In-situ test for Large Solar Thermal Collector Arrays

Results from the MeQuSo project

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Collector Arrays at FHW

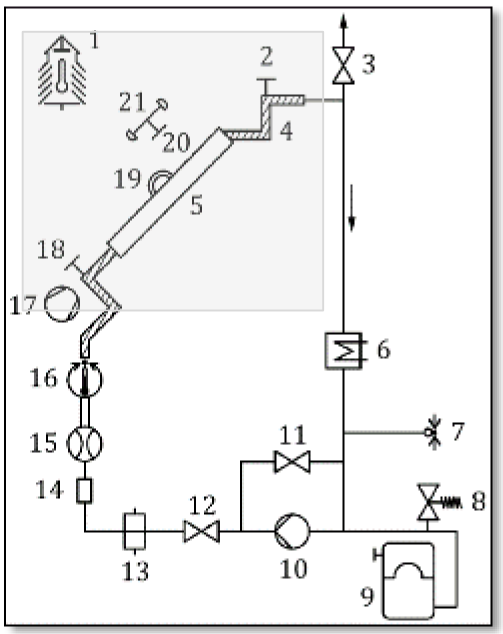
FHW = Fernheizwerk Graz

Source: Picfly.at Thomas Eberhard

Test Methods for Solar Thermal Collectors

Single collectors

- standard laboratory tests
- Solar Keymark, ISO 9806



Source: ISO 9806:2013

Collector arrays

- no standard tests available
- higher system complexity; in-situ tests required

D-CAT method

Project MeQuSo

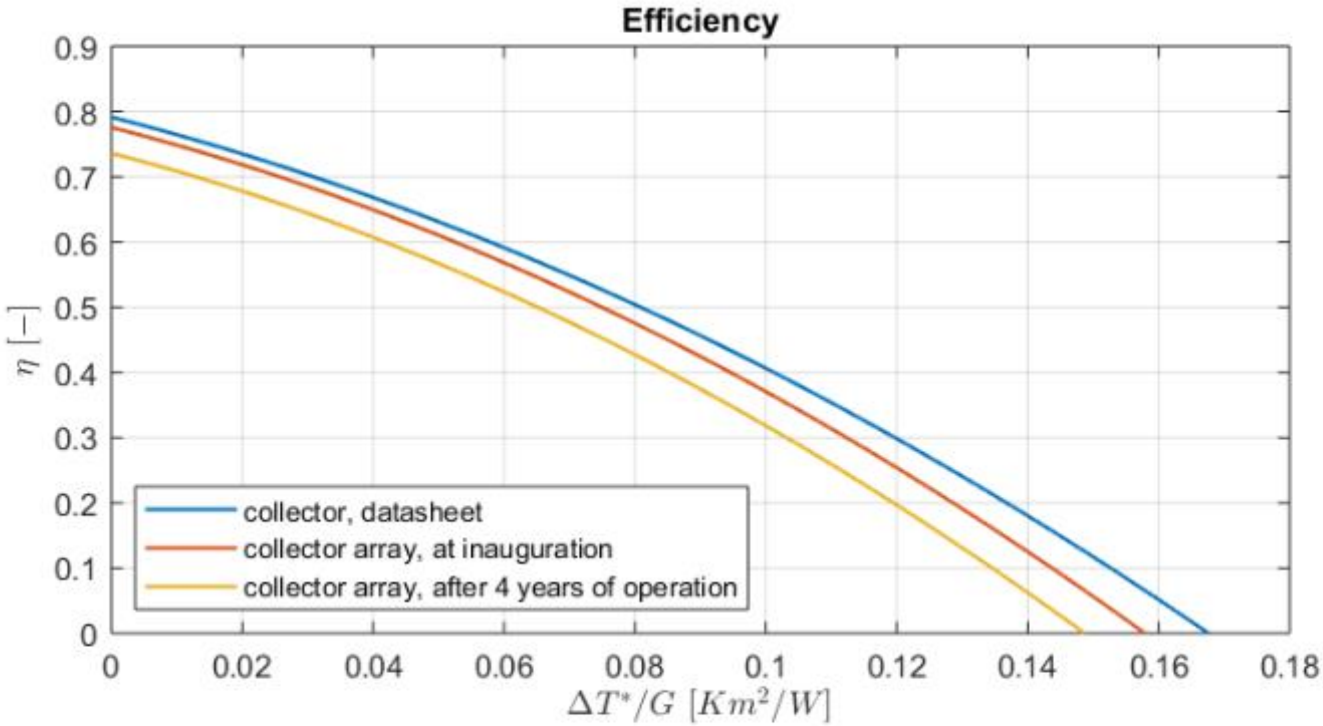
MeQuSo Goal

- **D-CAT: collector array test method**
  - Data-driven & model-based condition monitoring
  - In-situ = system size vs. lab size
  - Don‘t impair system operation

Performance parameters related to aperture area		η0	a1	a2						
Units		-	W/(m²K)	W/(m²K²)						
Test results - Flow rate and fluid see note 1		0.769	2.67	0.009						
Bi-directional incidence angle modifiers?	No	*Kϑ values are obligatory for 50°.*								
Incidence angle modifiers Kθ(θ)	Angle	10°	20°	30°	40°	50°	60°	70°	80°	90°
	Kθ(θ)	1.00	0.99	0.98	0.95	0.91	0.84	0.69	0.24	0.00
Incidence angle modifier not bi-directional - leave fields blank										

D-CAT: Automated System Tests

Exemplary result



D-CAT Grey Box Modelling

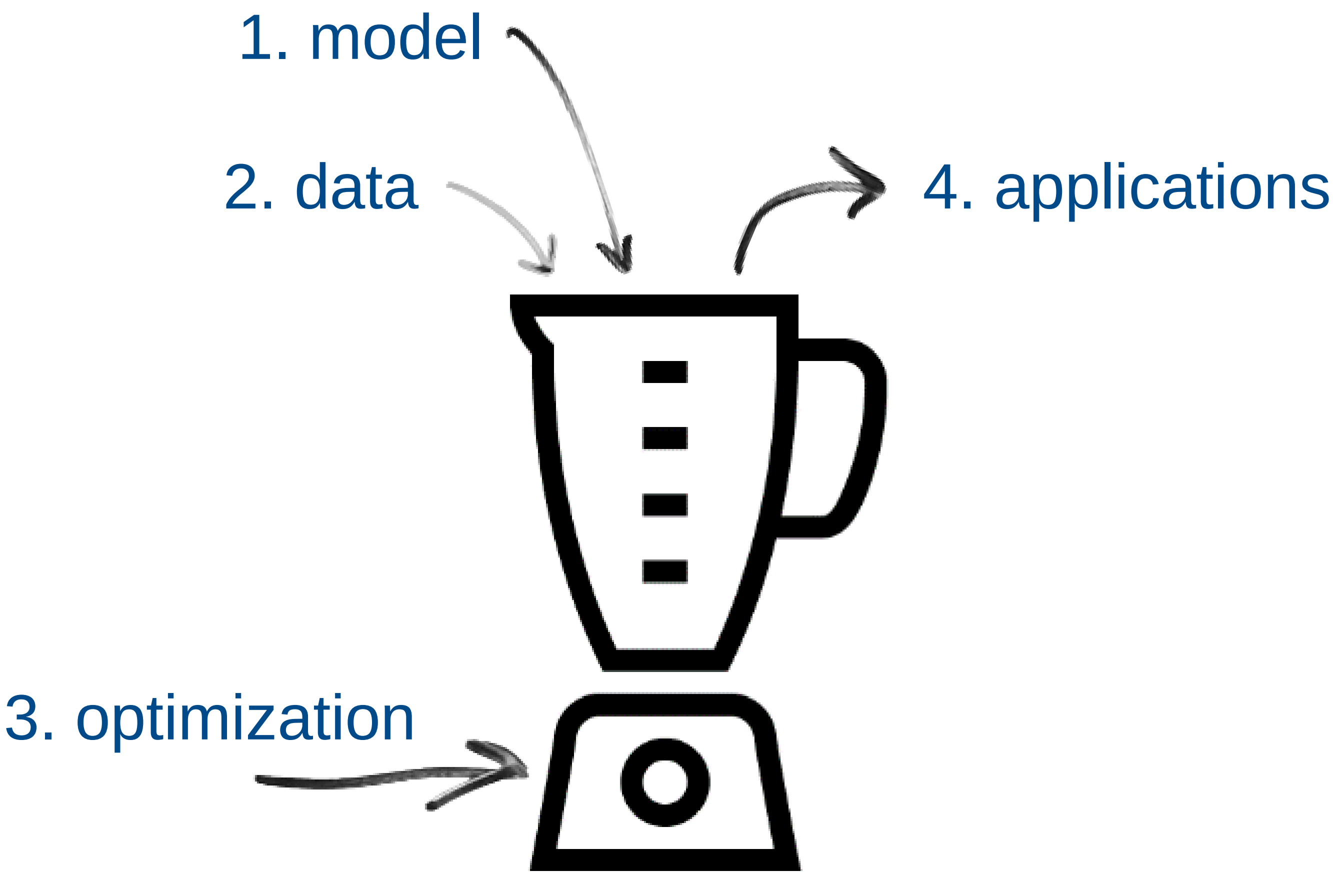
dynamic model & measurement data

↓

Learn model parameters from data

= Tune / optimize model parameters such that simulation output matches measurement data

Ingredients to Learning



What System?

System = collector array

- multiple solar thermal collectors connected in series
- multiple rows
- fluid travel time ~5 minutes

1. model
2. data
3. optimization
4. application

What Model?

