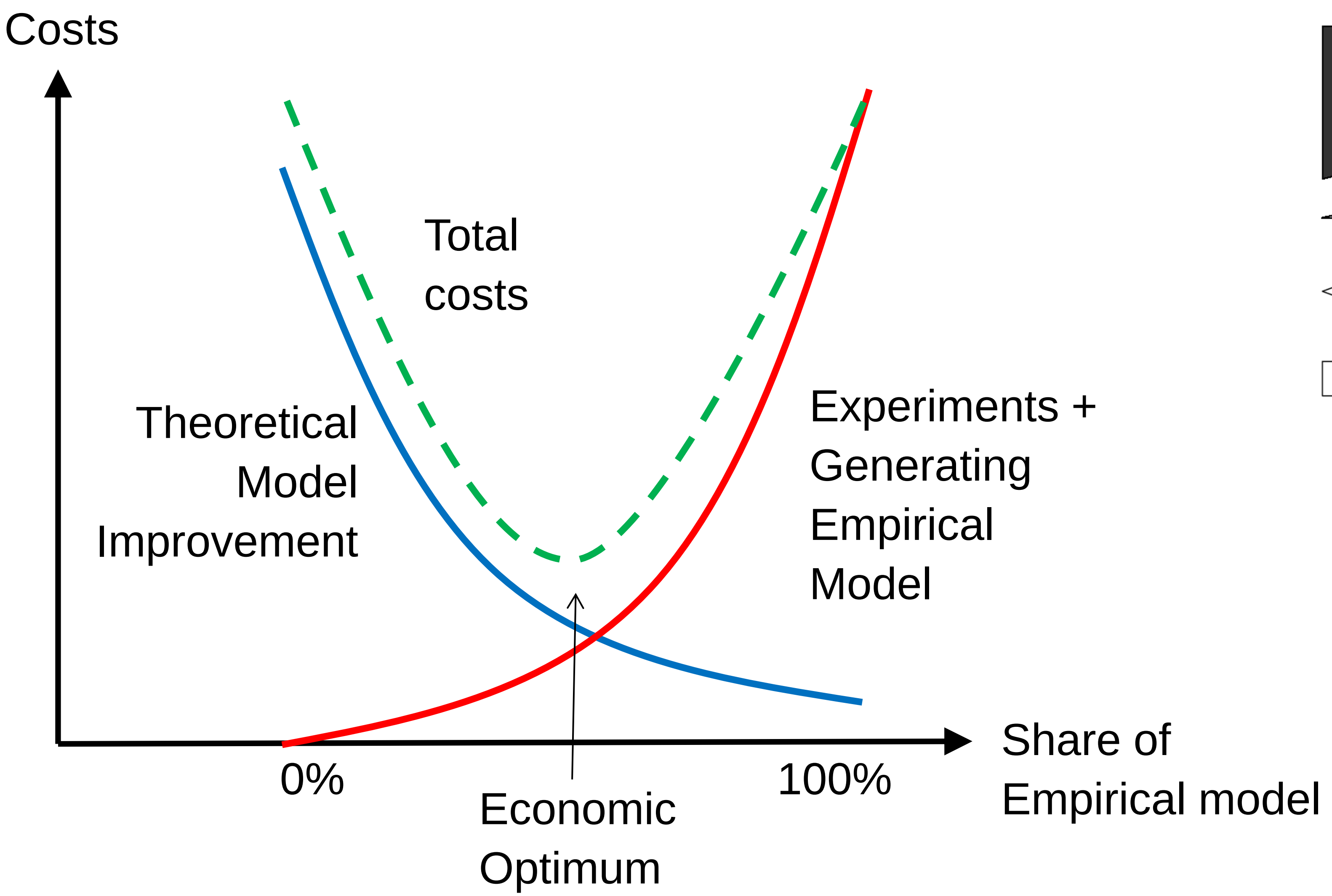
1) Design tests identifying dependencies
2) Approximate absolute and relative error of sensor
3) Subtract this error from indicated value

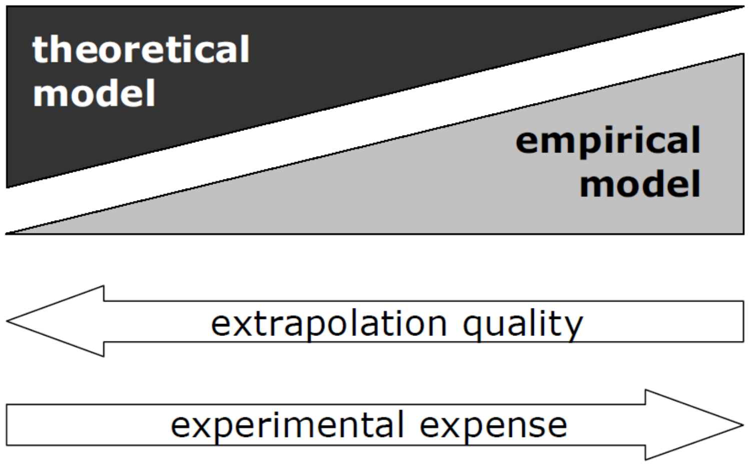
Complement Theoretical Model in Sensor Frontend with Empirical Model





Total Costs versus Empirical Model Share





Improvement of indicated values based either on absolute error A or relative error E (symbols with tilde on top are the approximations)

From theoretical model:

$$A = \dot{m}_{ind} - \dot{m}_{true}$$

Reference

Meter under test

$$\dot{m}_{true} = \dot{m}_{ind} - A$$

$$E = \frac{A}{\dot{m}_{true}} = \frac{\dot{m}_{ind} - \dot{m}_{true}}{\dot{m}_{true}}$$

$$\dot{m}_{true} = \frac{\dot{m}_{ind}}{E+1}$$

$\tilde{A}$ and $\tilde{E}$ are functions of disturbances (pressure, temperature) and flow rate

Approximation from empirical model:

$$w = train(z, \dot{m}_{true}, A) \qquad A = \dot{m}_{ind} - \dot{m}_{true}$$

$$\tilde{\dot{m}}_{true}(z, \dot{m}_{ind}) = \dot{m}_{ind} - \tilde{A}\ (z, \dot{m}_{ind}, w)$$

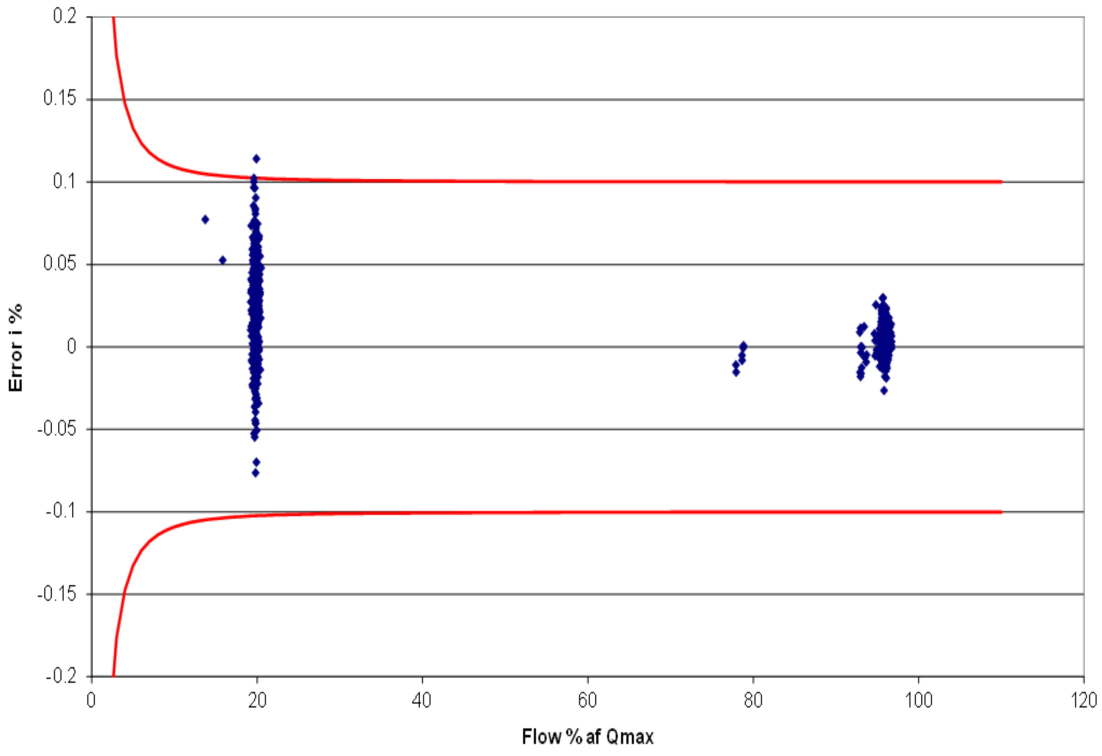
$$\tilde{E} = \frac{\dot{m}_{ind} - \tilde{\dot{m}}_{true}}{\tilde{\dot{m}}_{true}}$$

