Model-based analysis of granulation and drying in continuous manufacturing

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PSE Advanced Process Modelling Forum

Outline

- Introduction
- Tools for model-based analysis
- Examples of ConSigma
  - Twin screw wet granulation
  - Fluid bed drying
- Another promising tool

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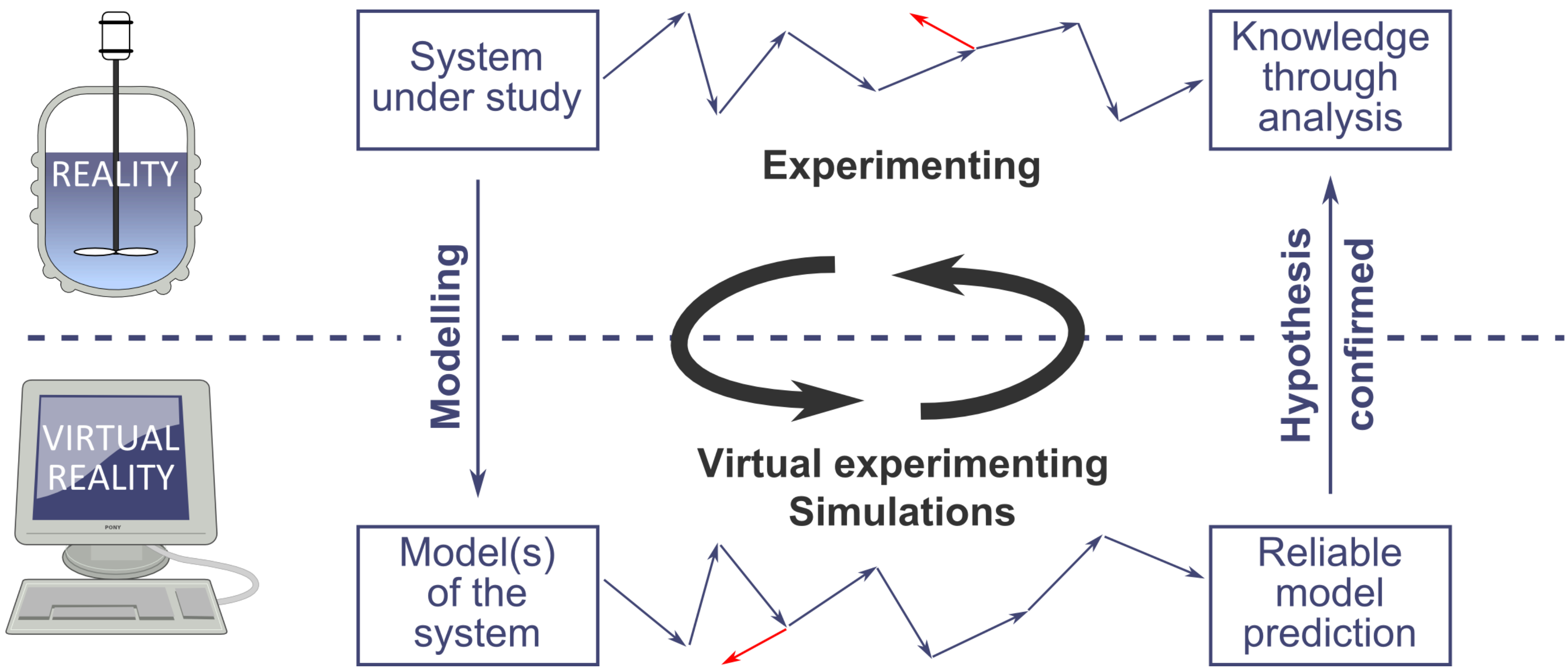
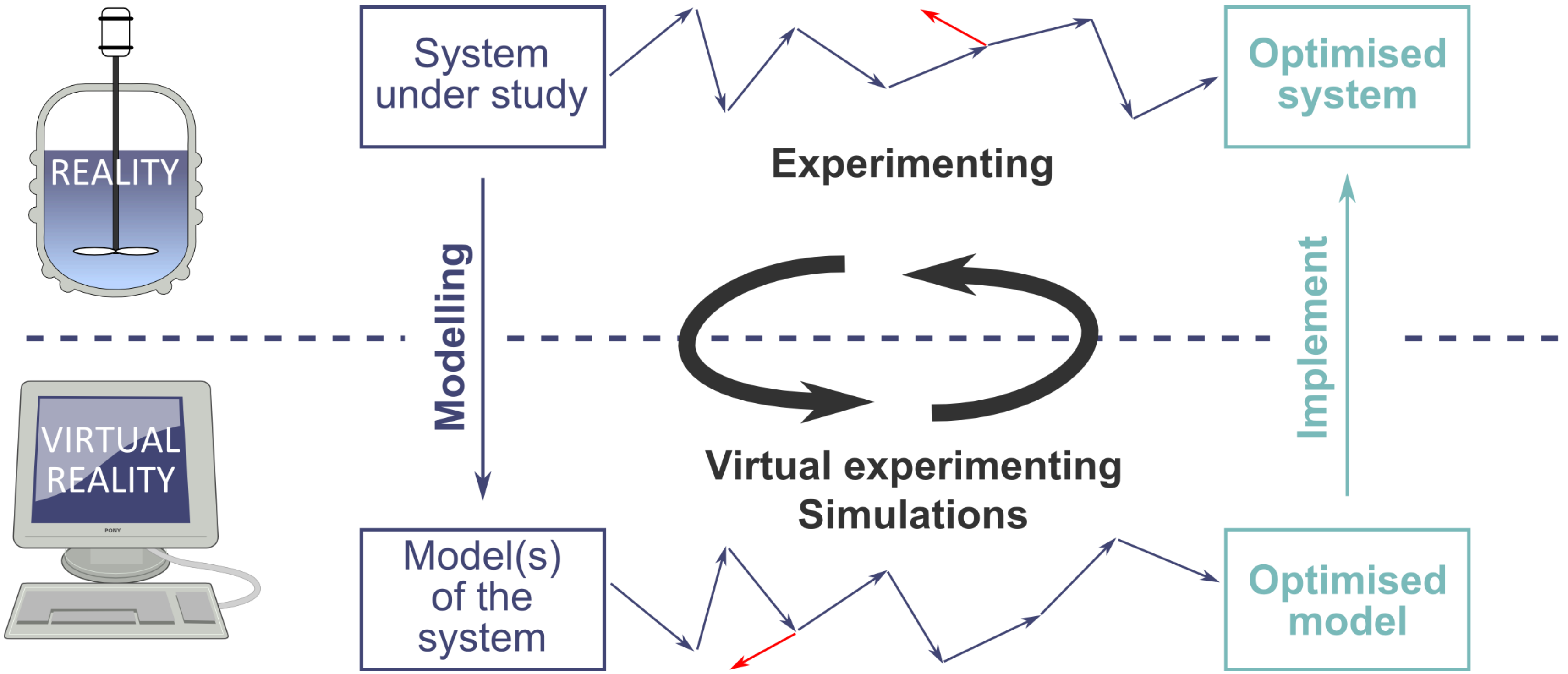
Why modelling?

Model-based ANALYSIS → build knowledge



Why modelling?