- Model used so far („QDT model“, ISO 9806):

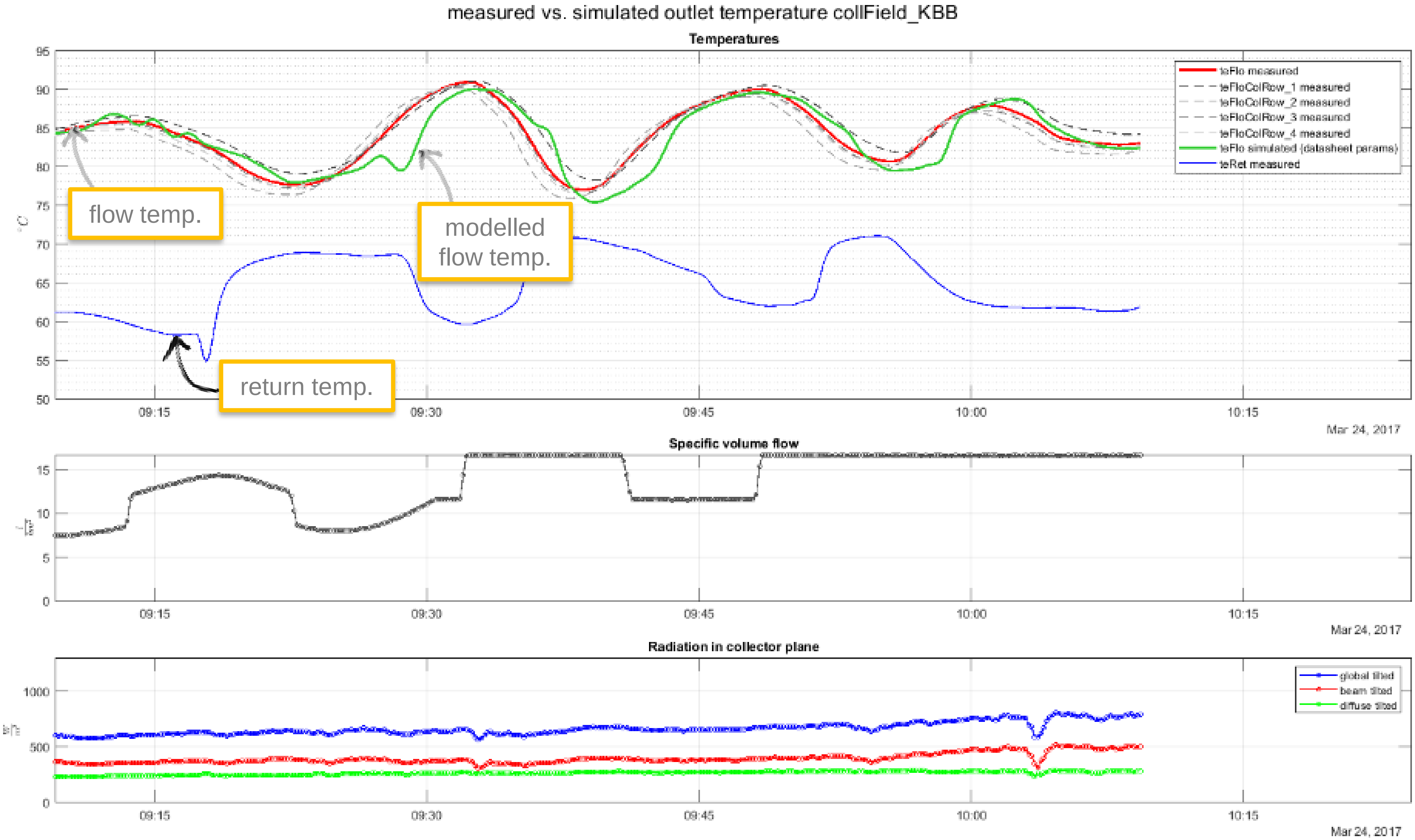
$$\dot{Q}_{sp} = F'(\tau\alpha)(K_b G_b + K_d G_d) - a_1(\bar{T} - T_a) - a_2(\bar{T} - T_a)^2 - (mc)\frac{dT}{dt}$$

- Simplest extension to collector arrays

$$(mc)\frac{\partial T}{\partial t} = F'(\tau\alpha)\,(K_b G_b + K_d G_d) - a_1(\bar{T} - T_a) - a_2(\bar{T} - T_a)^2 - \dot{C}_f\frac{\partial T}{\partial x}$$

System Dynamics

Model: fluid only



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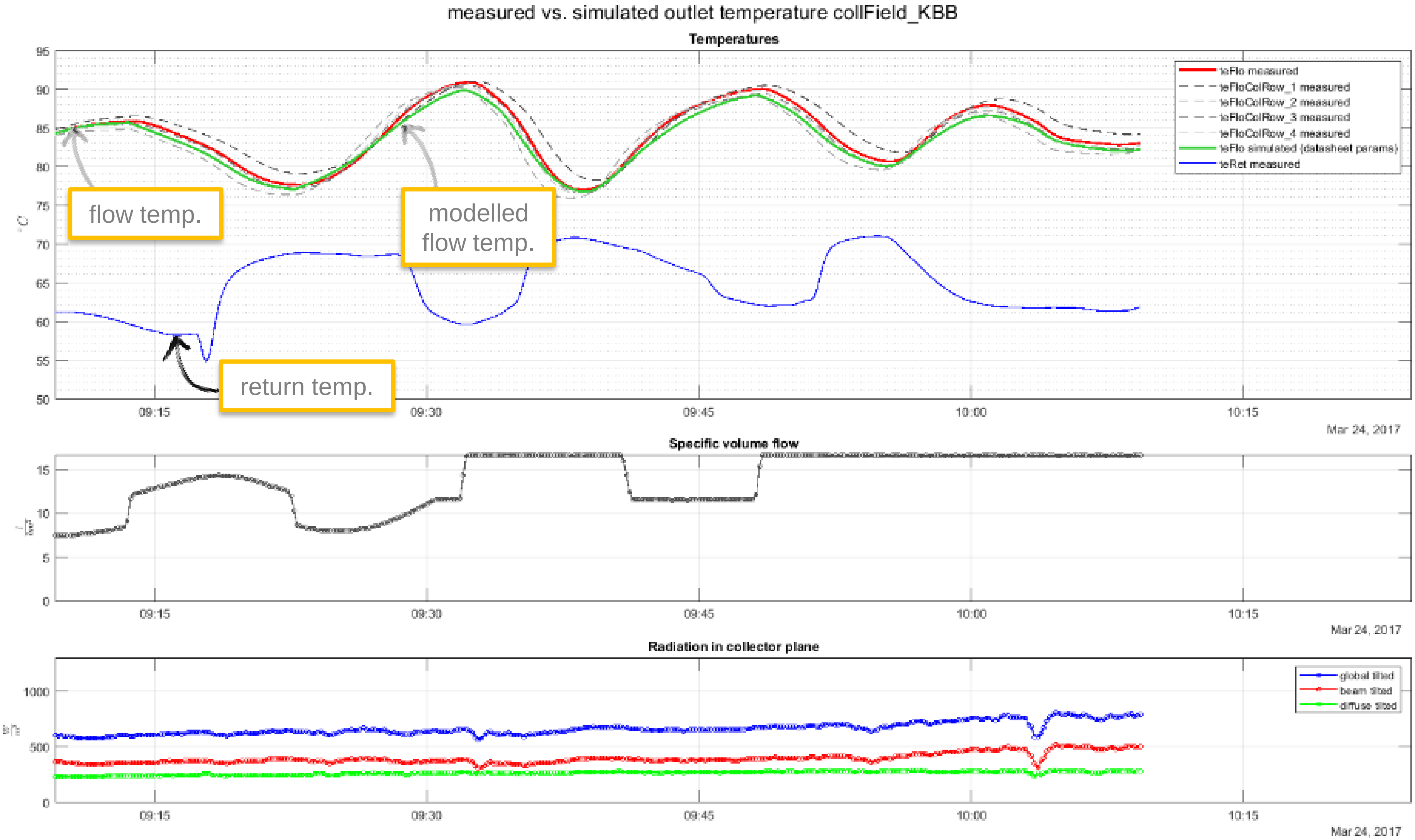
System Dynamics

Model: fluid & solid



What Model?

- Model used so far („QDT model“, ISO 9806):

$$\dot{Q}_{sp} = F'(\tau\alpha)(K_b G_b + K_d G_d) - a_1(\bar{T} - T_a) - a_2(\bar{T} - T_a)^2 - (mc)\frac{dT}{dt}$$

- Simplest extension to collector arrays: 1-N model

$$(mc)\frac{\partial T}{\partial t} = F'(\tau\alpha)\,(K_b G_b + K_d G_d) - a_1(\bar{T} - T_a) - a_2(\bar{T} - T_a)^2 - \dot{C}_f \frac{\partial T}{\partial x}$$

- Extension for improved dynamics: fluid & solid model

$$(mc)_m \frac{\partial T_m}{\partial t} = (\tau\alpha)(K_b(\theta) G_b + K_d G_d) - a_1(T_m - T_a) - a_2(T_m - T_a)^2 - D\alpha(T_m - T_f)$$

$$(mc)_f \frac{\partial T_f}{\partial t} = D\alpha(T_m - T_f) - \dot{C}_f \frac{\partial T_f}{\partial x}$$