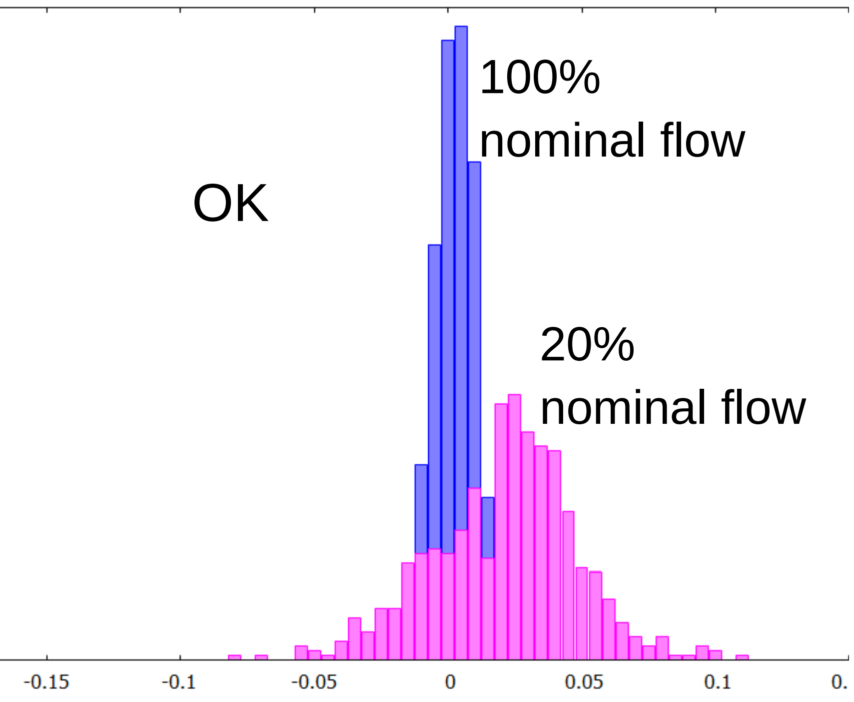
$$\tilde{\dot{m}}_{true} = \frac{\dot{m}_{ind}}{\tilde{E}+1}$$

$$E = \frac{\dot{m}_{ind} - \tilde{\dot{m}}_{ind} - \tilde{A}}{\tilde{\dot{m}}_{ind} - \tilde{A}} = \frac{-\tilde{A}}{\tilde{\dot{m}}_{ind} - \tilde{A}}$$

Pre-Requisite:

- Deterministic Behaviour
- Experimental data should be normally distributed
- Chaotic behaviour cannot be compensated



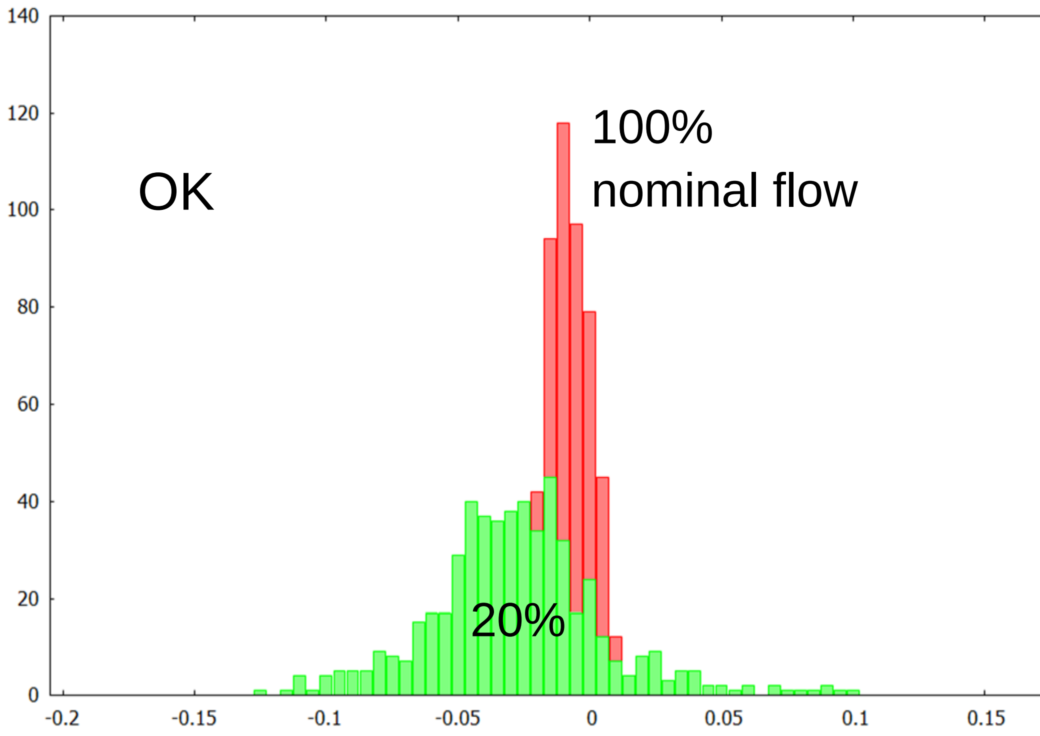


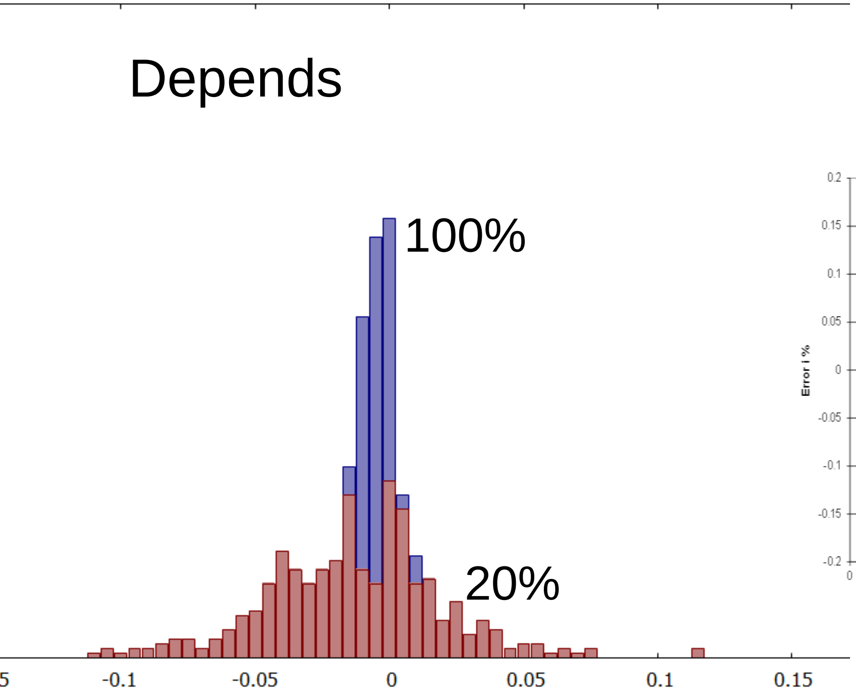
Histogram of relative error E [%]