Model-based OPTIMISATION → optimise



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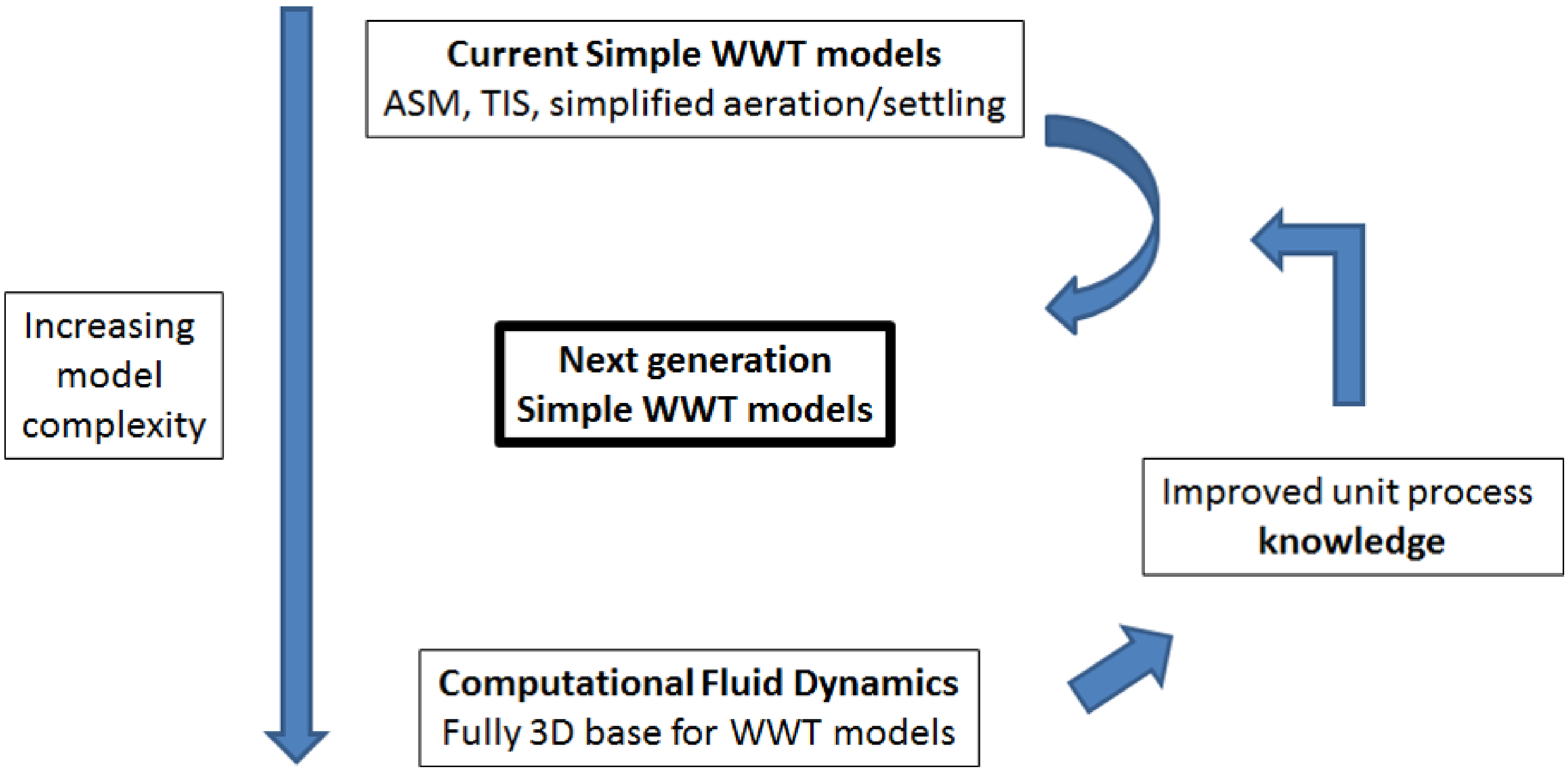
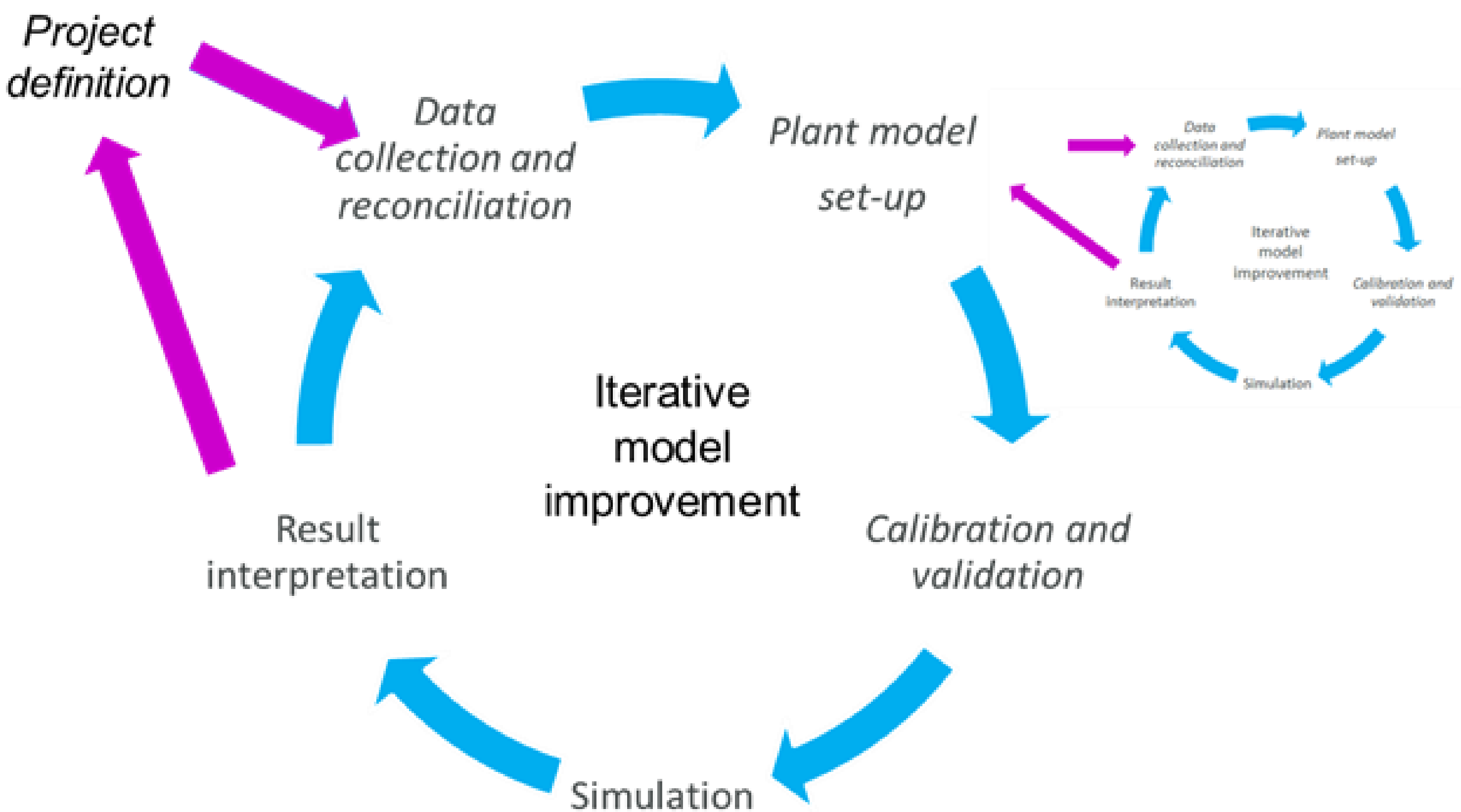
One or more models?

Different objectives require different models
One single model to meet all objectives for a unit process or flow sheet does not exist!



One or more models?

Models have a life cycle



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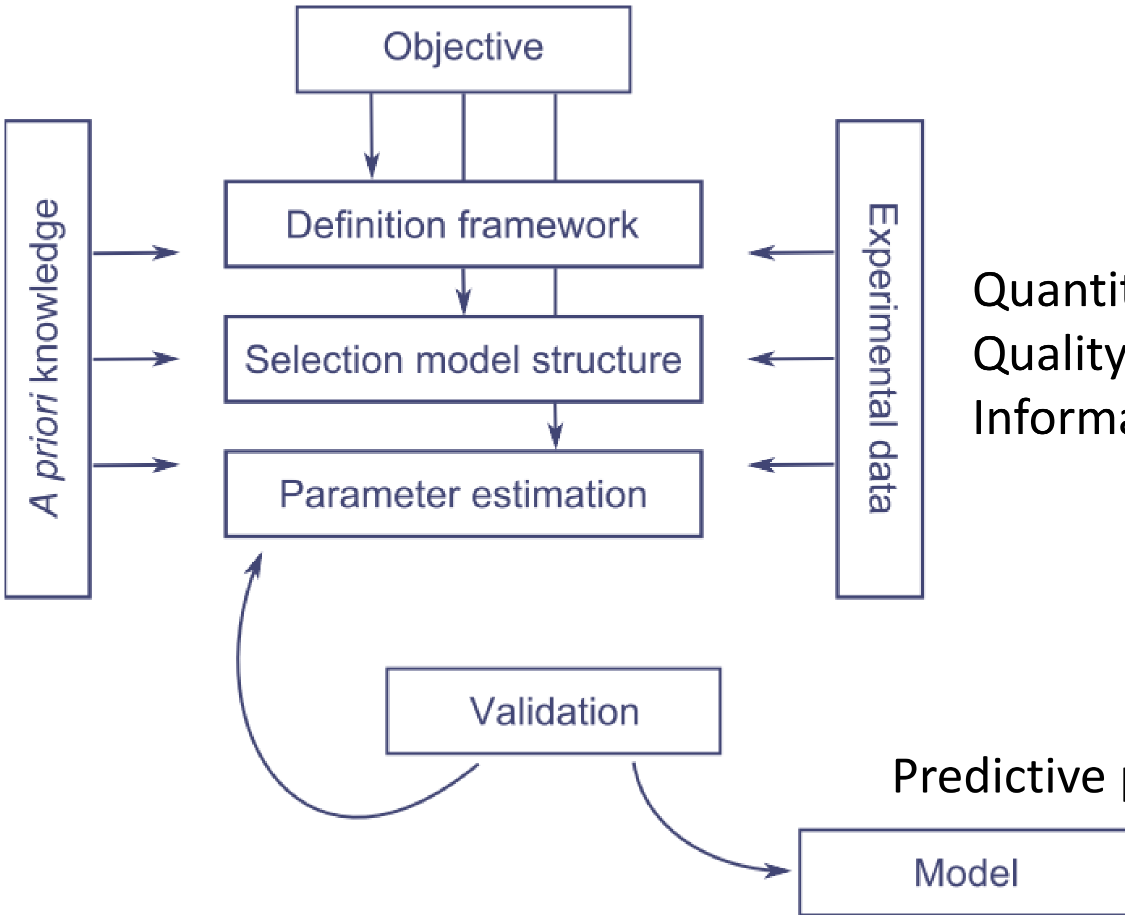
Model building process

Tedious step-wise and iterative approach



Quantity
Quality
Information content

Predictive power!!!

