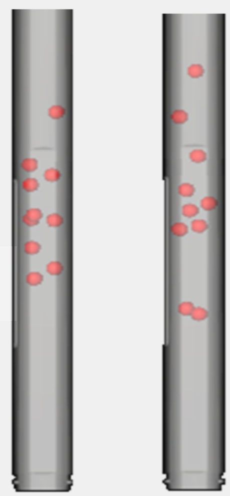
presented at the 15th Weimar Optimization and Stochastic Days 2018 |
Source: www.dynardo.de/en/library

DEM MODEL CALIBRATION FOR VERTICAL FILLING: SELECTION OF ADEQUATE TRIALS AND HANDLING RANDOMNESS

Filling
(VFFS)

Source:
Bosch Packaging Technology



Randomness +
Model Accuracy?

In cooperation with

TECHNISCHE UNIVERSITÄT DRESDEN

BOSCH

Agenda

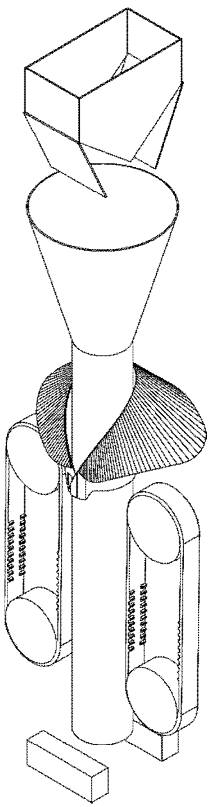
The VFFS Process and Goal

Parameter Identification for DEM

Randomness in the Process

Calibration with Optislang

Results and Conclusion



THE VFFS PROCESS AND GOAL

The VFFS Process and Goal

VFFS Process

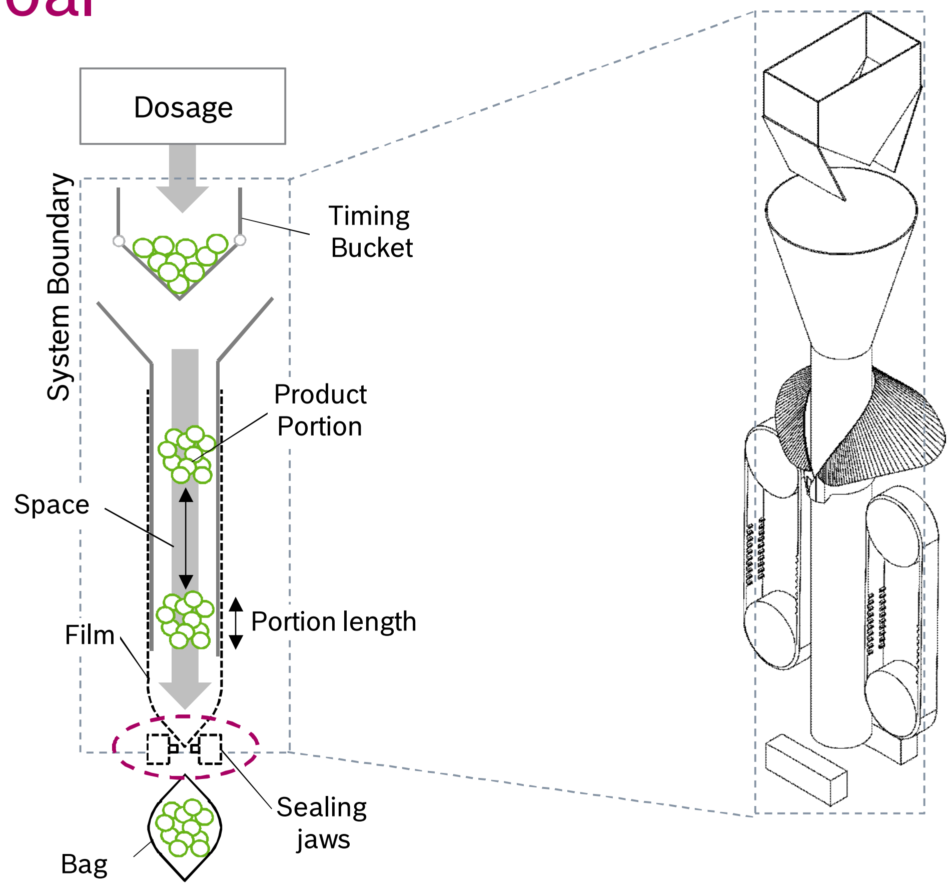
Industry Requirements

- Airtight bags
- High output rate (bags/minute)
- Flexibility

Critical for Process Safety

Compact portions required

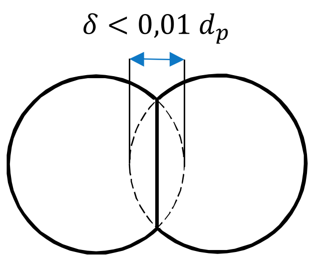
→ Goal: improve predictability



PARAMETER IDENTIFICATION FOR DISCRETE ELEMENT METHOD

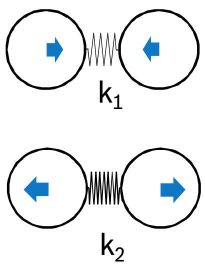
Parameter Identification for Discrete Element Method

DEM



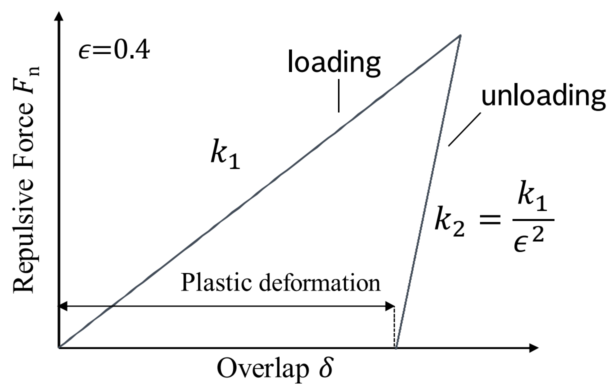
Assumption:
Deformation = Overlap

Elastic-Plastic Model:



$F_n(t) = k_1 \cdot \delta(t)$

$F_n(t) = k_2 \cdot (\delta(t) - \delta_0)$