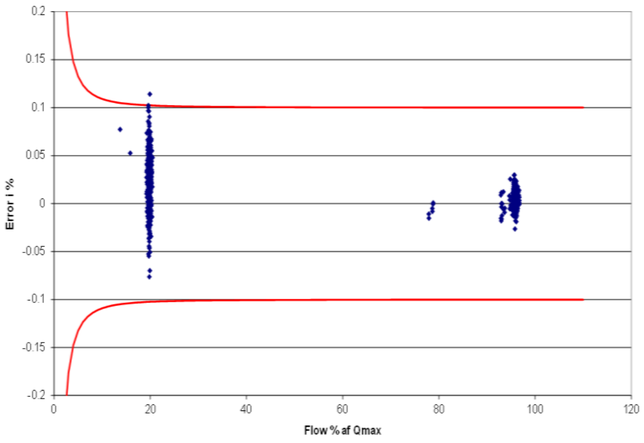
for 20% and 100% of nominal mass flow rate

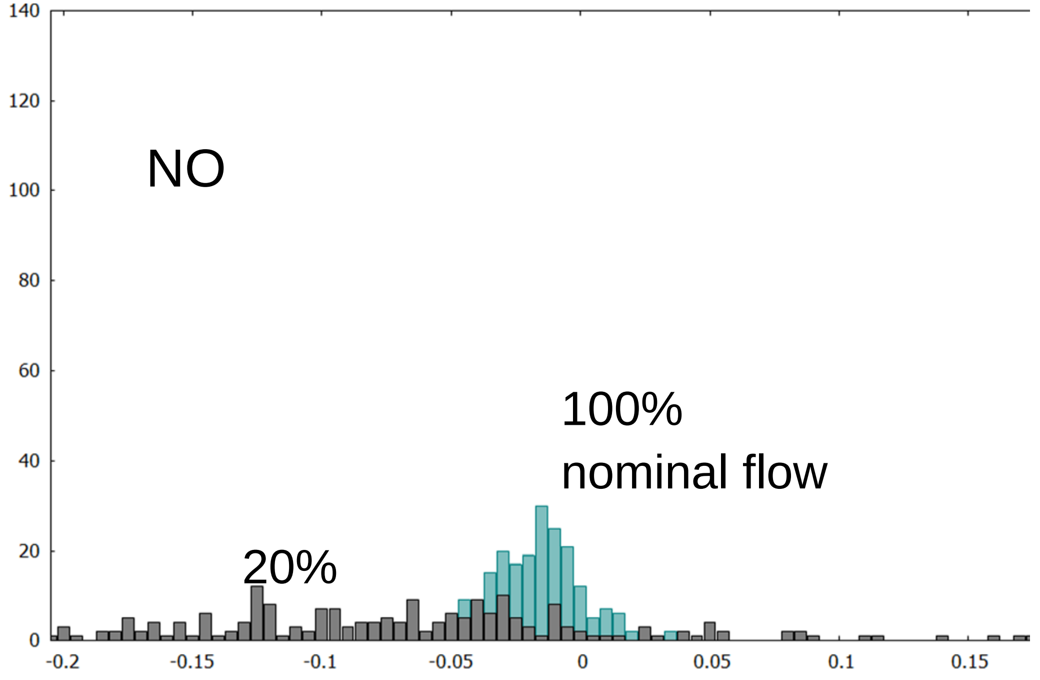
for four different pipe diameters

Bin width 0.005%

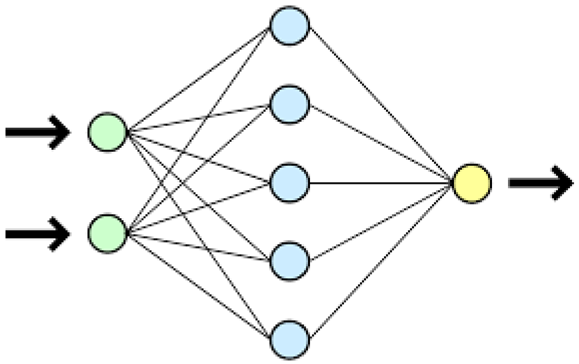








First Trial: Pure Empirical Model

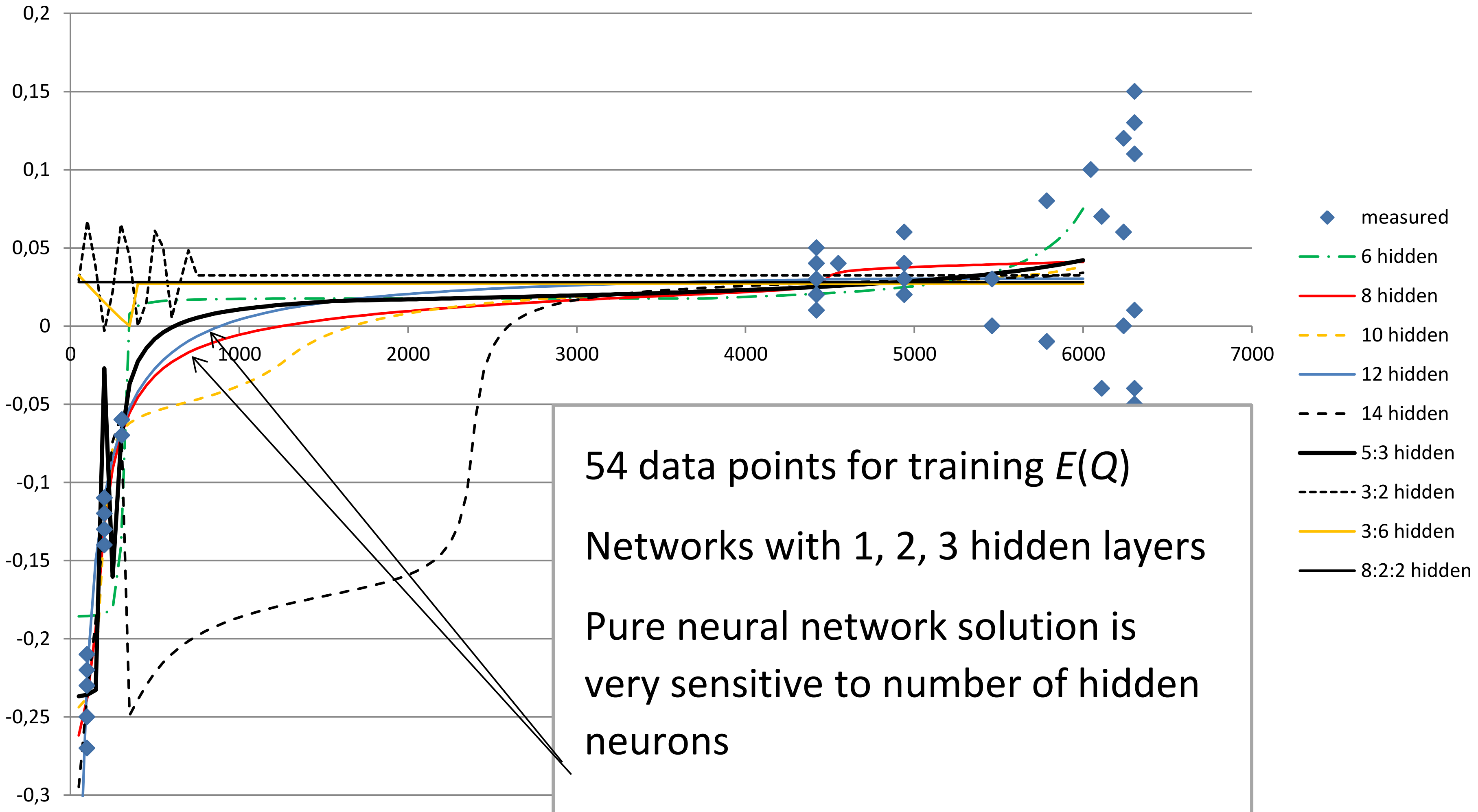


$E = f(Q)$
$E = f(Q, p)$

Example:
Unusual fluid in in food industry
Coriolis meter

Training of model with
x = mass flow rate in [kg/h]
y = relative error in [%]