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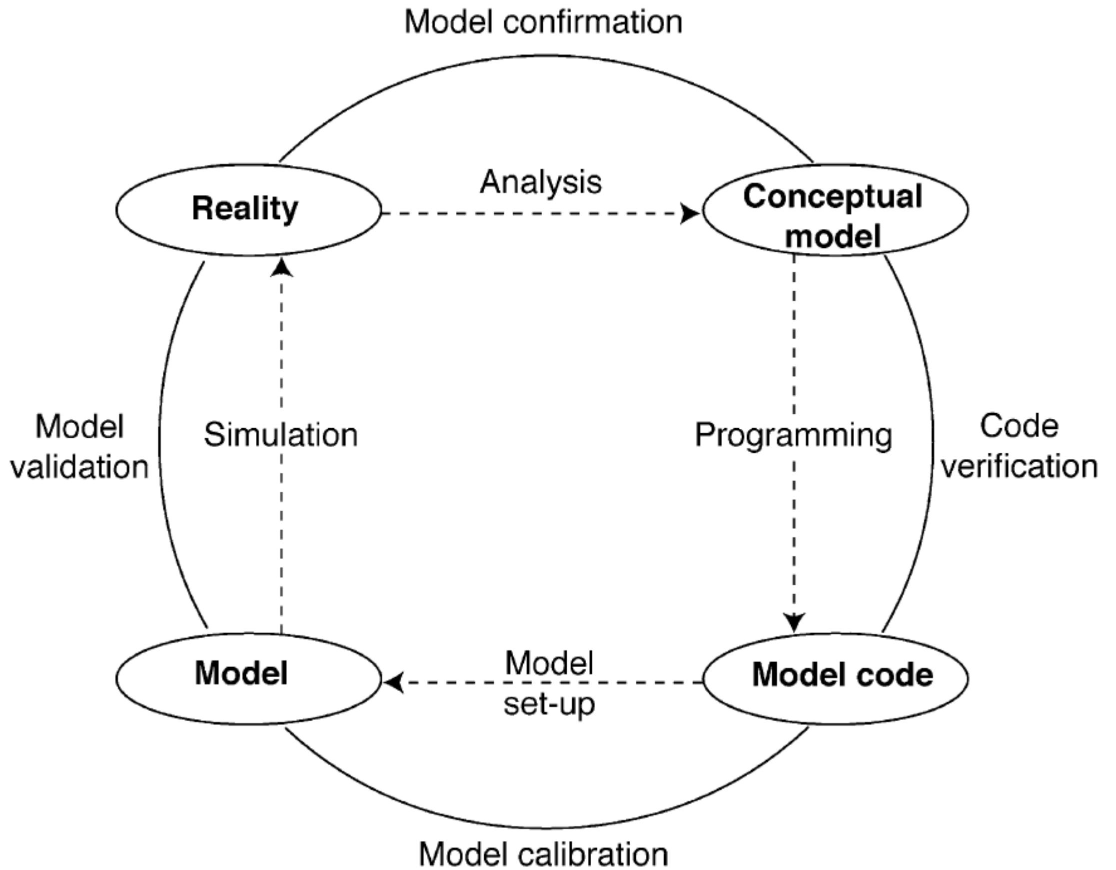
Terminology

Calibration – verification - validation



Refsgaard, J. C., & Henriksen, H. J. (2004)

Supporting tools (1)

Sensitivity analysis

- Select parameters for parameter estimation
- Model reduction
- Reducing model uncertainty
- Propose informative experiments
  - Model selection
  - Parameter estimation

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Supporting tools (1)

Sensitivity analysis

- Local
  - 1 point in parameter space
  - Fast computation
- Global
  - “average” sensitivity in bounded parameter space
  - Computationally expensive

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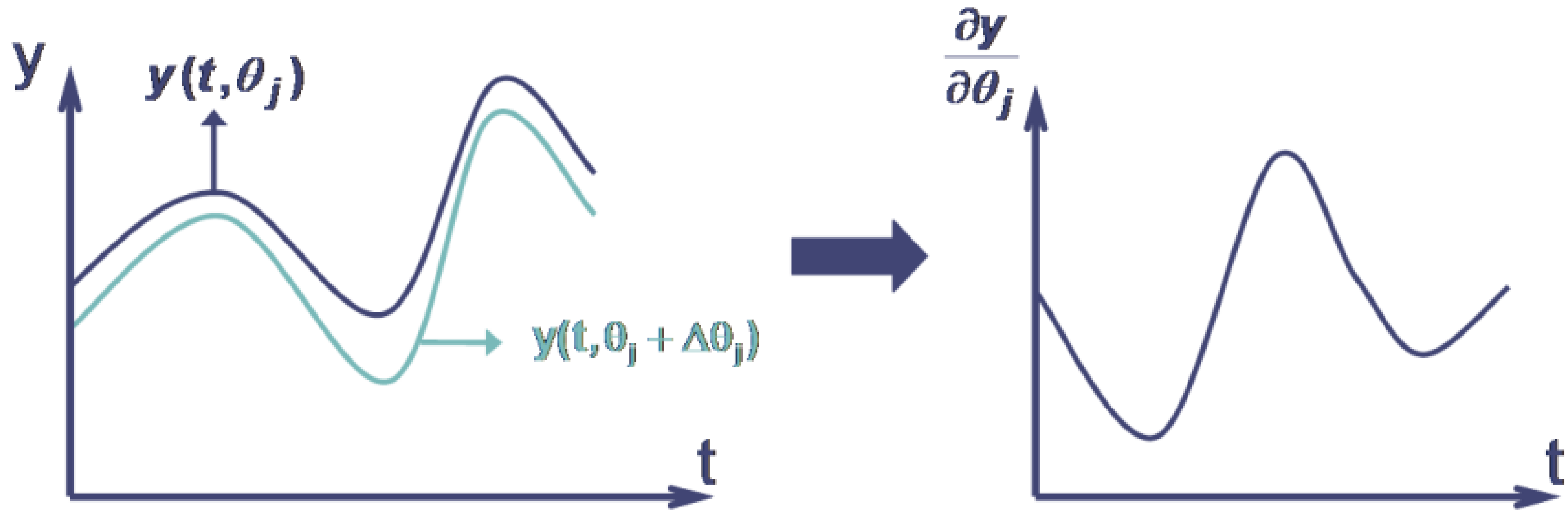
Supporting tools (1)

Local Sensitivity analysis

$$\frac{\partial y}{\partial \theta}$$

- Finite difference approximation

$$\frac{\partial y(t)}{\partial \theta_j} = \lim_{\Delta\theta_j \to 0} \frac{y(t,\theta_j + \Delta\theta_j) - y(t,\theta_j)}{\Delta\theta_j}$$

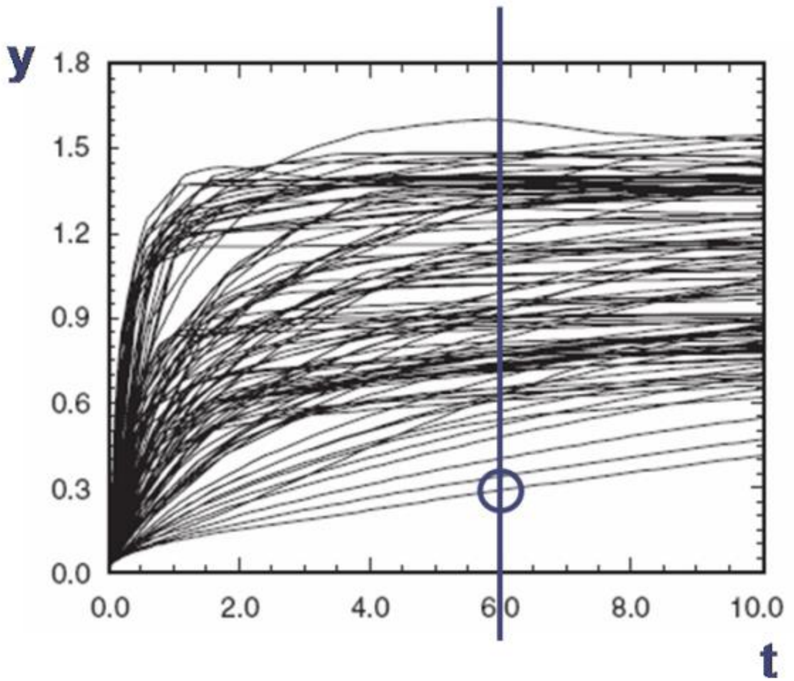


Supporting tools (1)

Global Sensitivity analysis

- Standardised regression coefficients

→ Linear regression of Monte Carlo analysis



$$Y = \Theta \cdot B + E$$

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & \theta_{11} & \theta_{12} & \cdots & \theta_{1p} \\ 1 & \theta_{21} & \theta_{22} & \cdots & \theta_{2p} \\ \vdots & \vdots & \vdots & & \vdots \\ 1 & \theta_{n1} & \theta_{n2} & \cdots & \theta_{np} \end{bmatrix} \begin{bmatrix} b_0 \\ b_1 \\ \vdots \\ b_p \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_n \end{bmatrix}$$

$$SRC_{\theta_i} = b_i \cdot \frac{\sigma_{\theta_i}}{\sigma_y}$$

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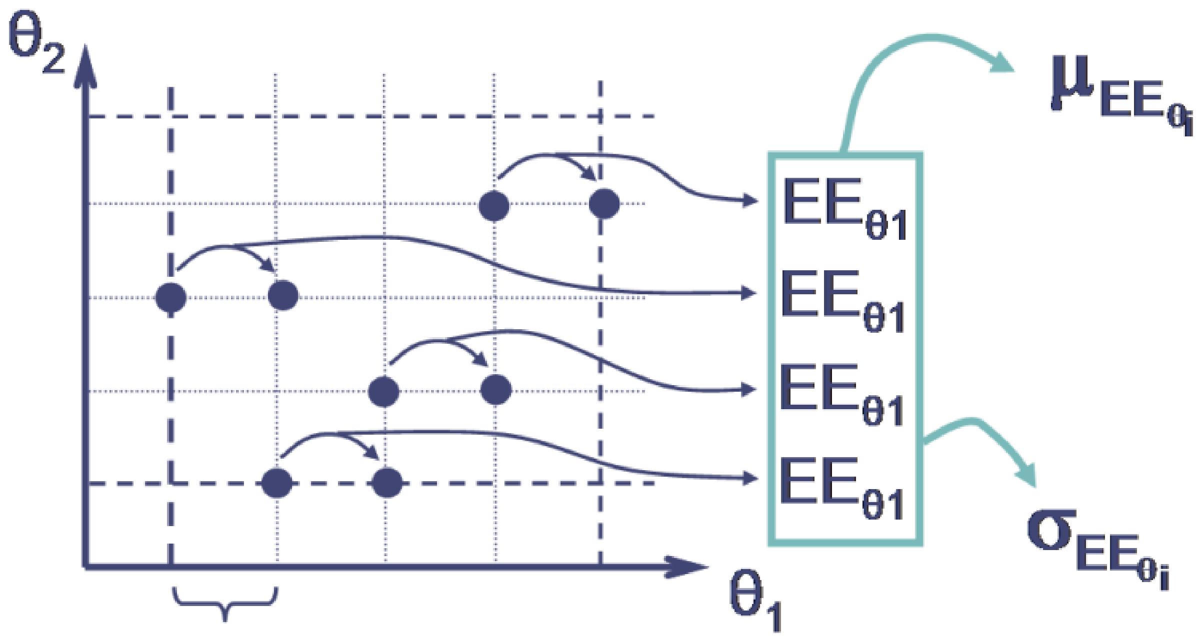
Supporting tools (1)