Parameters

- Young's Modulus
- Poisson ratio
- Dynamic friction + (P-P, P-B)
- Static friction + (P-P, P-B)
- Coefficient of Restitution + (P-P, P-B)
- Rolling Resistance +

+ variable parameters here

How to find parameters?

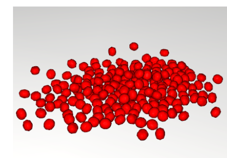
15th Annual Weimar Optimization and Stochastic Days 2018

Parameter Identification for Discrete Element Method

Model Calibration + **Validation** [1]

Experiment

Model



Iterative Parameter Identification [2]

Qualitative

- ► Representative trial
- ► Validation = “Plausibility check” [3]
- \+ Well established
- \- No information about error in %
- \- Unused potential

Quantitative

- ► Representative trial or in process
- ► Validation = **quantitative determination of error**
- \+ Certainty
- \+ Reproducible
- \- Additional effort

[1] Gröger et al., 2006. On the numerical calibration of discrete element models for the simulation of bulk solids

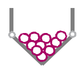
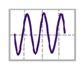
[2] Benvenuti, 2016, Identification of DEM Simulation Parameters by Artificial Neural Networks and Bulk Experiments

[3] Markauskas et al., 2010, Investigation of rice grain flow by multi-sphere particle model with rolling resistance