First Disappointment: Result Sensitive to Neural Net Structure → No-Go



54 data points for training $E(Q)$

Networks with 1, 2, 3 hidden layers

Pure neural network solution is very sensitive to number of hidden neurons

Example: Correction of Error due to Fluid Pressure

Indicated Mass Flow Rate ⟷ Zero Mass Flow Rate

Zero flow rate [kg/s]

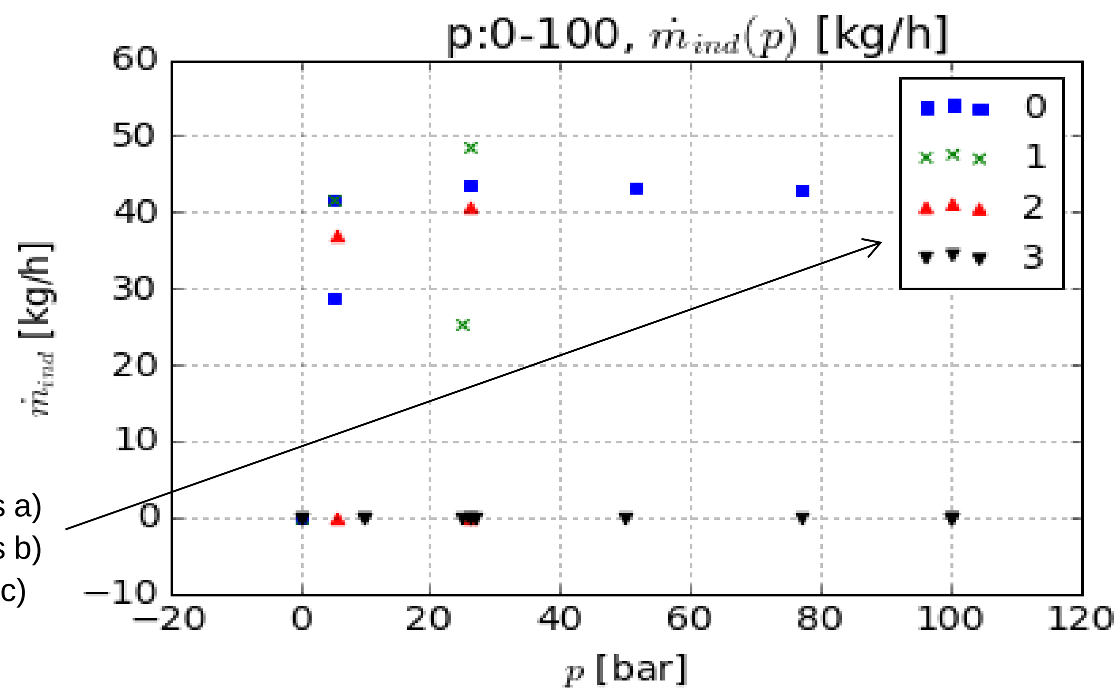
(ideally: 0)

No flow

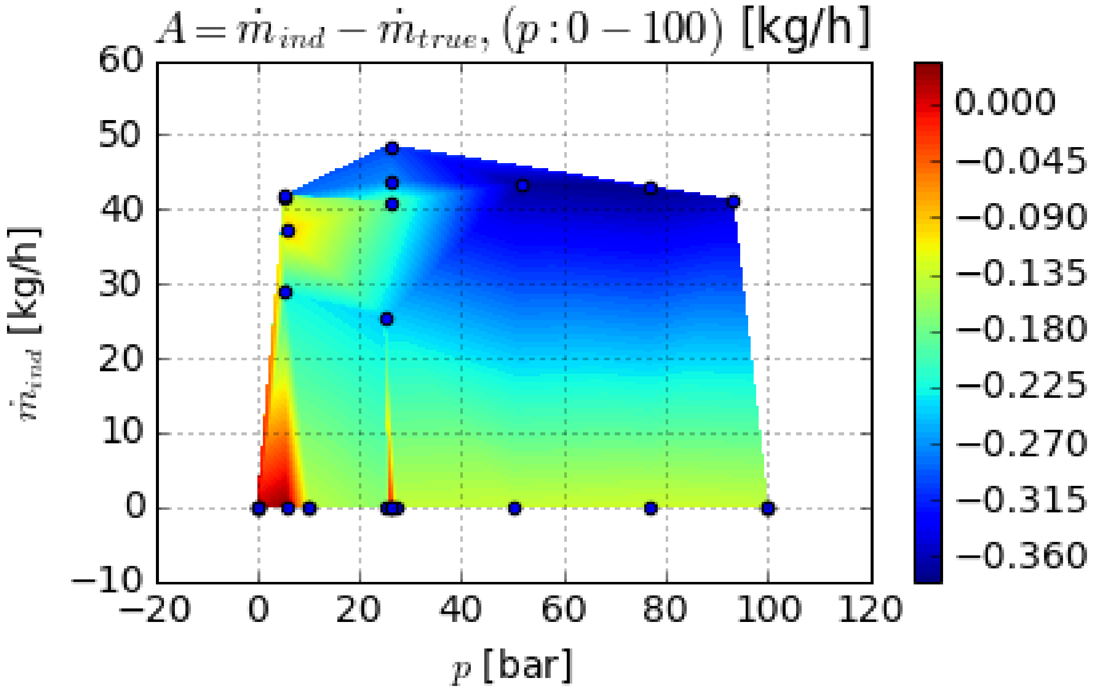
Indicated mass flow rate [kg/s]