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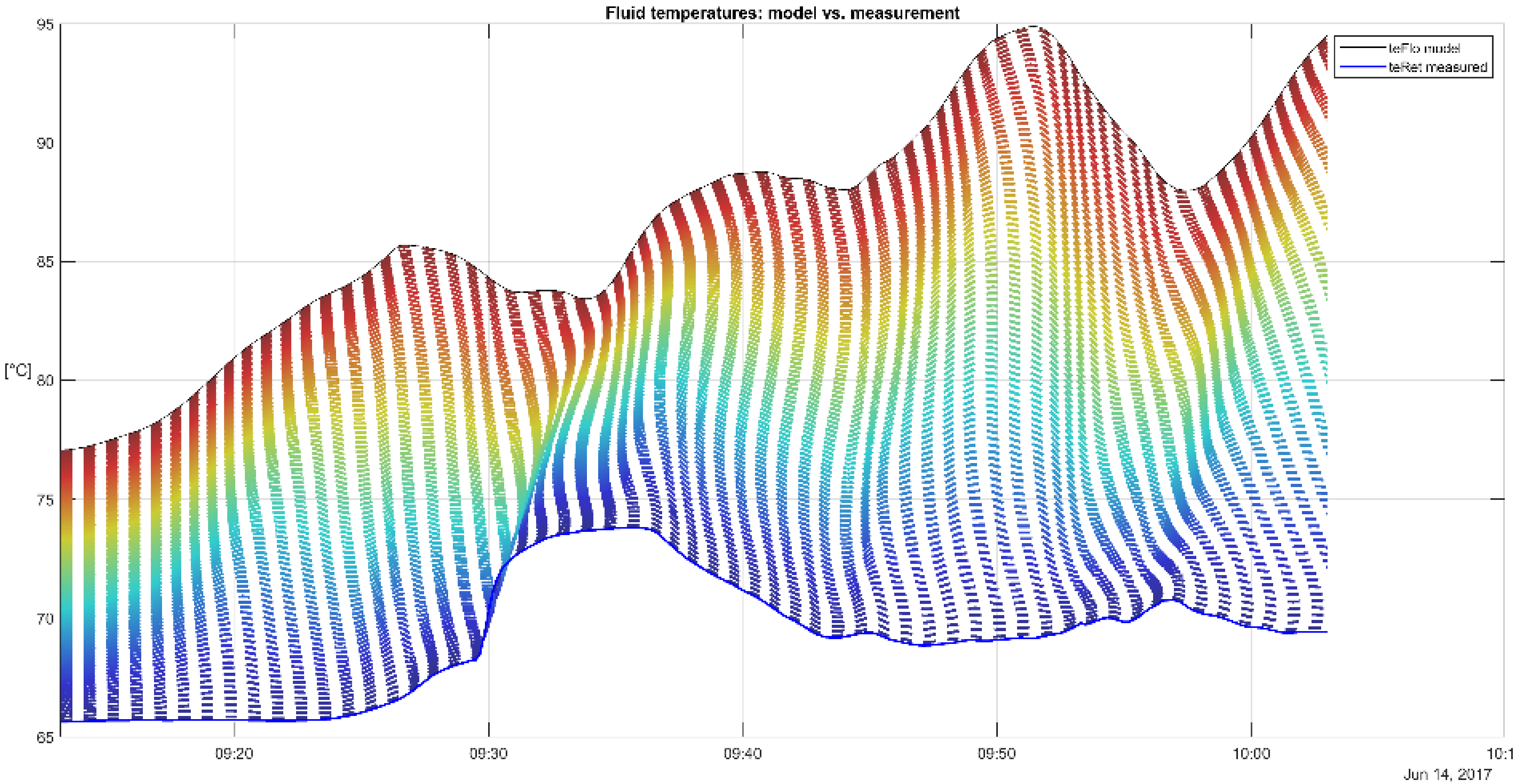


Fluid temperatures: model vs. measurement
95
90
85
[°C] 80
75
70
65
09:20
09:30
09:40
09:50
10:00
10:10
Jun 14, 2017
teFlo model
teRet measured

Final Model

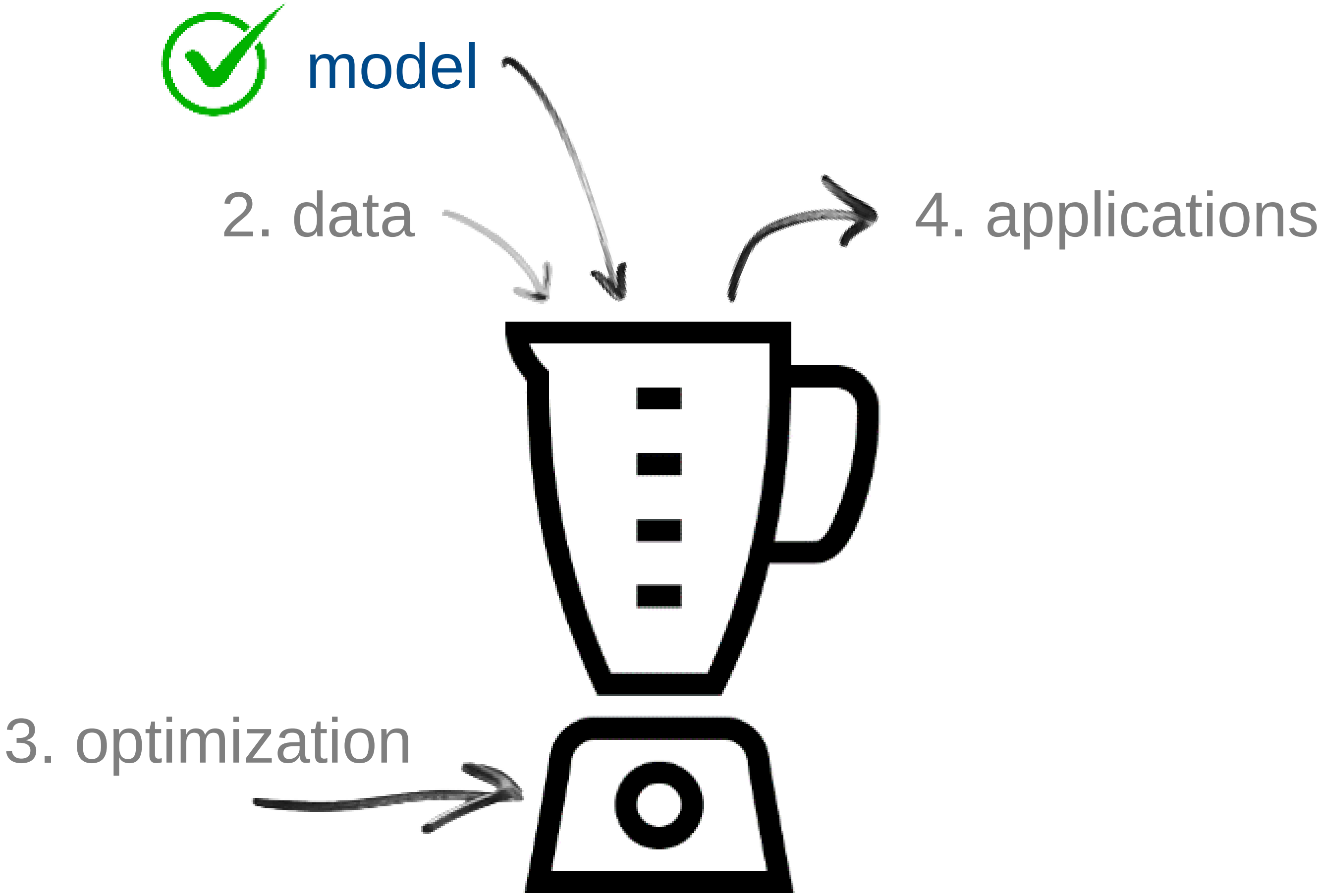
Summary

- Nonlinear coupled PDE model

- **Parsimonious**
  - Good enough: explains data / system dynamics well, low autoregression
  - Cheap: only 9 parameters vs. 6

- **Applicable** to a wide range of data
  - Fully dynamic, accepts a lot of data → important for estimation process

- **Model properties**
  - Efficient and accurate numeric solution, analytic Jacobians
  - Method of lines / finite volume discretization, stiff ODE solver
  - Nonlinear in states, but linear in parameters
  - Used also for steady-state initialization of simulations
  - Suitable for short- and long-term system predictions