Global Sensitivity analysis

- Morris screening – Elementary effects

$$EE_{\theta_i} = \frac{y(\theta_i + \Delta) - y(\theta)}{\Delta}$$



Parameter importance

Non linearity
Interaction effects
(correlation)

Supporting tools (1)

Global Sensitivity analysis

- Variance decomposition

$$\sigma_y^2 = \sigma_1^2 + \sigma_2^2 + \sigma_3^2 + \sigma_{12}^2 + \sigma_{13}^2 + \sigma_{23}^2 + \sigma_{123}^2$$

$$1 = S_1 + S_2 + S_3 + S_{12} + S_{13} + S_{23} + S_{123}$$

- FAST (Fourier Amplitude Sensitivity Test)
- Sobol indices
- Computationally expensive
  - Valid for non-linear models

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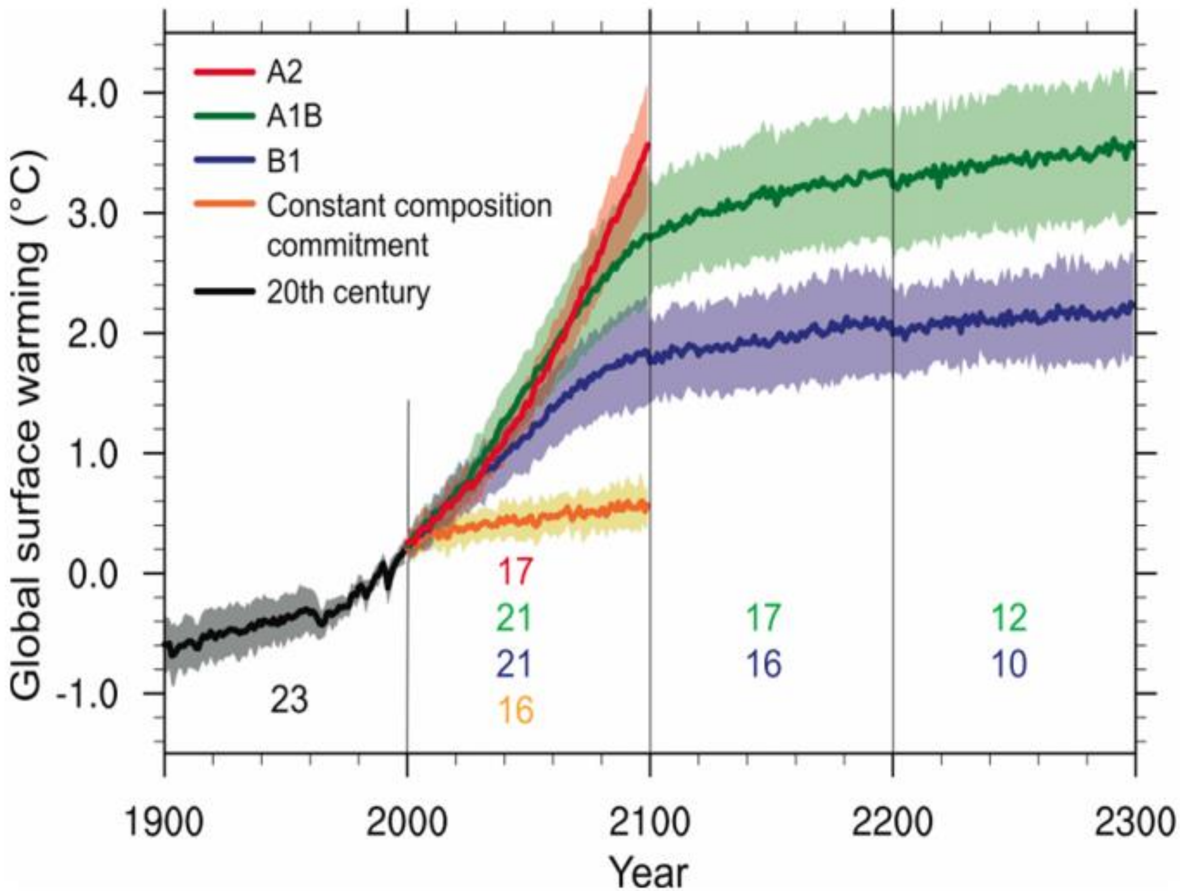
Supporting tools (2)

Uncertainty analysis



Supporting tools (2)

Uncertainty analysis

Uncertainties in

- Model structure
- Model implementation
- Measurement error (calibration)
- Model input (predictive)
- Model parameters (uncertainty in estimation)

Supporting tools (2)

Uncertainty analysis

Linear approximation: differential analysis

$$y = f(x_1, x_2, \ldots, x_n) \quad \rightarrow \quad \sigma_y^2(t) = \sum_n \sigma_{x_i}^2 \left(\frac{\partial y(t)}{\partial x_i} \right)^2$$

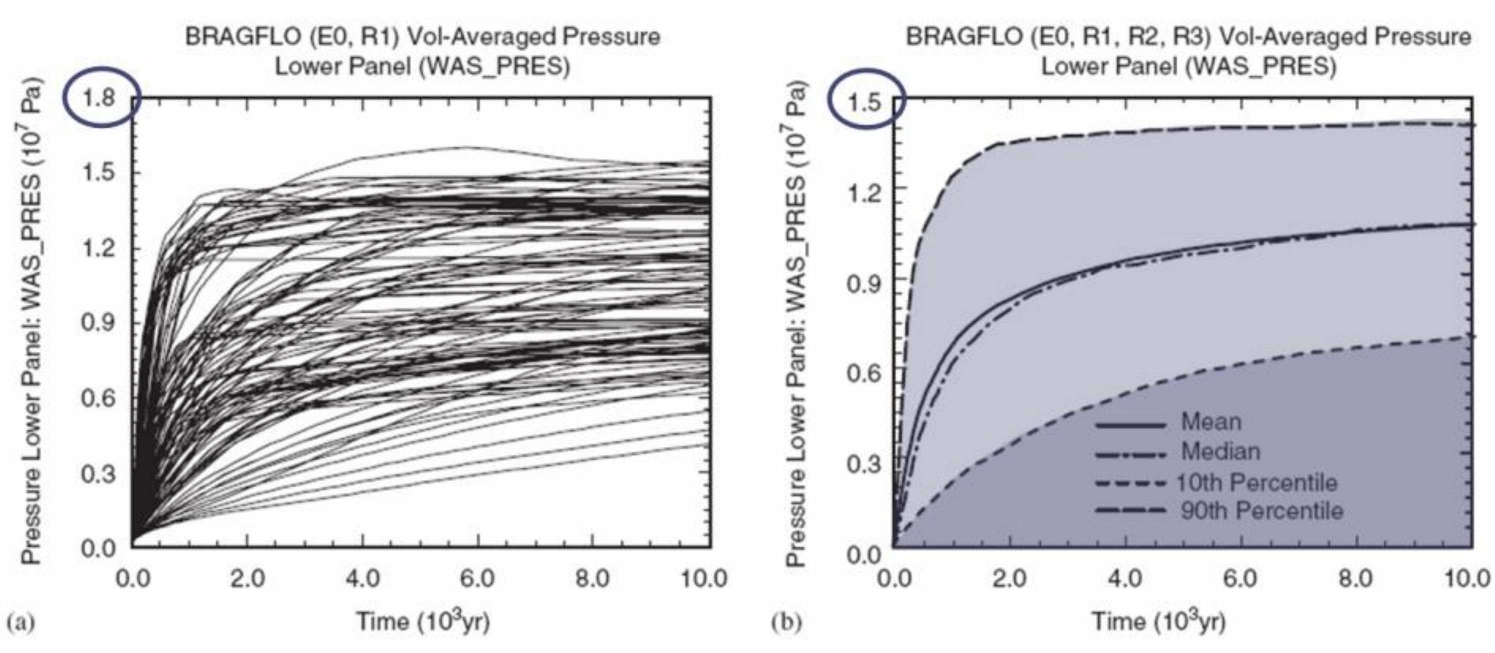
Output CI

$$\delta_y = \pm t_{N-p}^{\alpha} \sigma_y$$

Supporting tools (2)