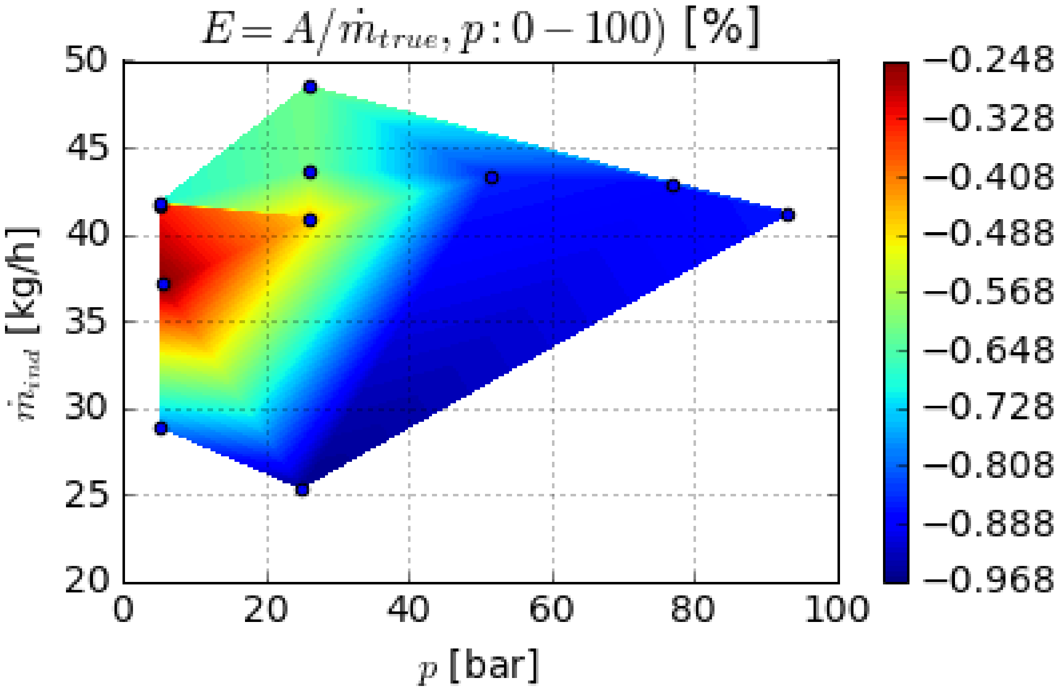
Conventional true mass flow rate [kg/s]

Meter 1: Errors of indicated data,
A: absolute error [kg/h], E: relative err. [%]

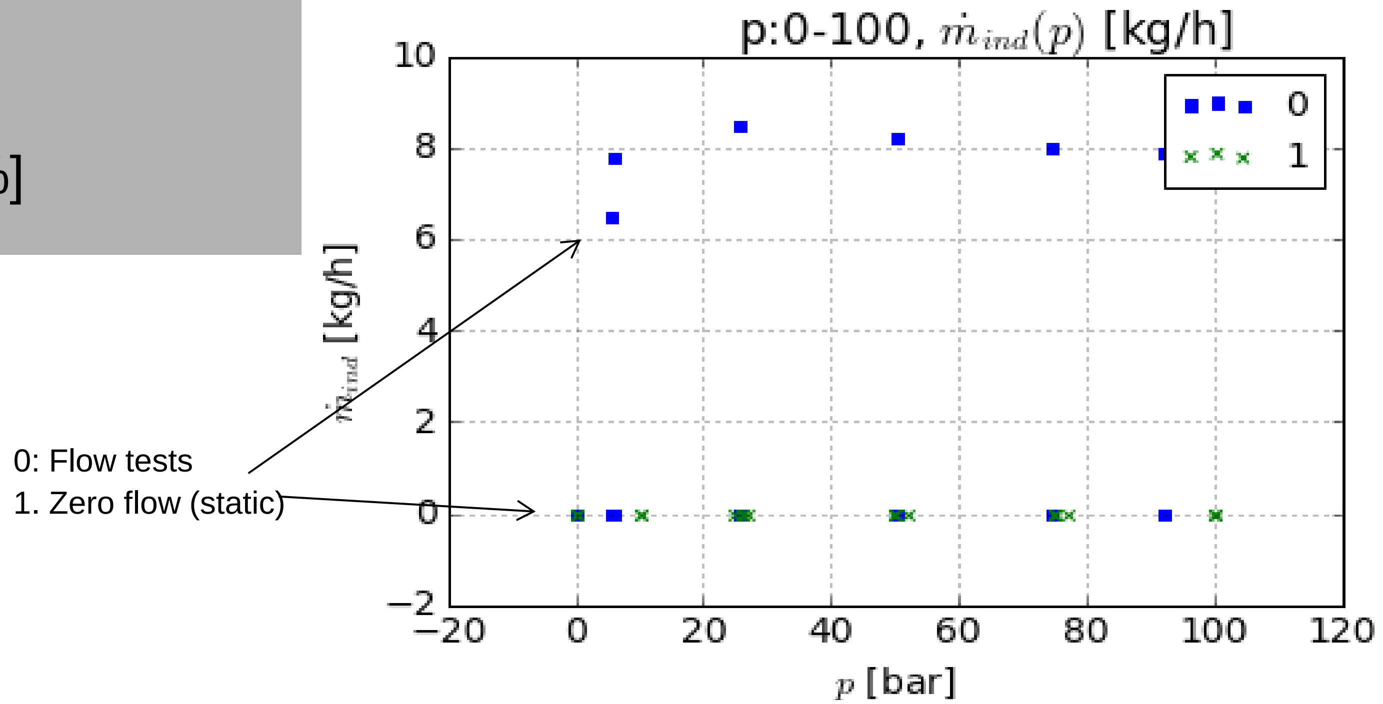


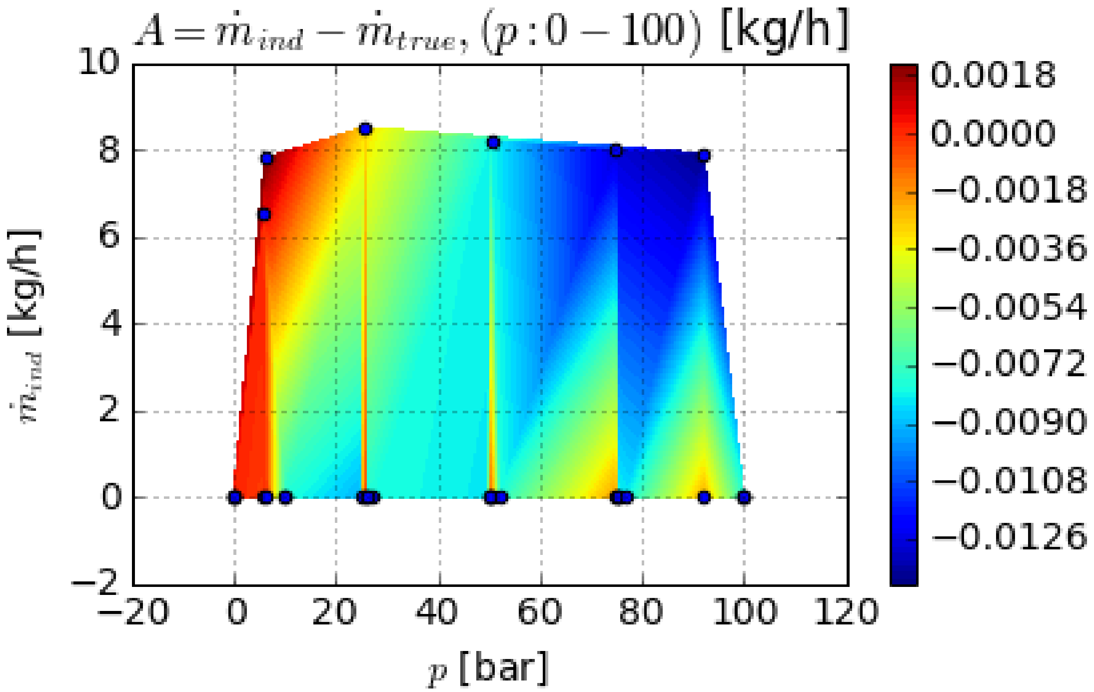
0: Original test
1: Additional tests a)
2. Additional tests b)
3. Zero flow (static)