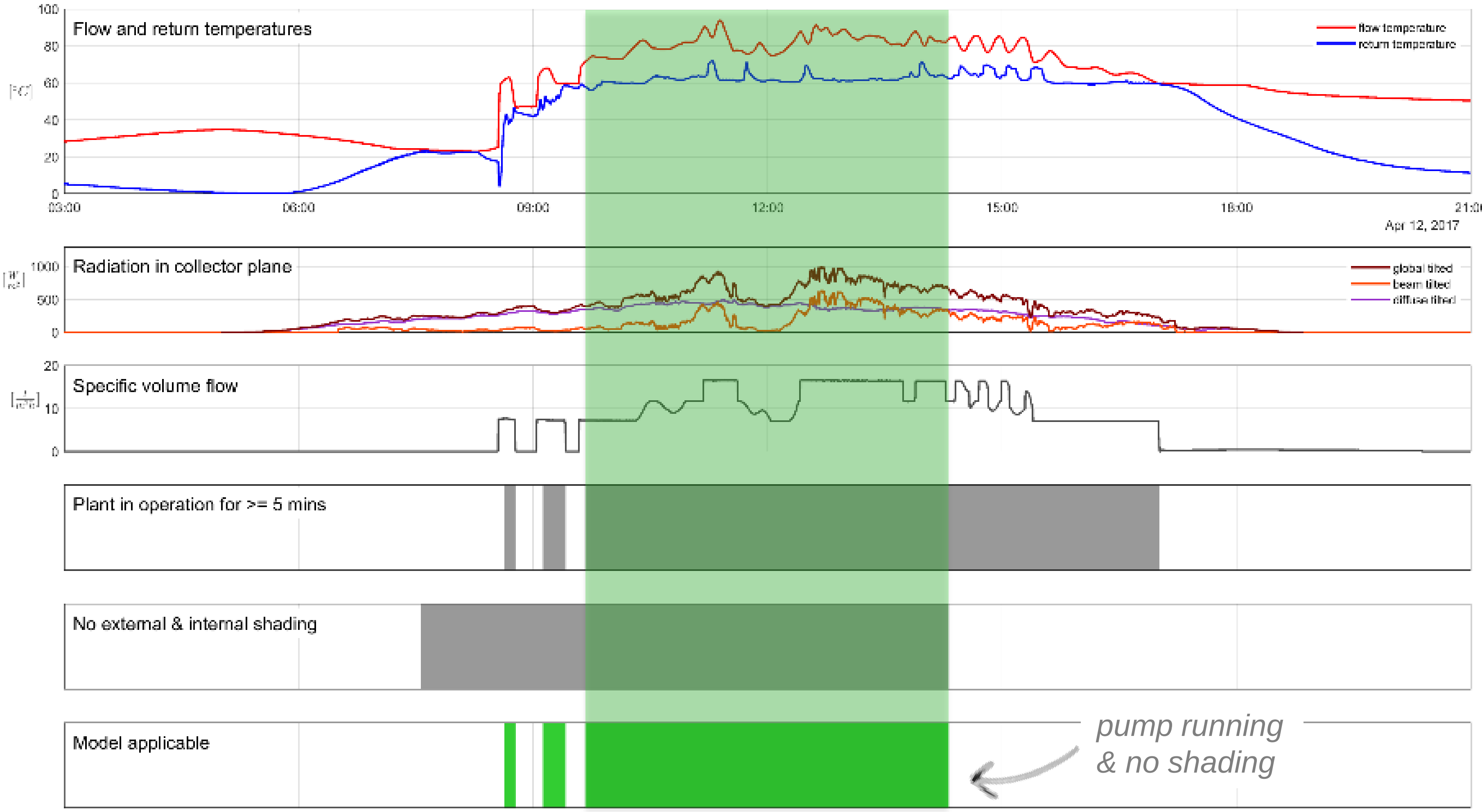

model
2. data
4. applications
3. optimization

What Data?

- 6 collector arrays, each ~500 m²
- Collector array measurements
  - volume flow
  - inlet & outlet temperature
  - solar radiation (beam & diffuse)
  - ambient temperature

- 1s sampling rate, 10s averages
- ~3 years of data
- Offline / batch estimation

Model Validity



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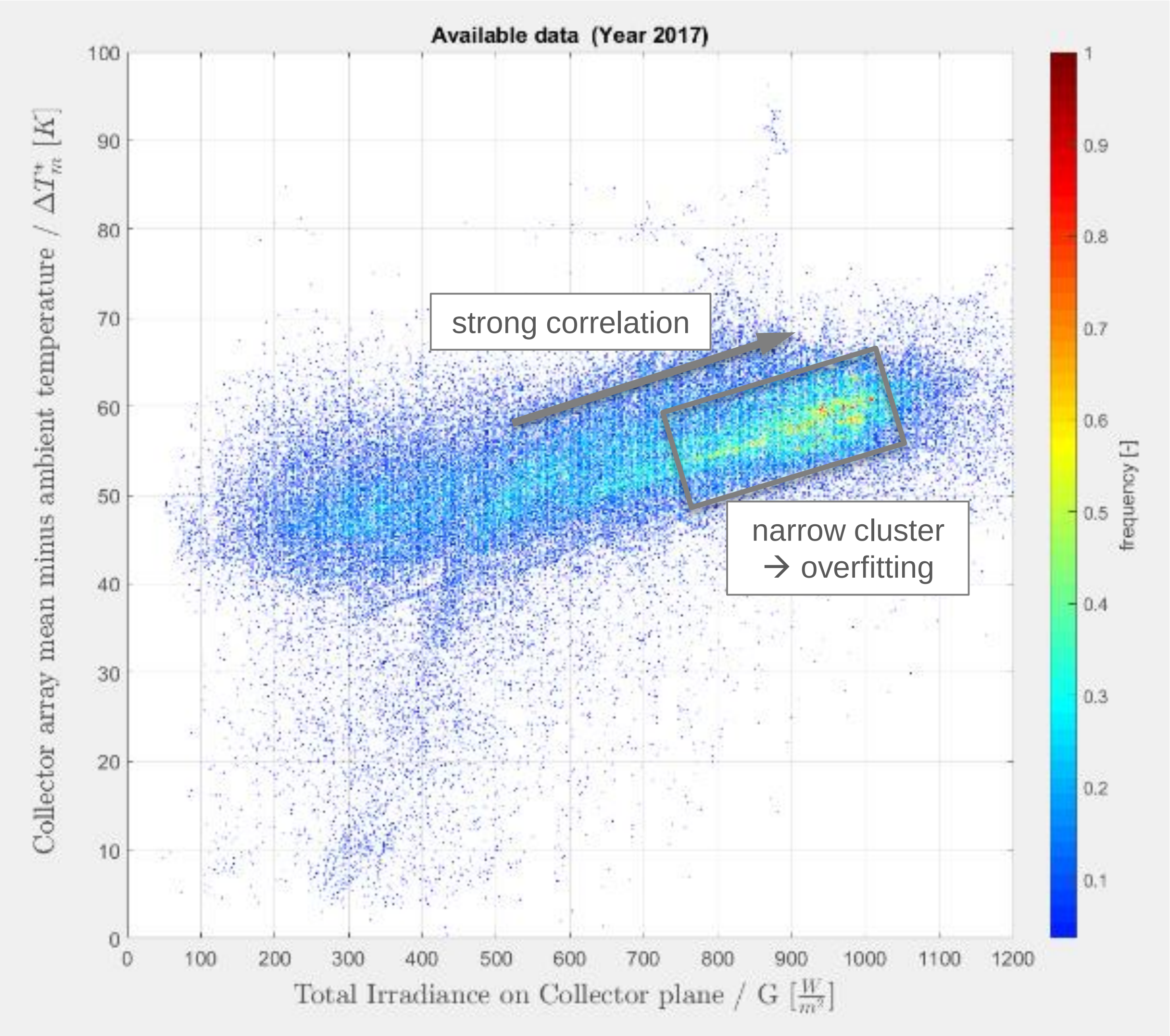
Data Processing

- Separated chunks of interesting data
  - subdivided into 1-hour intervals
  - ~500 intervals per year
- This data heap is not very helpful for estimation
  - lots of data → **expensive** simulation
  - lots of **similar** data / undesired clustering → overfitting

Clustered Data

2D cut of data



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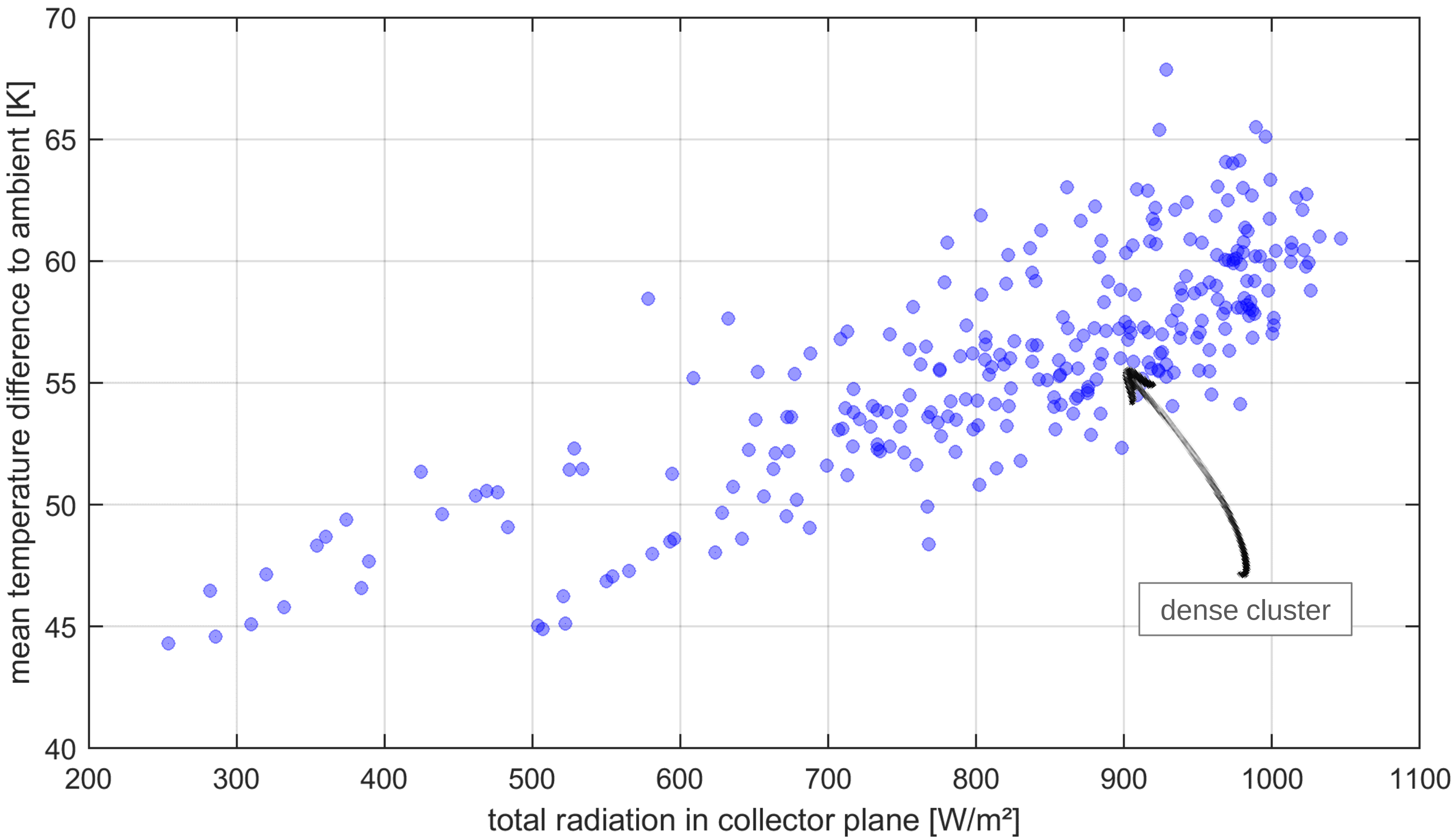
D-optimal Data Selection