Uncertainty analysis

Statistics of Monte Carlo analysis



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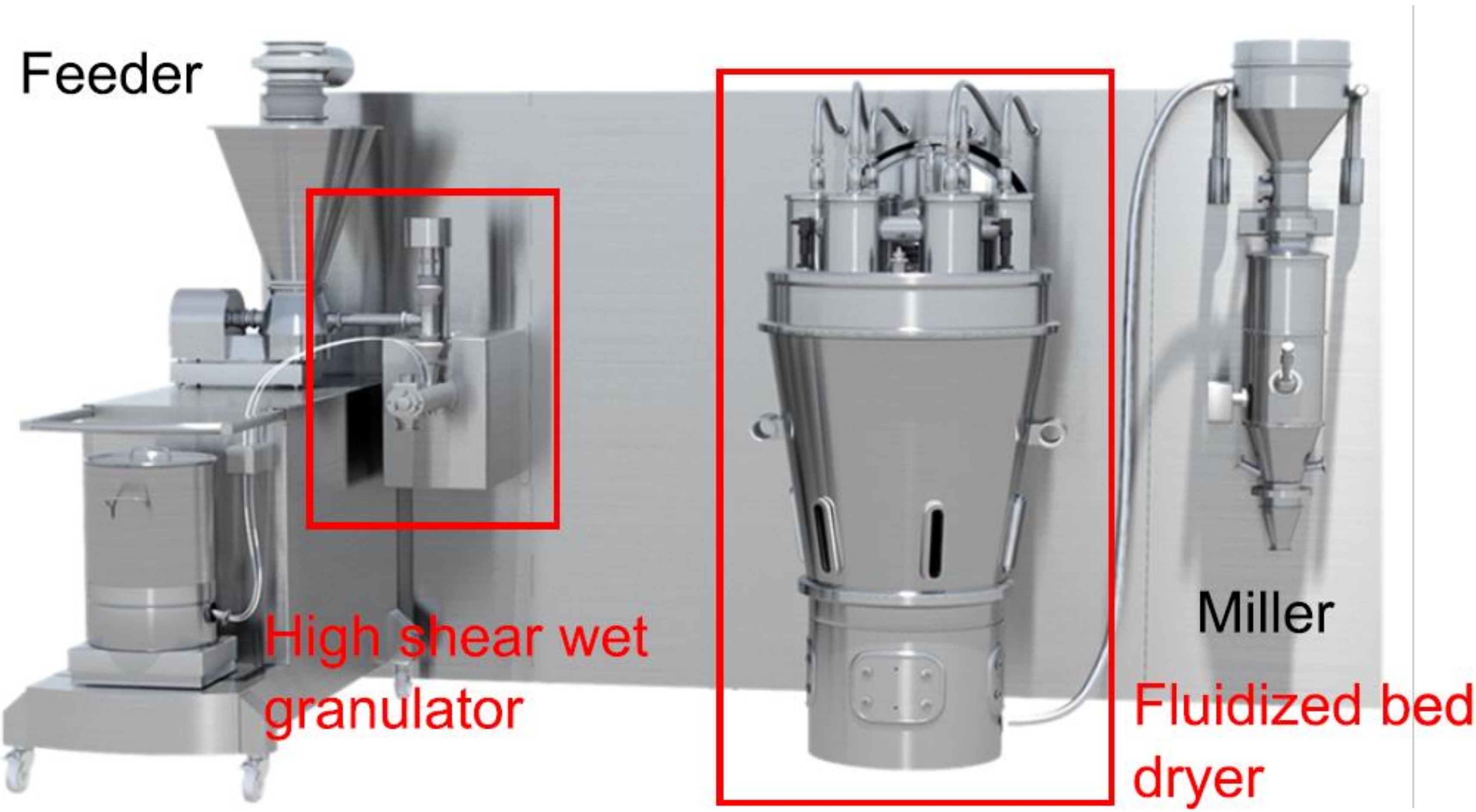
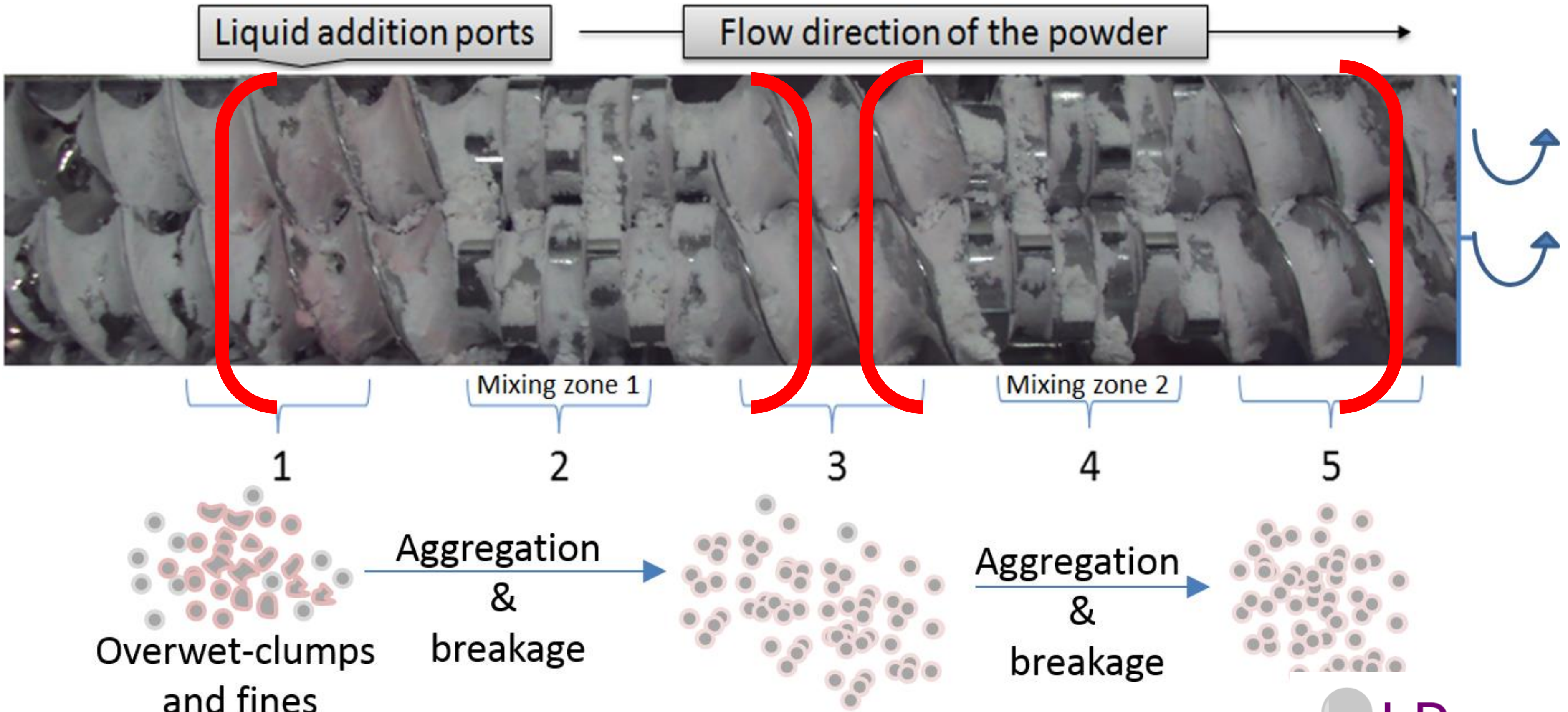
The process under study: ConsiGma^{TM}-25



Case: Twin-screw granulator

The system and its mechanisms:



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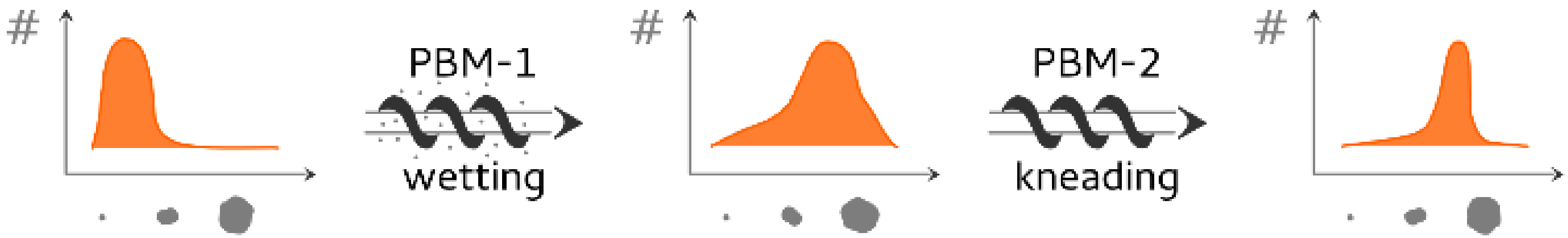
Case: Twin-screw granulator

Slide with breakdown in PBMs



Combination of aggregation and breakage
→ Kernel choice
→ parameters unknown
Tough optimisation problem

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Case: Twin-screw granulator

Local optimisation likely fails

Calibration requires **global search algorithms**:

- **Global Sensitivity Analysis**
  - Which parameter in the PBM-kernels (breakage or aggregation) is sensitive
    - → Parameters to be calibrated
- **Global Optimisation Algorithms**
  - Exploring the **whole parameter space**
  - **Thousands** of simulations