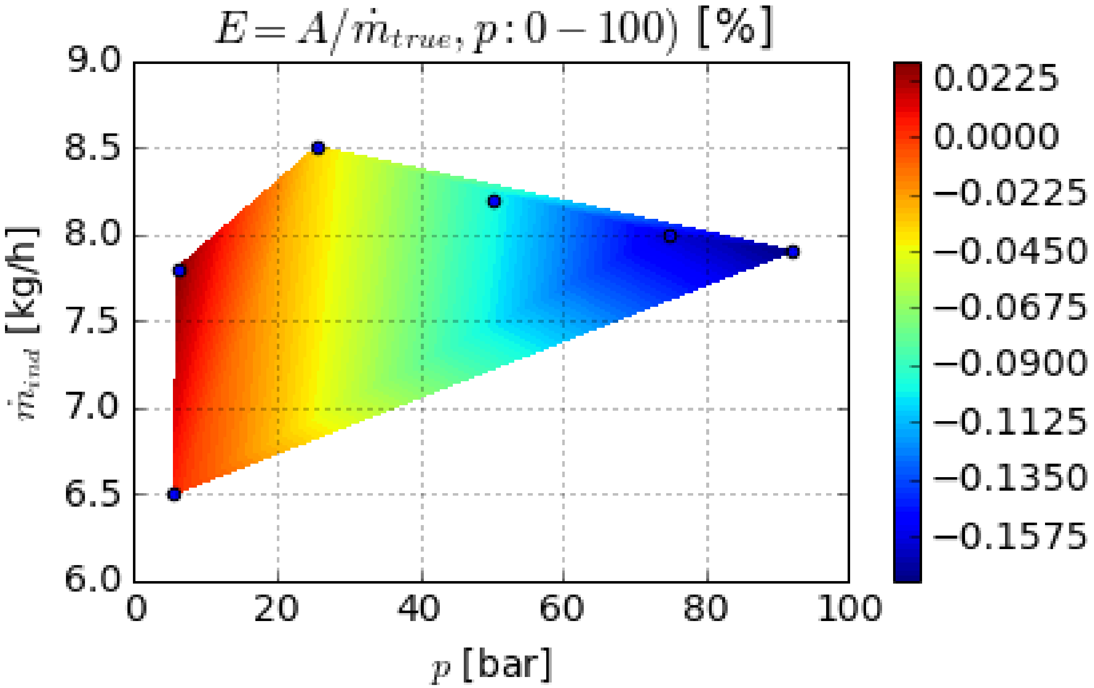


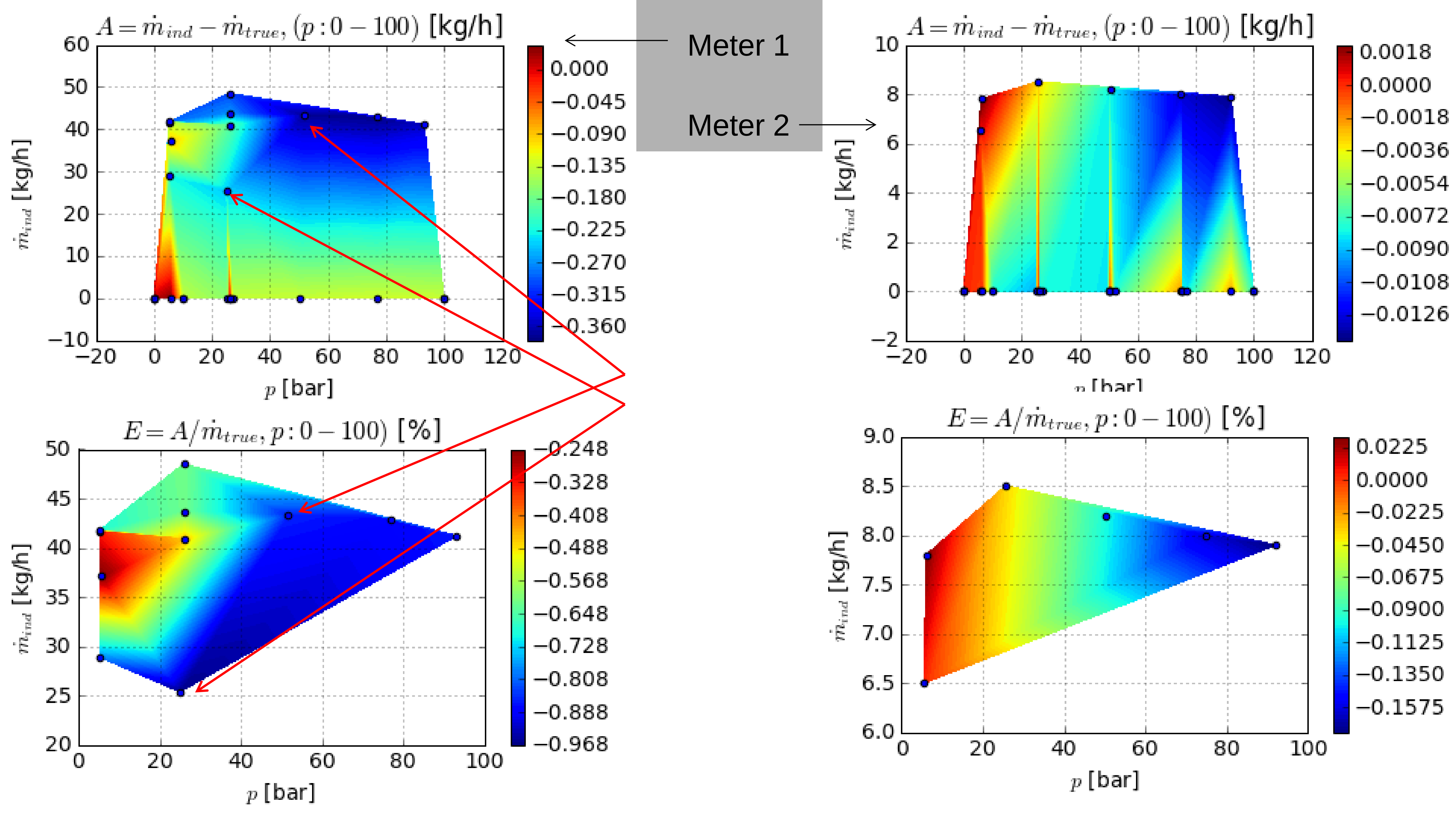


Meter 2: Errors of indicated data,
A: absolute error [kg/h], **E: relative err.** [%]