All 1-hour intervals



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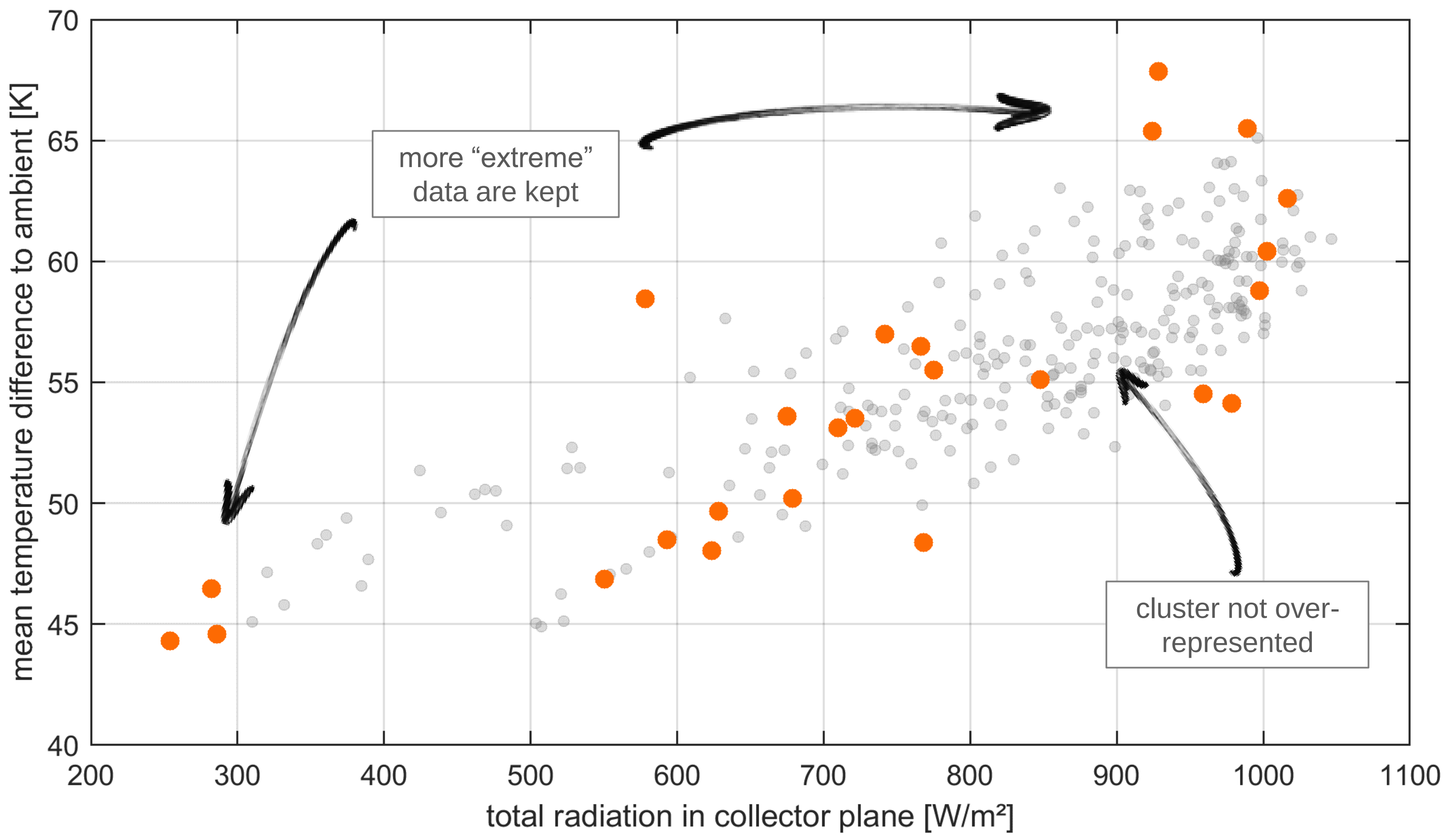
D-optimal Data Selection

Most informative intervals



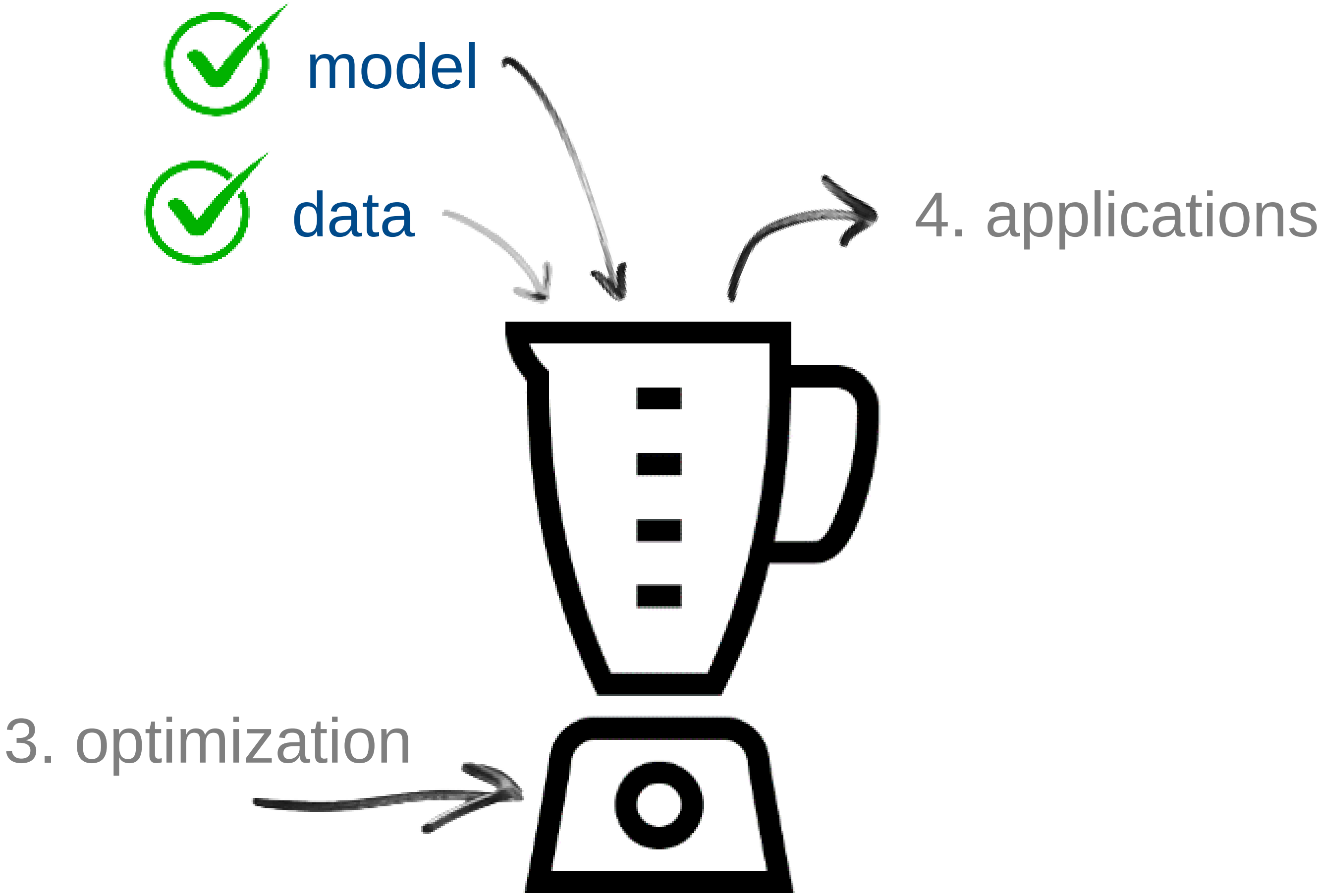
Optimal Data Selection

- Concept similar to Design of Experiments (DoE)
  - Here data “as-recorded” → optimal data **selection**
  - Fisher information

$$(\mathcal{I}(\theta))_{i,j} = \mathrm{E}\left[\frac{\partial}{\partial\theta_i}\ln f(X;\theta)\frac{\partial}{\partial\theta_j}\ln f(X;\theta)\right]$$

- **D-optimality**
  - Use the **most informative data** for estimation
  - Use data where model is most **sensitive** to parameter changes