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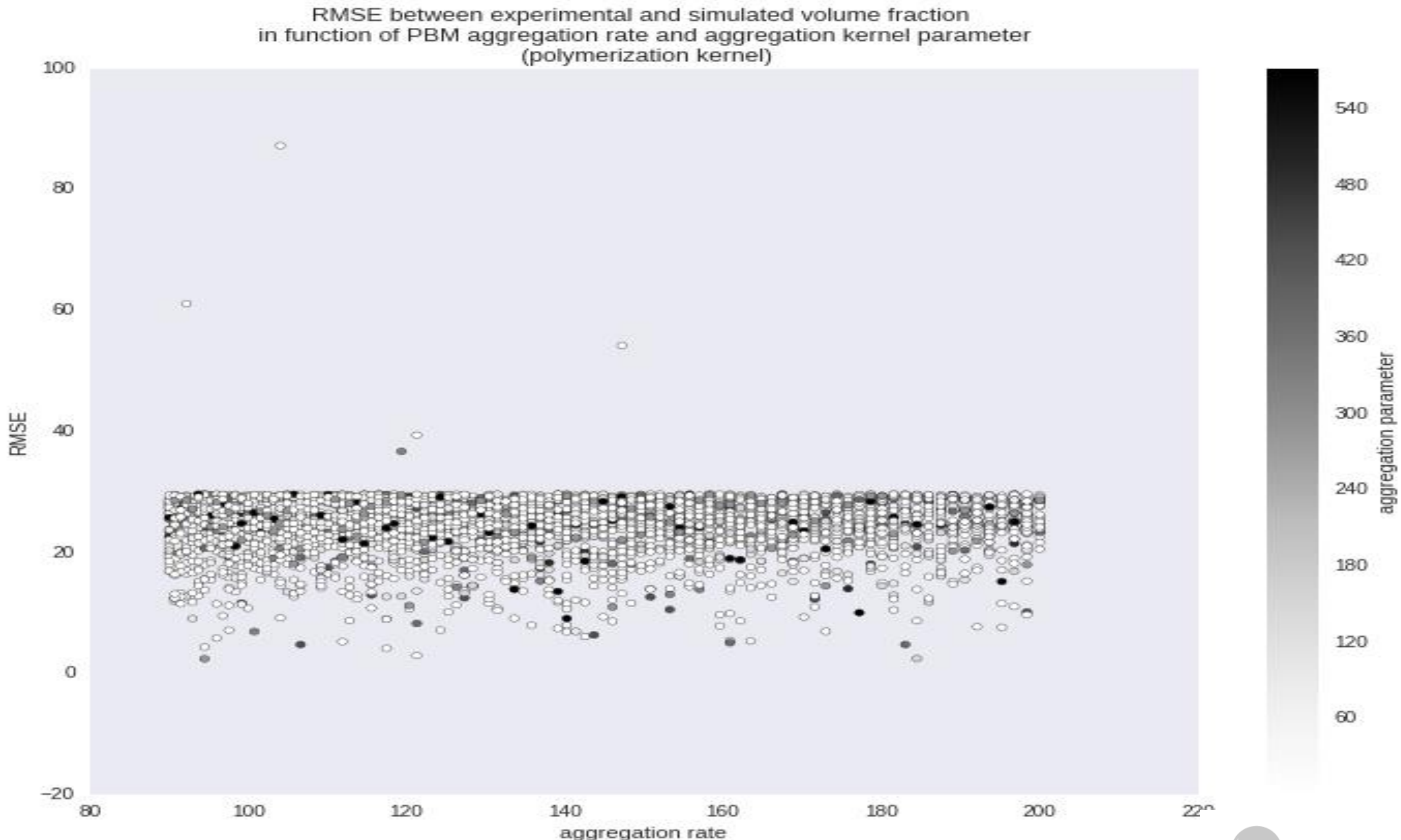
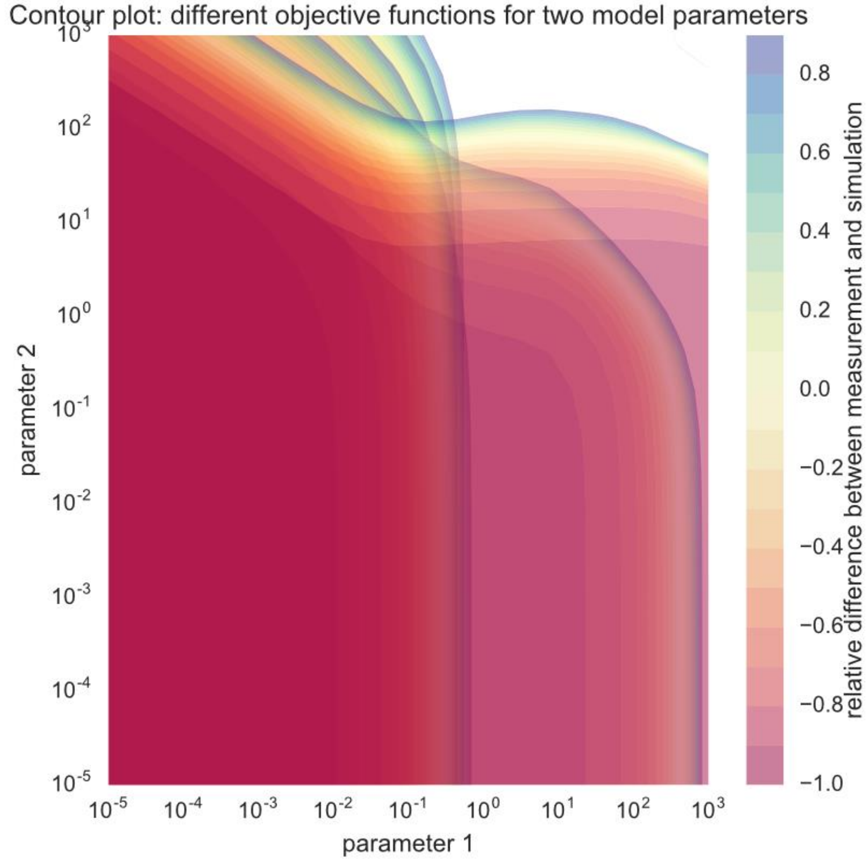
Case: Twin-screw granulator



Case: Twin-screw granulator

Impact of choice of objective function (RMSE, SSE, D43,...)



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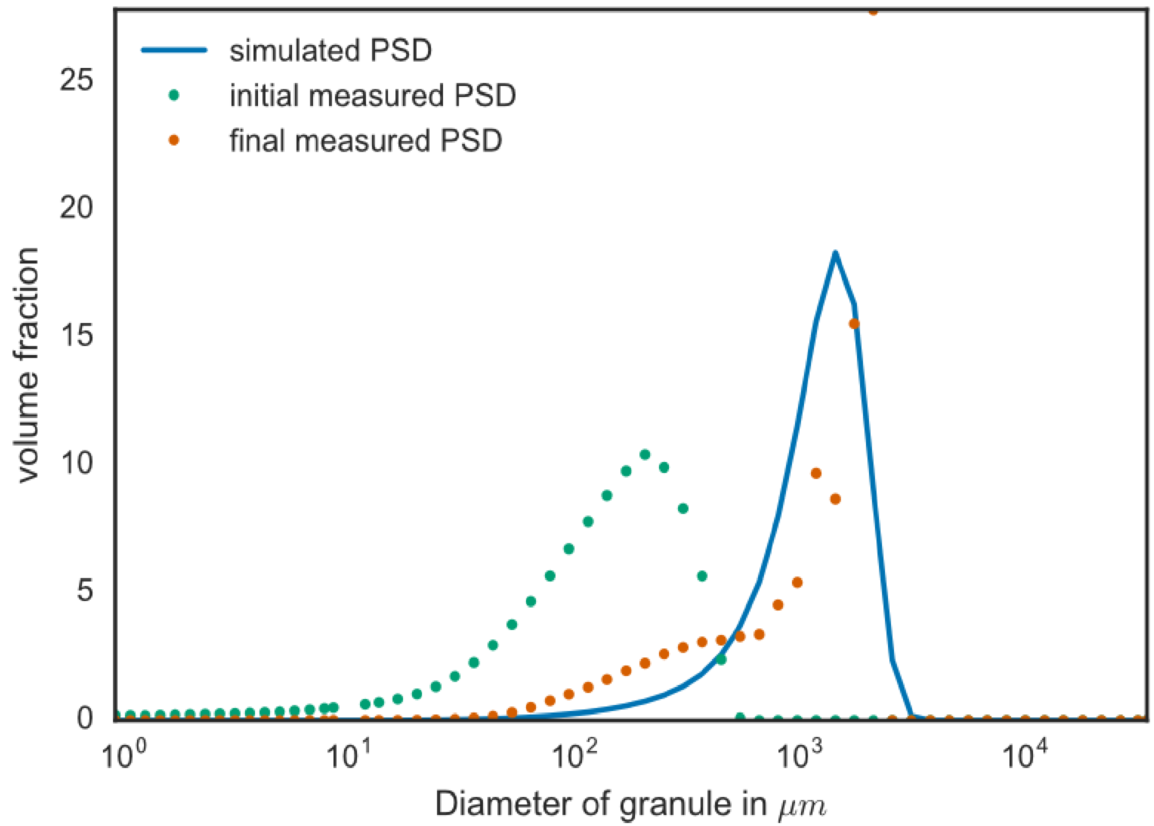
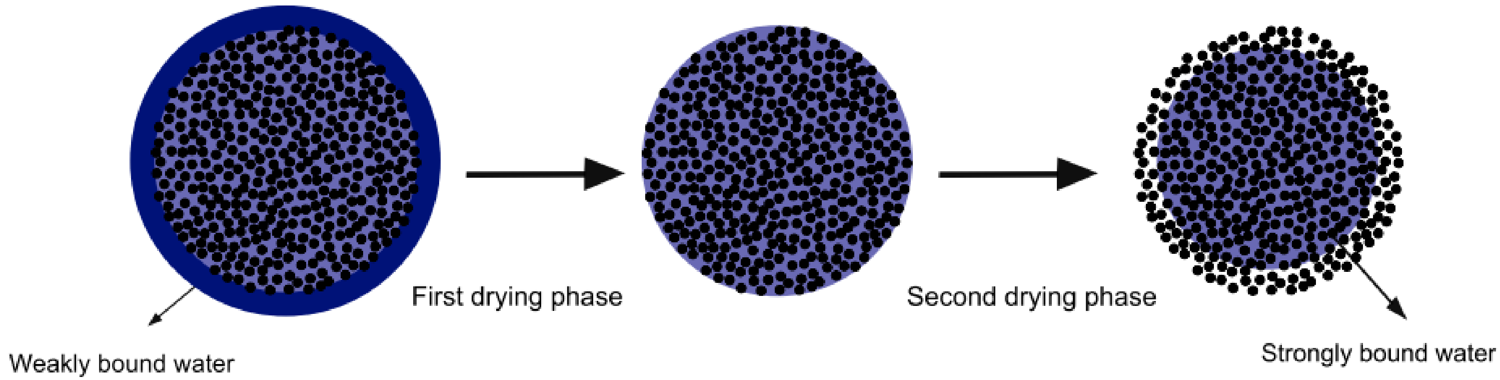
Case: Twin-screw granulator

Simulation results with calibrated model parameters



Case: Fluid bed dryer

Conceptualisation of reality:



1. Fast drying phase

$$\dot{m}_v = h_D(\rho_{v,s} - \rho_{v,\infty})A_d$$

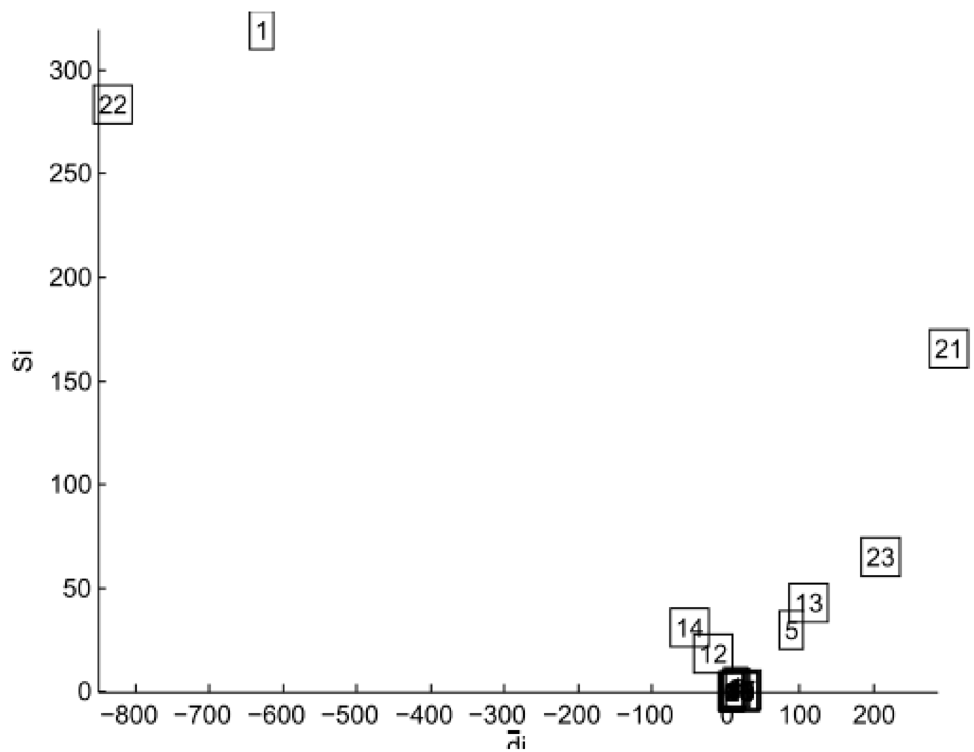
2. Slow drying phase

$$\dot{m}_v = -\frac{8\pi\epsilon^{\beta_1 e^{-\beta_2 T_g}} D_{v,cr} M_w p_g}{\Re(T_{cr,s} + T_{wc,s})} ln\left[\frac{p_g - p_{v,i}}{p_g - (\frac{\Re}{4\pi M_w h_D R_p^2}\dot{m}_v + \frac{p_{v,\infty}}{T_g})T_{p,s}}\right]$$

Case: Fluid bed dryer

Global Sensitivity Analysis

Nr.	Factor	Nominal value
1	$\mathbf{T_g}$	**55 °C**
2	V_g	200 m^3/h
3	$\mathbf{p_g}$	**101000 Pa**
4	$\mathbf{R_p}$	**0.6 mm**
5	Humidity	9%
6	$T_{p,0}$	25 °C
7	ϵ	**0.05**
8	μ_{gas}	0.00002 kg/m/s
9	ρ_{gas}	1.2 kg/m^3
10	k_{gas}	0.0285 W/m/K
11	$c_{p,gas}$	1009 kg/m^3
12	**Mw**	**18.015e-3 kg/mol**
13	$\rho_{\mathbf{liquid}}$	**1000 kg/m^3**
14	$\rho_{\mathbf{solid}}$	**1525 kg/m^3**
15	$k_{droplet}$	0.07 W/m/K
16	k_{liquid}	0.63 W/m/K
17	k_{solid}	0.75 W/m/K
18	$c_{p,s}$	1252 kg/m^3
19	TWC	647.13 K
20	ϵ_{rs}	0.8
21	$\beta_{\mathbf{1}}$	**4912.4**
22	$\beta_{\mathbf{2}}$	**-0.024282**
23	$\mathbf{R_{w,0,fac}}$	**1.025**



Case: Fluid bed dryer

Global Sensitivity Analysis

Technique	k	N	Most sensitive factors
Morris screening	23	240	β_2-T_g-β_1-$R_{w,0,fac}$
CSM plot	10	400	β_2-T_g-...
SRC	10	1000	-
SRRC	10	1000	β_2-$R_{w,0,fac}$-T_g-ρ_{solid}
S_i	10	1000	β_2-T_g-β_1-Mw
S_{Ti}	10	1000	β_2-T_g-β_1-ρ_{liquid}

Choose parameters to estimate

Check model robustness (uncertainty)

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Case: Fluid bed dryer

Uncertainty Analysis

Case	Parameter	Calibrated value	Range in uncertainty
1	ϵ	0.05	50%
1	V_g	200 m^3/h	50%
1	R_p	0.6×10^{-3} m	50%
2	β_1	4.91×10^3	20%
2	β_2	2.43×10^{-2}	20%
3	ϵ	0.05	[0.03–0.06]
3	V_g	200 m^3/h	20%
3	R_p	0.6×10^{-3} m	$[0.30–0.65 \times 10^{-3}]$
3	β_1	4.91×10^3	20%
3	β_2	2.43×10^{-2}	[0.022–0.026]

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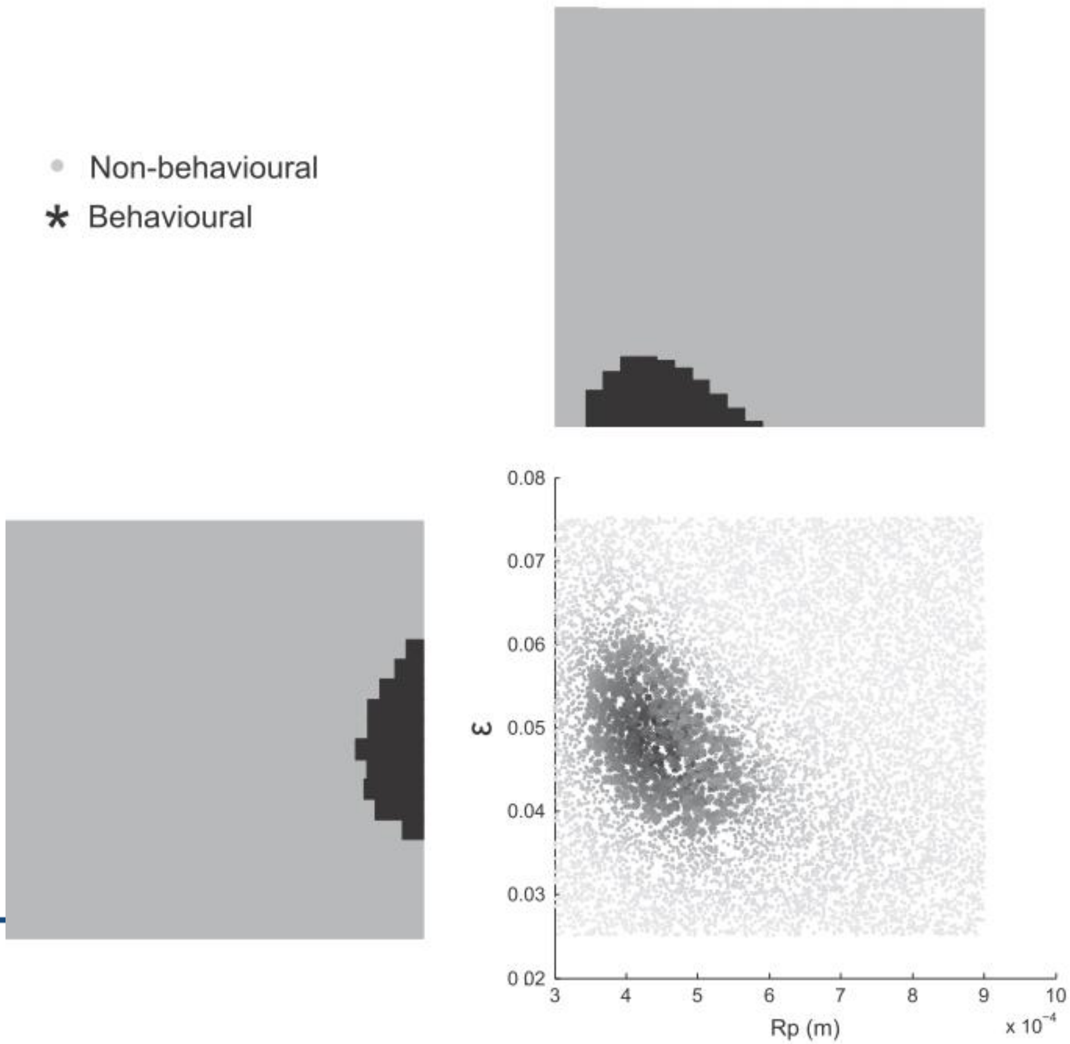
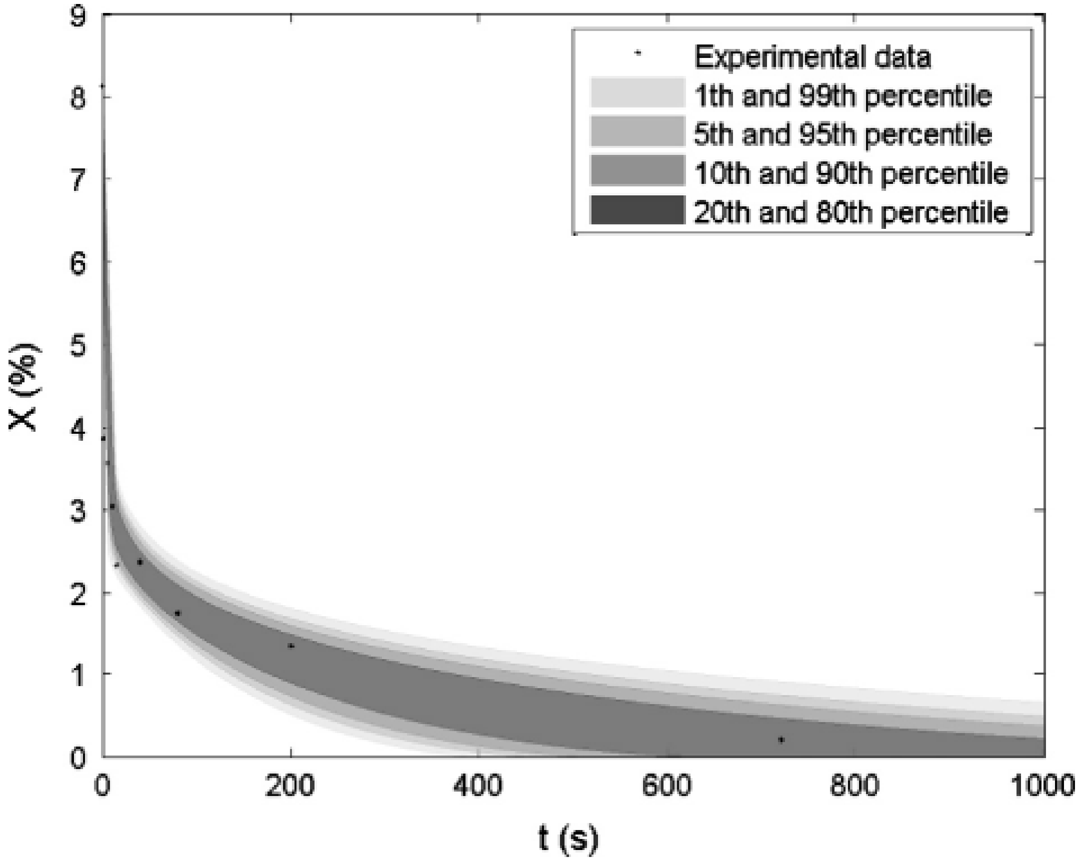
Case: Fluid bed dryer