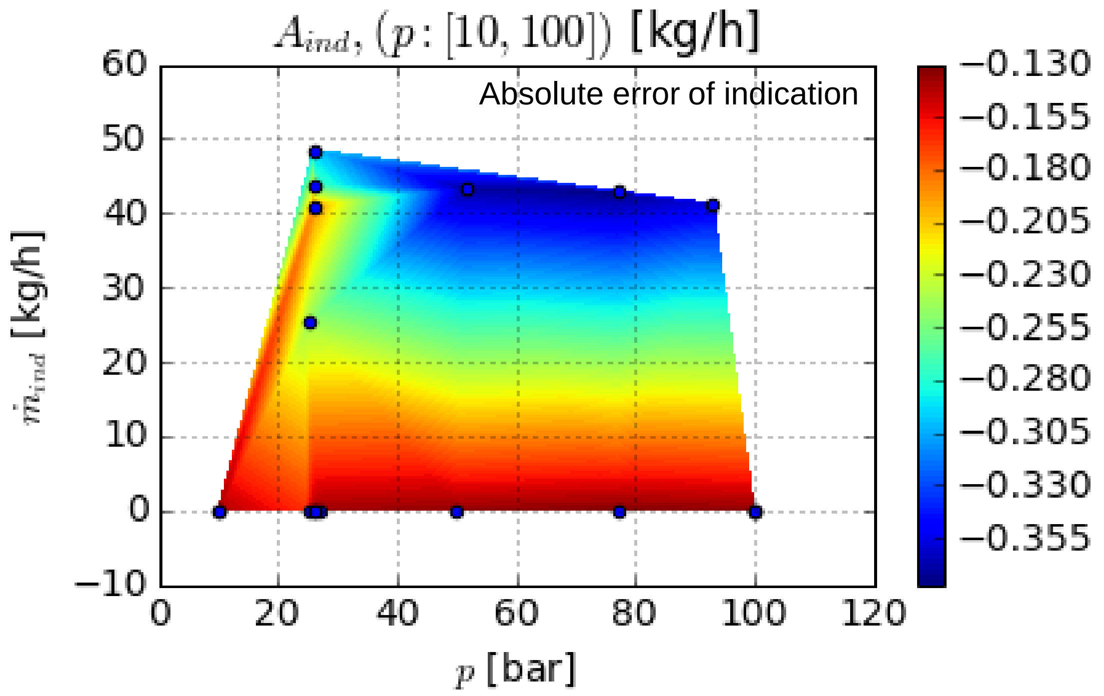


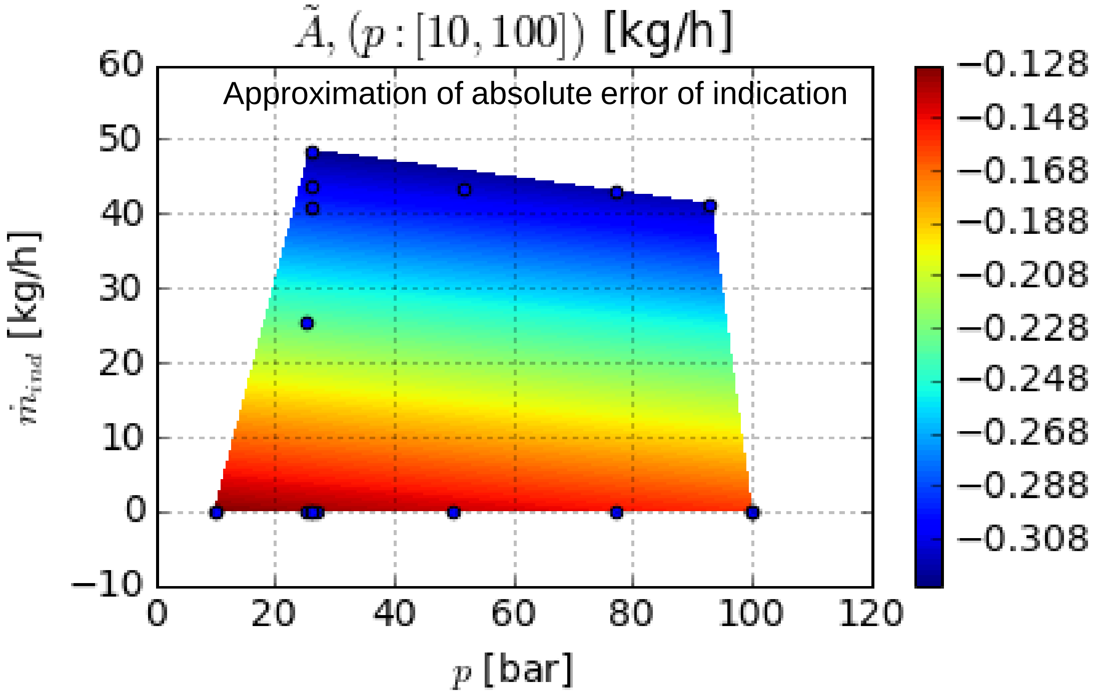


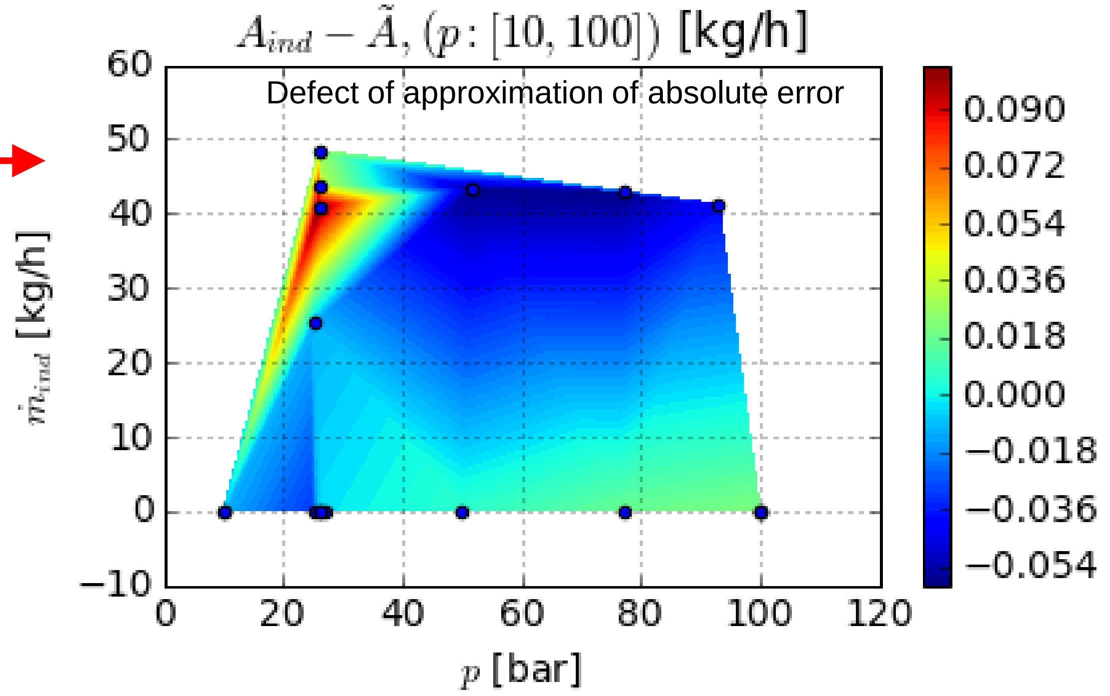


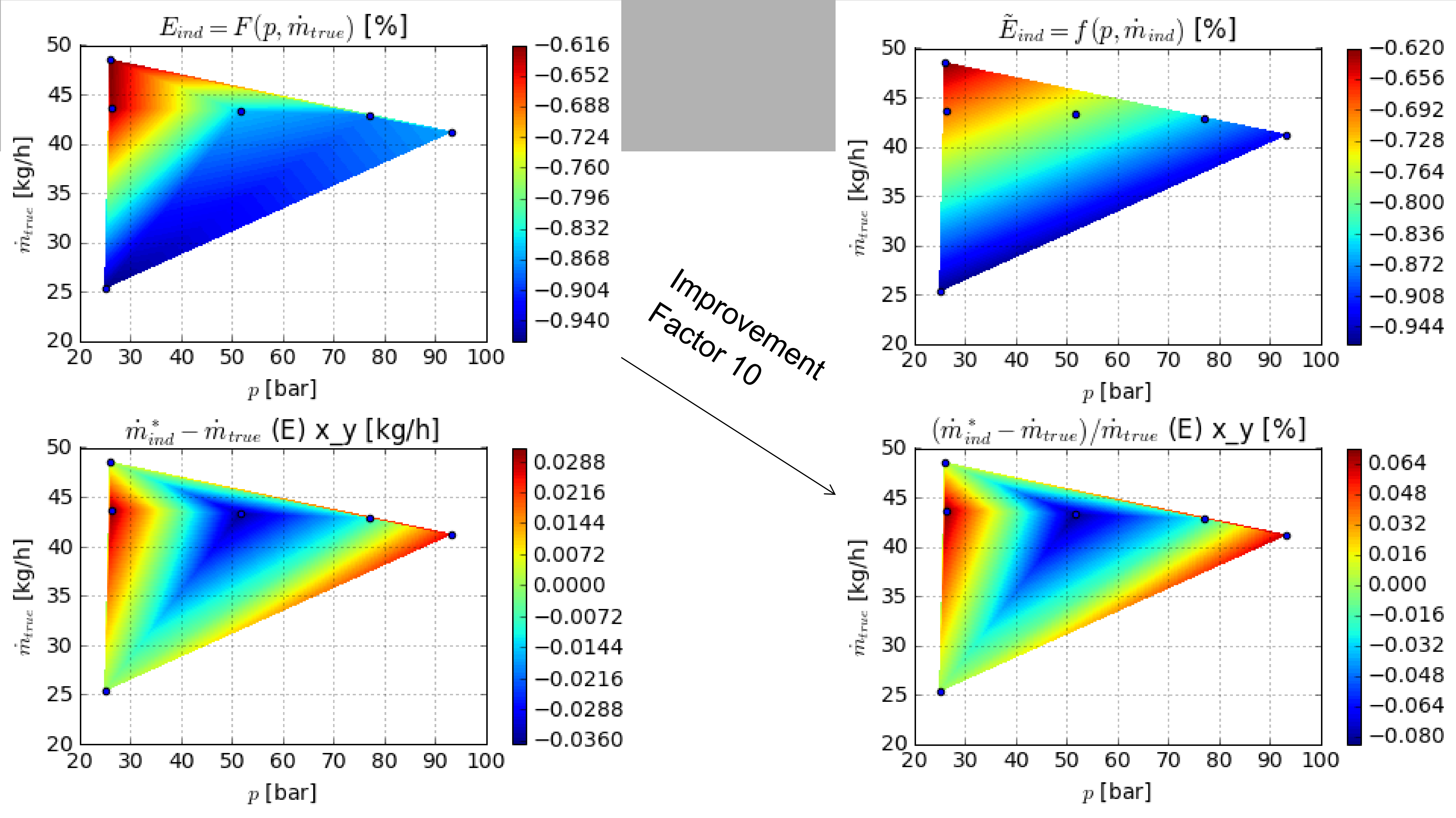
Meter 1
Meter 2
$A = \dot{m}_{ind} - \dot{m}_{true}, (p: 0-100)$ [kg/h]
$\dot{m}_{ind}$ [kg/h]
p [bar]
0.000
−0.045
−0.090
−0.135
−0.180
−0.225
−0.270
−0.315
−0.360
$A = \dot{m}_{ind} - \dot{m}_{true}, (p: 0-100)$ [kg/h]
0.0018
0.0000
−0.0018
−0.0036
−0.0054
−0.0072
−0.0090
−0.0108
−0.0126
$E = A/\dot{m}_{true}, p: 0-100)$ [%]
−0.248
−0.328
−0.408
−0.488
−0.568
−0.648
−0.728
−0.808
−0.888
−0.968
$E = A/\dot{m}_{true}, p: 0-100)$ [%]
0.0225
0.0000
−0.0225
−0.0450
−0.0675
−0.0900
−0.1125
−0.1350
−0.1575

Meter 1: Absolute Error A_{ind}, Approximation of absolute error $\widetilde{A}$ & defect in range p=10..100 bar

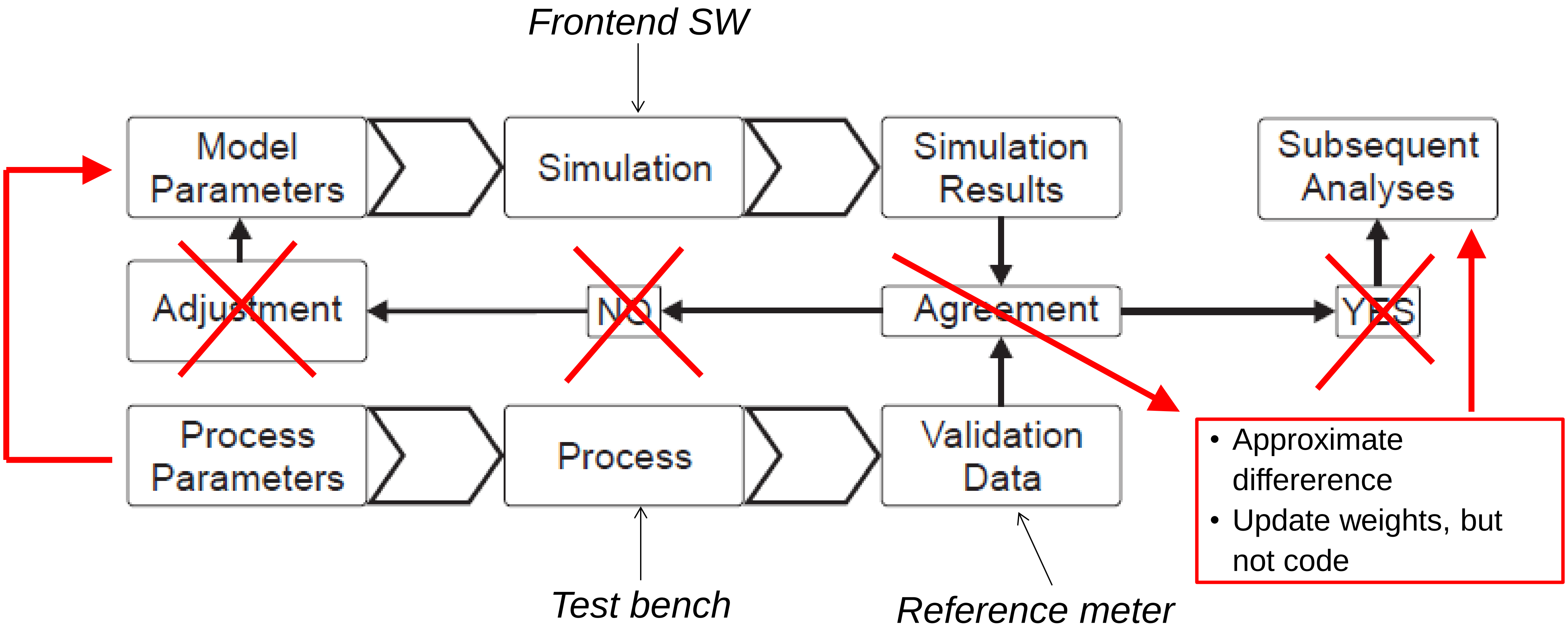







$E_{ind} = F(p, \dot{m}_{true})$ [%]
$\tilde{E}_{ind} = f(p, \dot{m}_{ind})$ [%]
$\dot{m}^*_{ind} - \dot{m}_{true}$ (E) x_y [kg/h]
$(\dot{m}^*_{ind} - \dot{m}_{true})/\dot{m}_{true}$ (E) x_y [%]
$\dot{m}_{true}$ [kg/h]
p [bar]
Improvement
Factor 10

Perspective: Linear Improvement of Theoretical Model with Empirical Model



Summary

Pro

- Less dependent on theoretical model in sensor front end
- Lowers number of iterations in model improvement
- Empirical model compensates for the complete error chain
- Extrapolation capability of empirical model can be scaled (exp. expense vs. extrapolation)
- Only one-time SW change (weights will be loaded)

Contra

- Hybrid model require capability and willingness to work abstractly on architecture level
- Significant change of theoretical model might require new experiments