- **Advantages**
  - **Automatic optimal data selection**
    Fedorov optimization algorithm: fast, exhaustive optimization
  - **Fast simulation** (only need **~20** out of ~500 intervals)
  - **Good generalization** to new system operating conditions
  - Improves optimization surface


model
data
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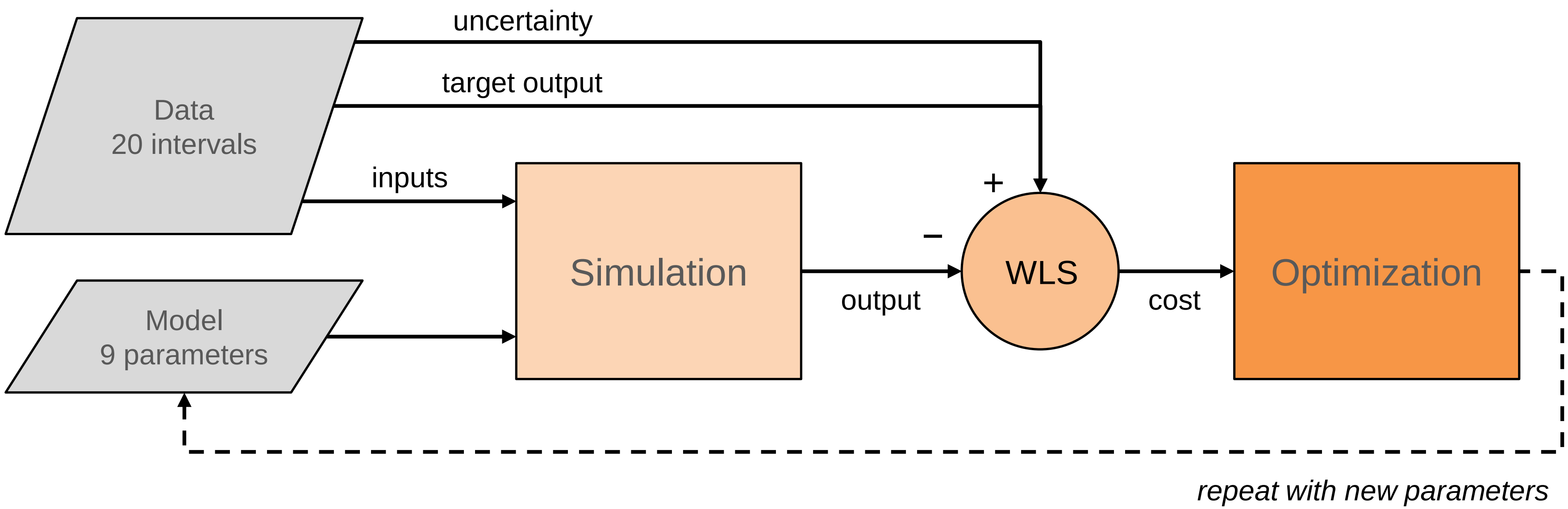
Estimation Setup

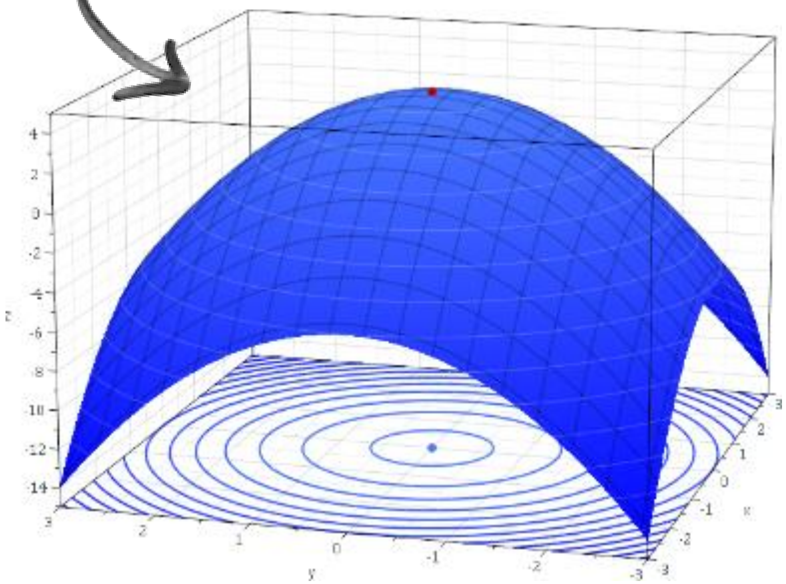
Single Shooting



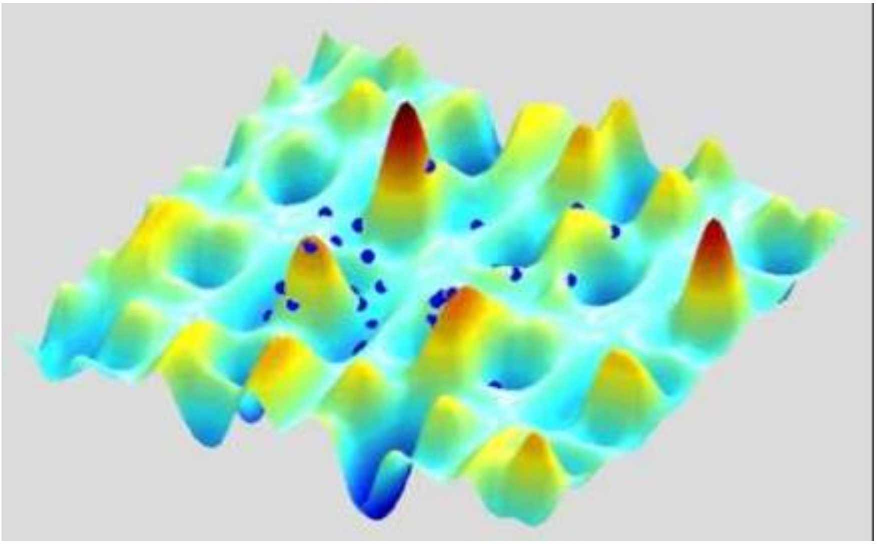
Optimization

- Nonlinear dynamic optimization
  - rough / peaky surface, local minima…

we'd like to have this cost function shape…



…but our problem looks something like this…

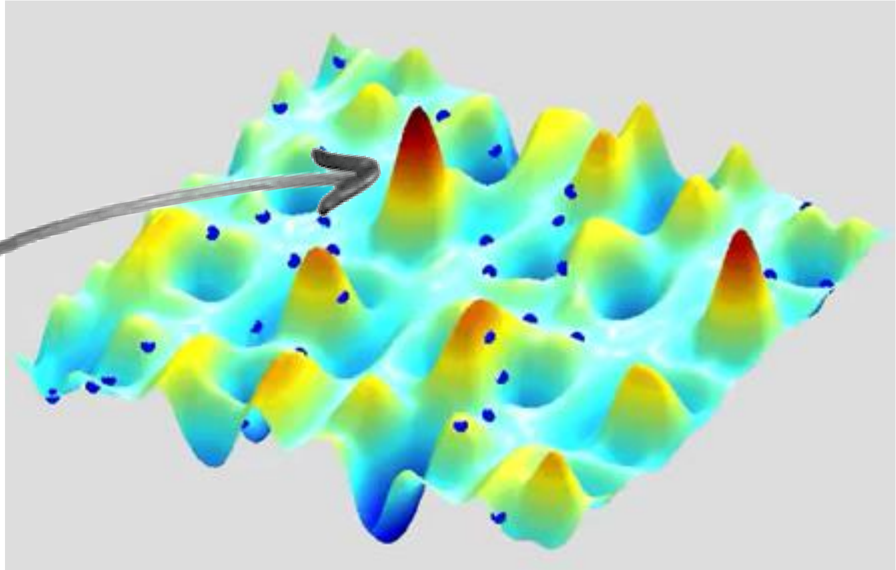


Optimization Algorithms

- **Need stochastic global optimizer**
  - Deterministic algorithms → easily trapped in local minima

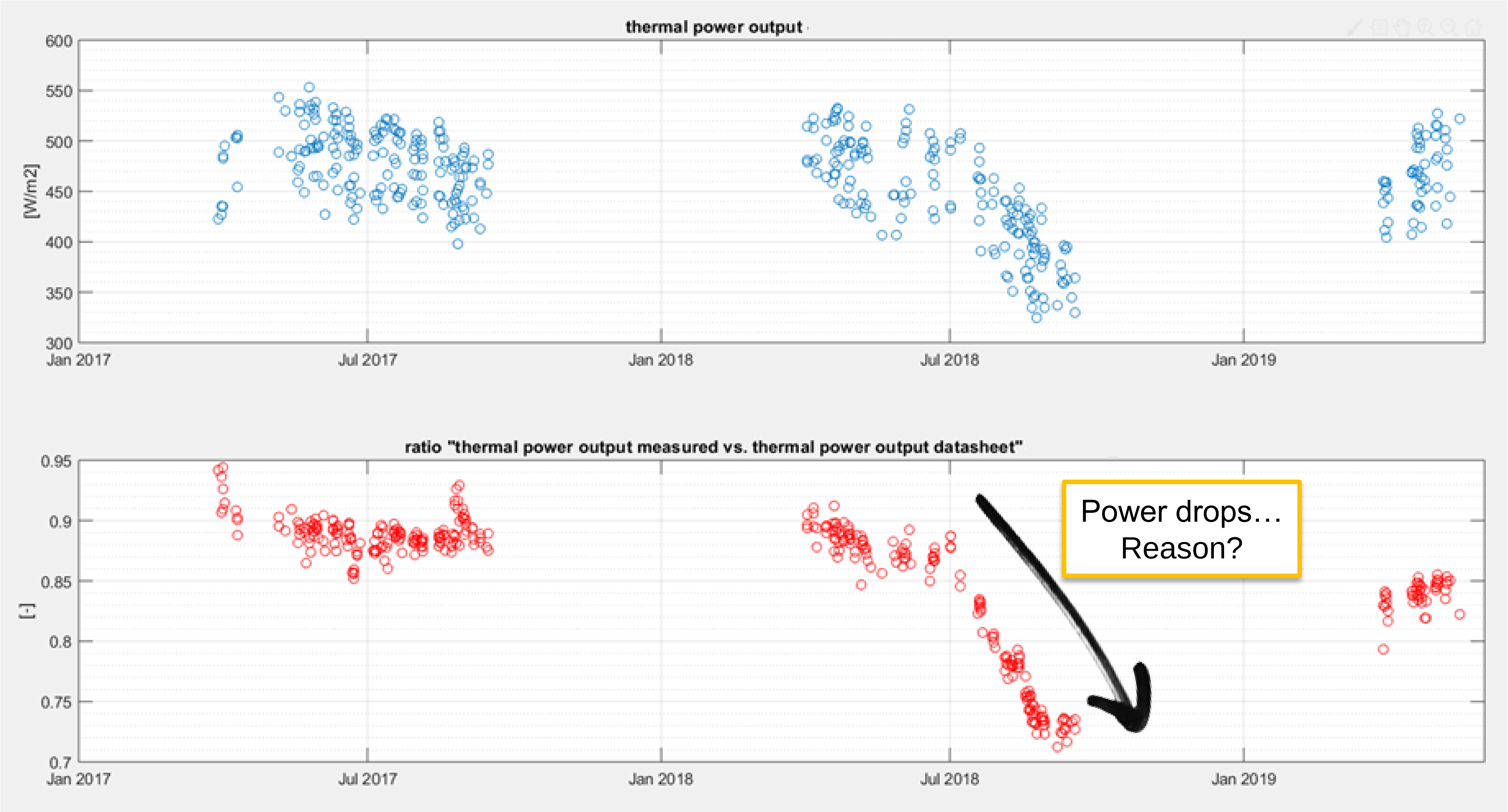
- **Suitable algorithms e.g.**
  - genetic algorithms
  - simulated annealing
  - differential evolution
  - particle swarm optimization