Uncertainty Analysis



Case: Fluid bed dryer

Uncertainty Analysis: model predictive power



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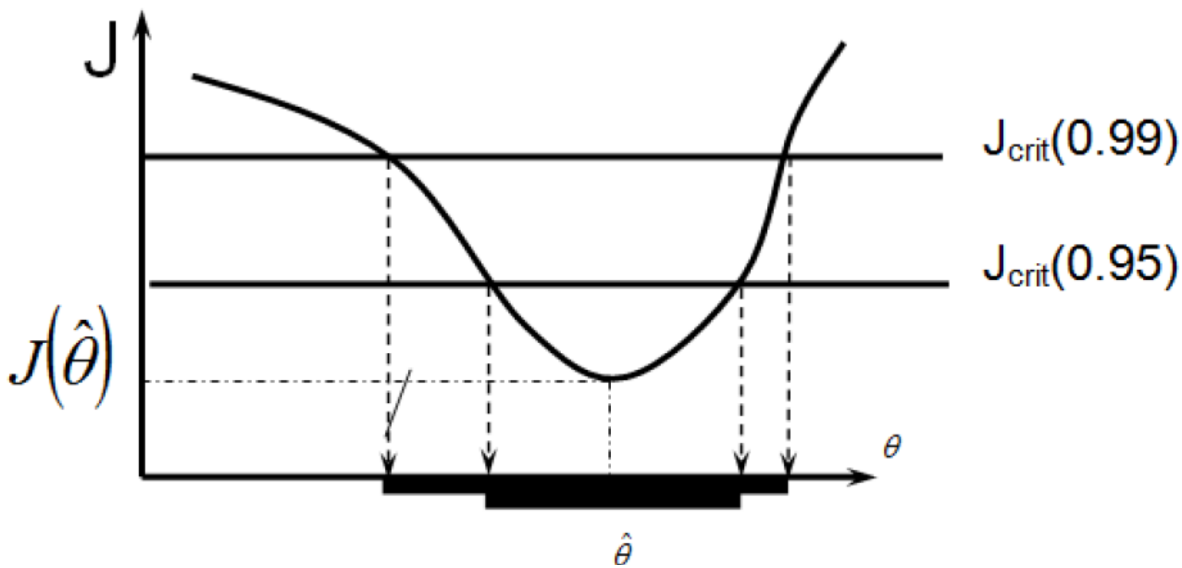
Supporting tools (3)

Optimal experimental design (OED)

- Quality of parameter estimate

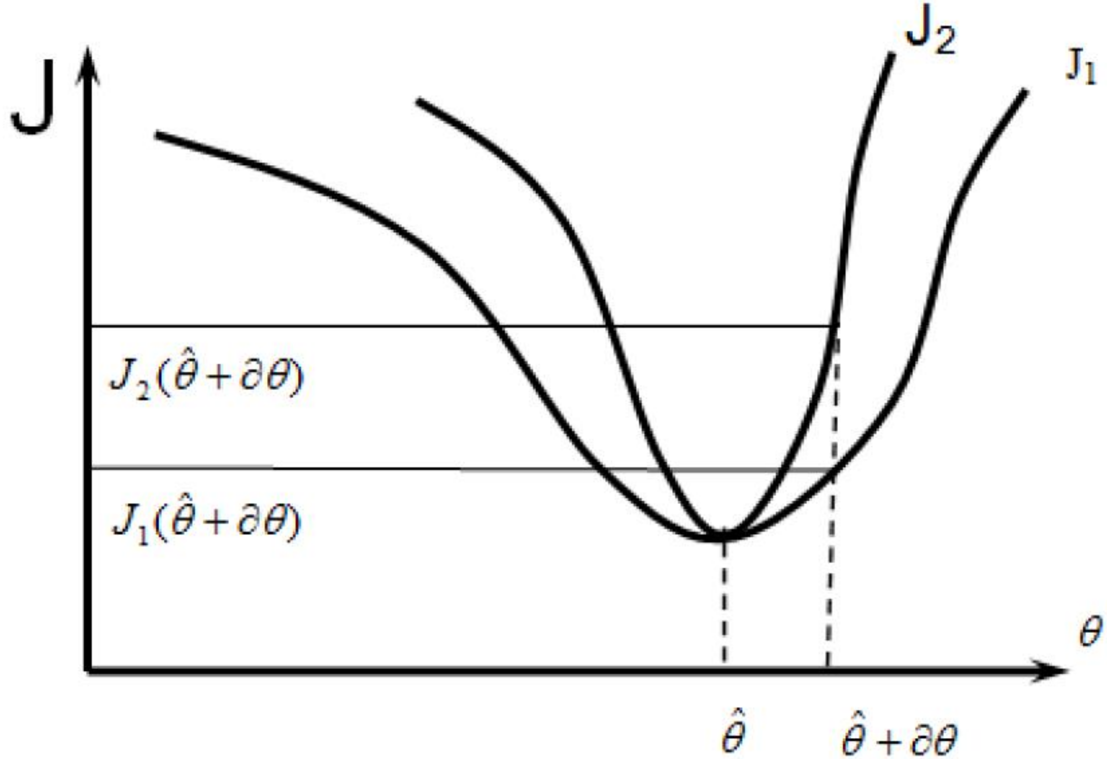


$$\left\{\boldsymbol{\theta} \ : \ J(\boldsymbol{\theta}) \leq c \times J(\hat{\boldsymbol{\theta}})\right\}$$

Supporting tools (3)

Optimal experimental design (OED)

- How to improve quality of parameter estimate?



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Supporting tools (3)

Optimal experimental design (OED)

- How to improve quality of parameter estimate?

$$E\left[J\left(\hat{\theta}+\delta\theta\right)\right] = J\left(\hat{\theta}\right) + \delta\theta^T \left[\sum_{i=1}^{N_{data}} \left(\frac{\partial y}{\partial \theta}\right)_i^T Q_i \left(\frac{\partial y}{\partial \theta}\right)_i\right] \delta\theta$$

Fisher Information Matrix (FIM)

- Iterative procedure
  - Conduct exp, calibrate, propose new exp, etc
  - Reduction of # exp (vs. DOE)

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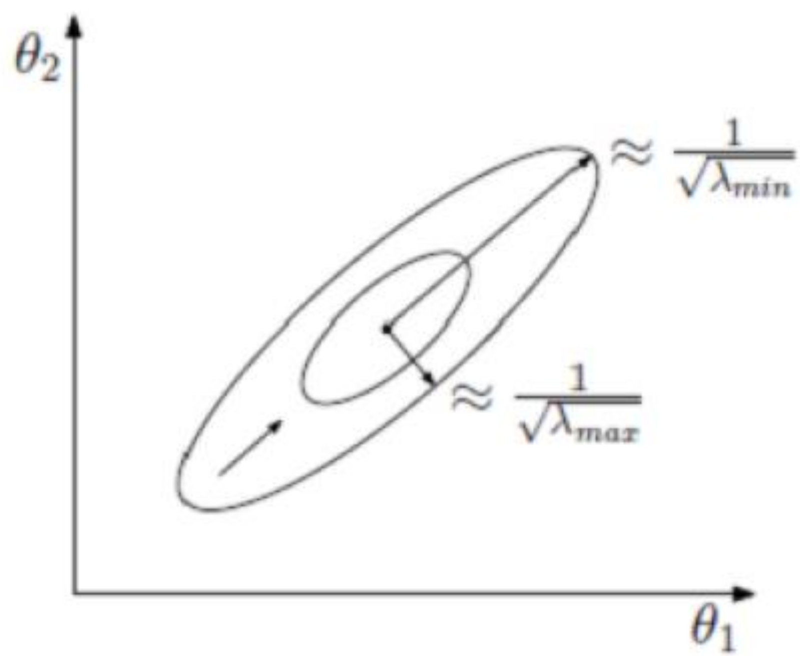
Supporting tools (3)

Optimal experimental design (OED)

- How to improve quality of parameter estimate?
- Maximise FIM
  - D-optimal $\max\left[\det(FIM)\right]$



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Conclusions

- Model-based analysis → Powerful for gathering process knowledge
- Good modelling practice is important
- Use appropriate modelling tools to make choices
- E.g. calibration of complex models → use global methods
  - Computationally expensive
  - But yield a lot of information on the model and can assist in experimental data collection (Optimal Experimental Design)
- Techniques exist, we need to use them

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