optimal data selection
makes peaks steep & separated



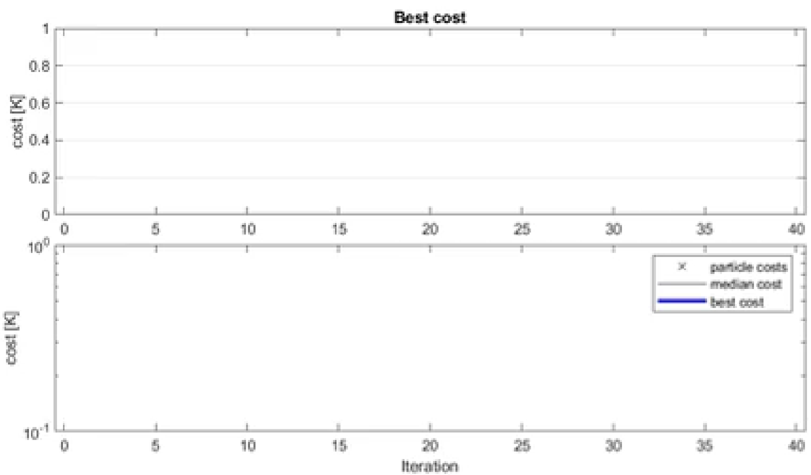
Static Analysis

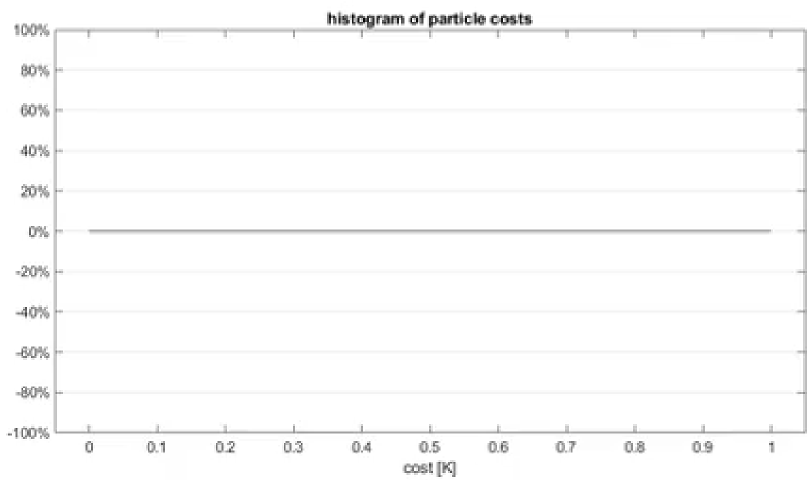
Solution used so far

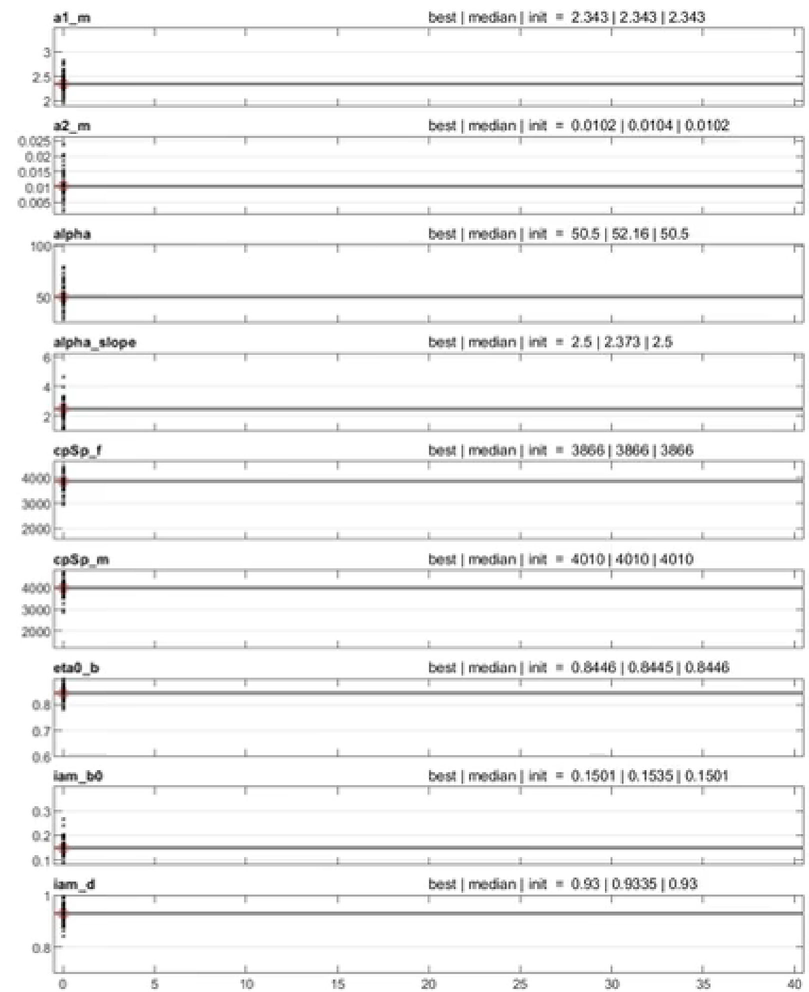


Optimization Run

Particle Swarm

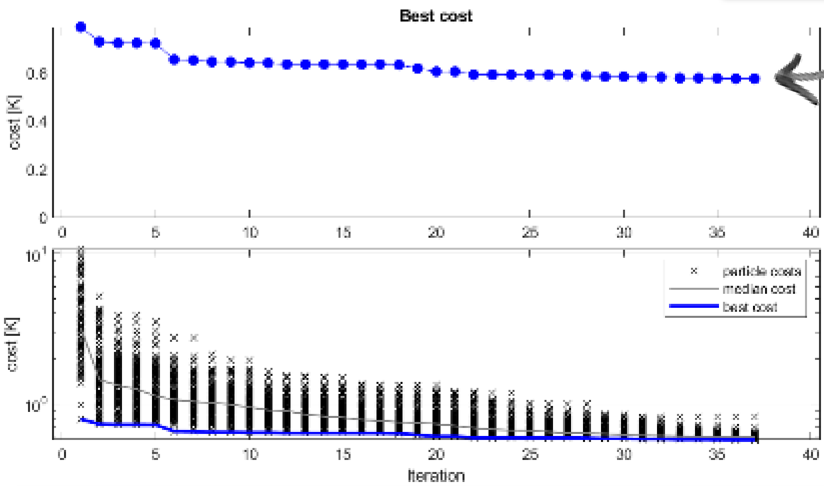


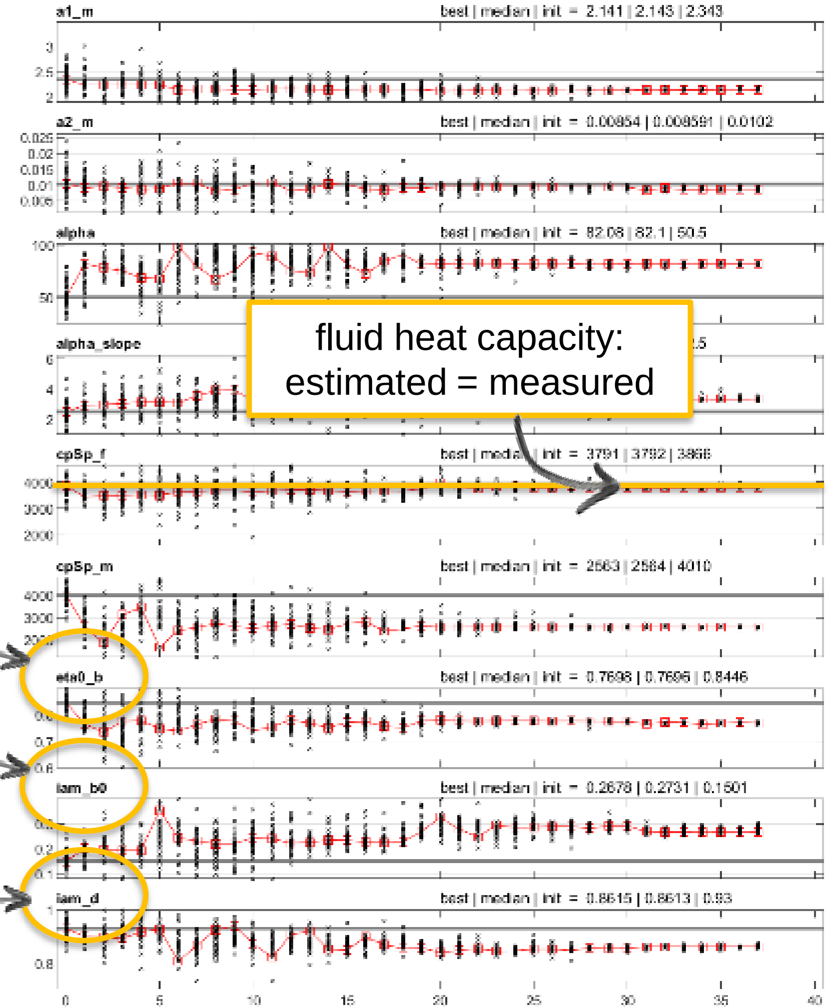




Parameter Interpretation

RMSE ~ 0.5 K





fluid heat capacity:
estimated = measured

Optimization results

Parameter statistics

- Result = model parameters
  - Parameters have some **uncertainty**
  - parameter noise, model noise, numeric noise
  - sample in param. space → confidence regions (without MCMC)

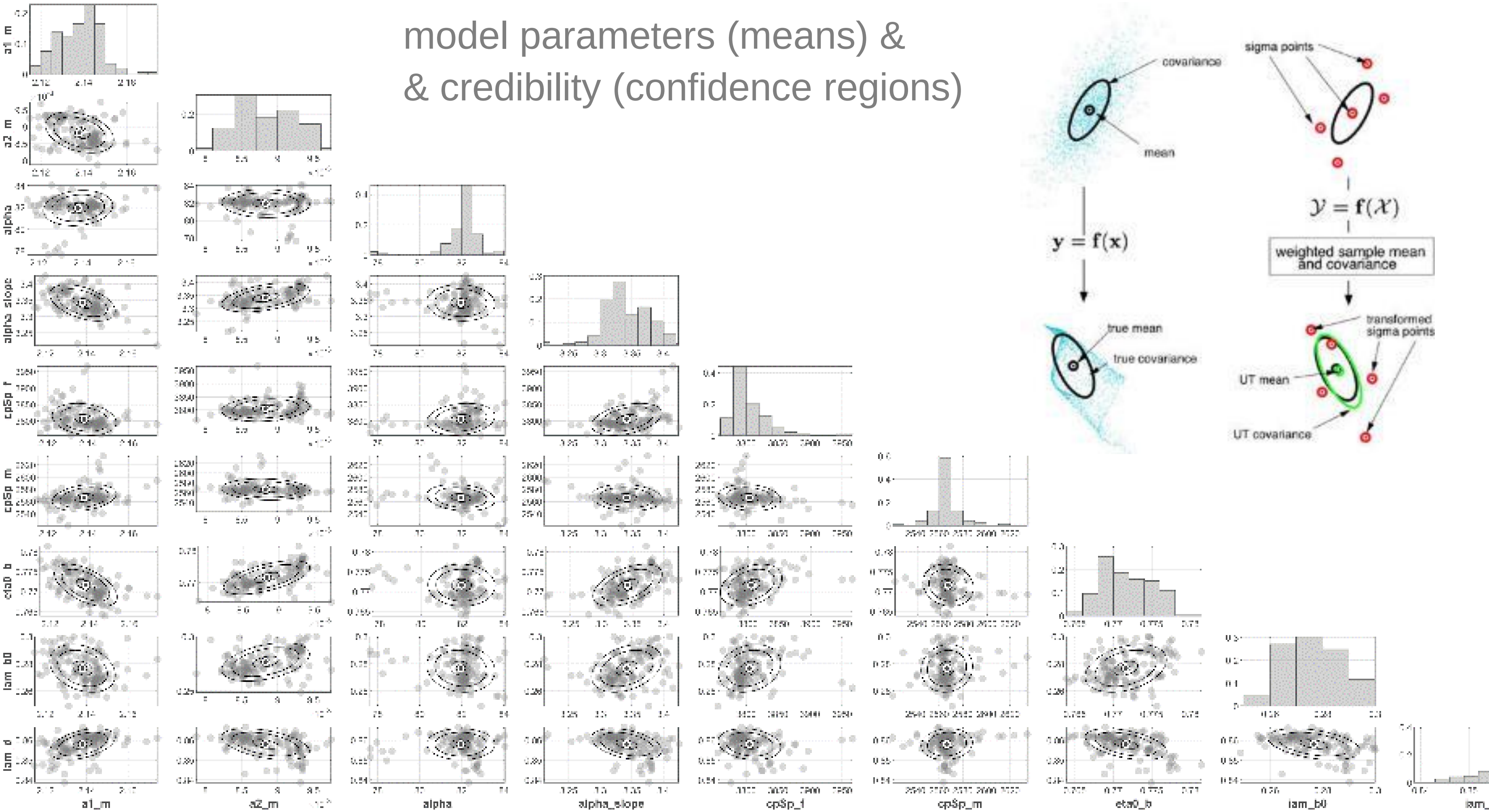
- **Confidence regions**
  - assuming Gaussian measurement noise
  - we know something about the parameter confidence:
  - parameters are *F*-distributed around optimum

$$J(\theta) = J(\theta_{opt})\left(1 + \frac{p}{n-p} F_{p,n-p}^{1-\alpha}\right)$$

Optimization results

Rich system information

model parameters (means) &
& credibility (confidence regions)



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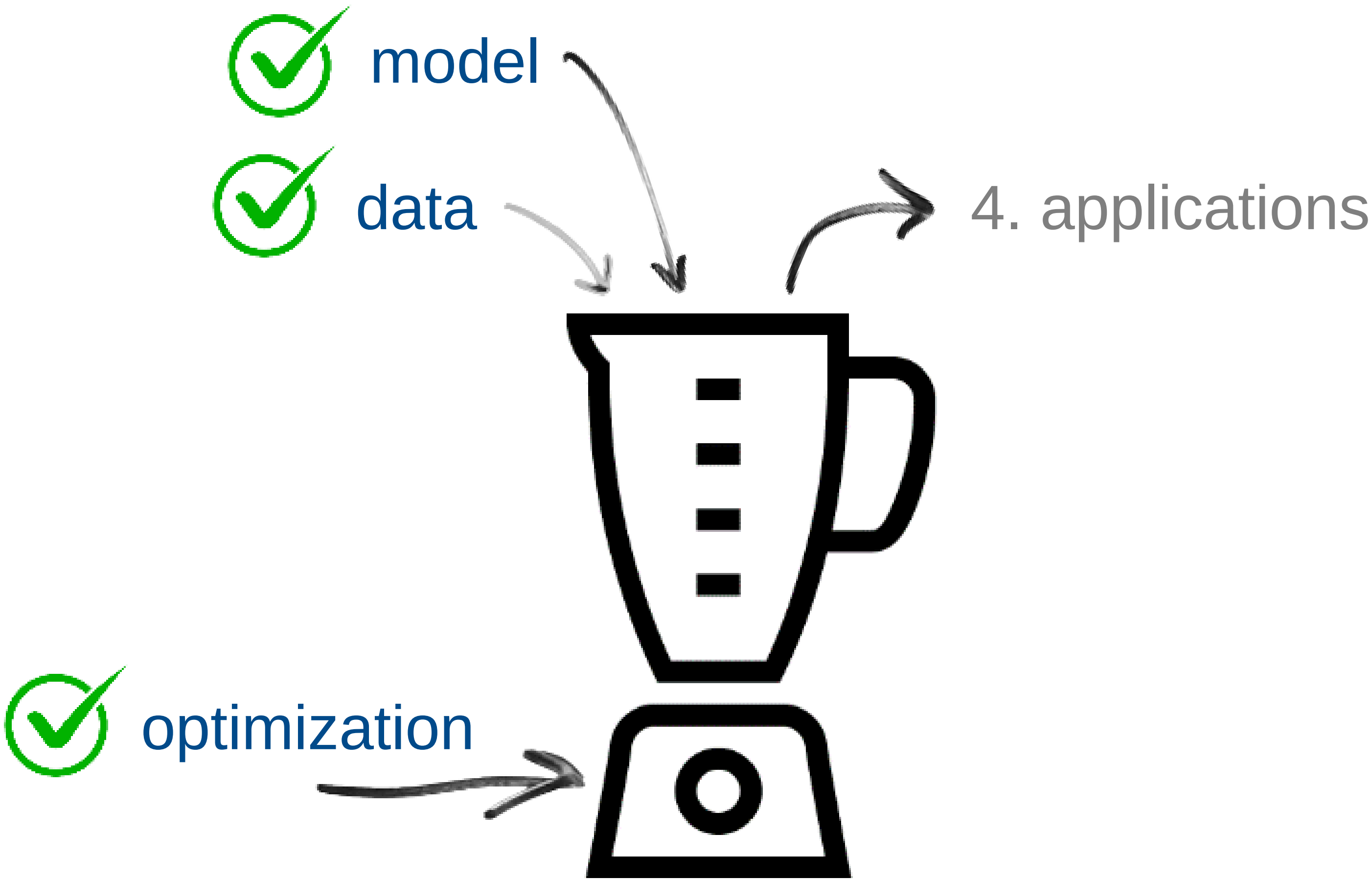

Applications & Use Cases

1) Detailed system learning
   – "Rich" system description, parameters with physical interpretation
   – **Understand** observed system behavior → **increase confidence**
2) System surveillance
   – E.g. target-actual comparison: system condition vs. datasheet / guaranteed output
3) Predictive maintenance
   – Periodically repeat test (parallel to normal system operation)
   – System KPIs based on parameters, e.g. energy cost
   → take **timely actions,** make **informed decisions**
   – Parameter uncertainty + unscented transform → **quantify prediction uncertainty**
4) System control
   – Improved system modelling → use calibrated model for MPC
5) Test at different locations
   – D-CAT allows separation of weather and component effects
   – characterization of collector array as technical component
   – D-CAT = reproducible, automated test method

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IDEA TO ACTION

Danke für Ihre Aufmerksamkeit