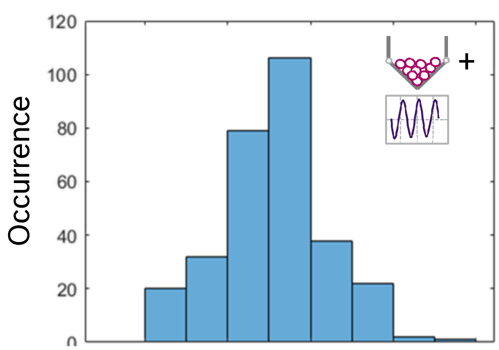
RANDOMNESS IN THE PROCESS

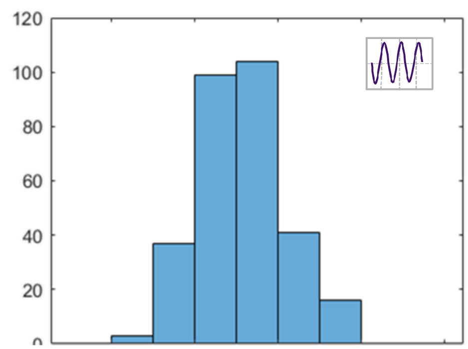
Randomness in the Process

Sources of Randomness

- Variation in initial conditions 
- Numerical Noise 

\+ amplification over time

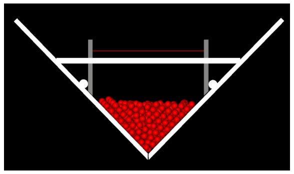


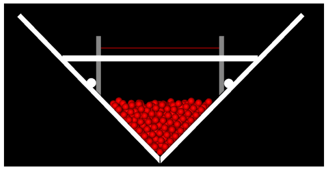


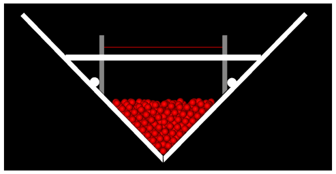
Drop time

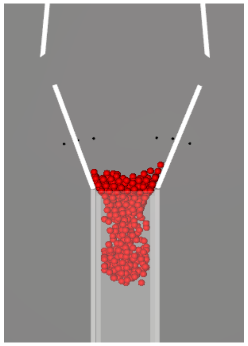
Standard
deviation:

Small
variations…









… lead to
different results!

Uncertainty affects optimization/calibration

Kirsch et al., 2018, Simulation of Vertical Filling Processes of Granular Foods for typical Retail Amounts

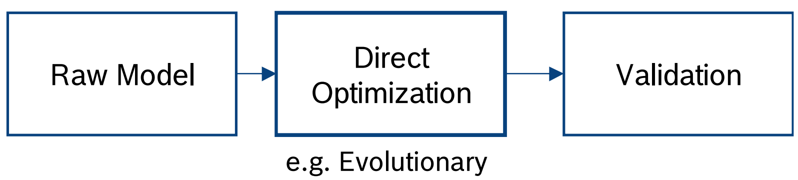
CALIBRATION WITH OPTISLANG

Calibration with Optislang

Goal

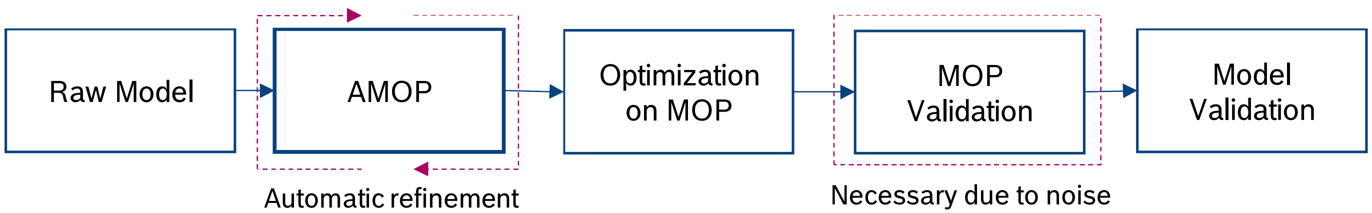
- Identify candidate parameter sets that represent real product
- Only calculate parameter sets in the interesting area

a)



+ Simple to implement
- Computational cost ↑ due to noise

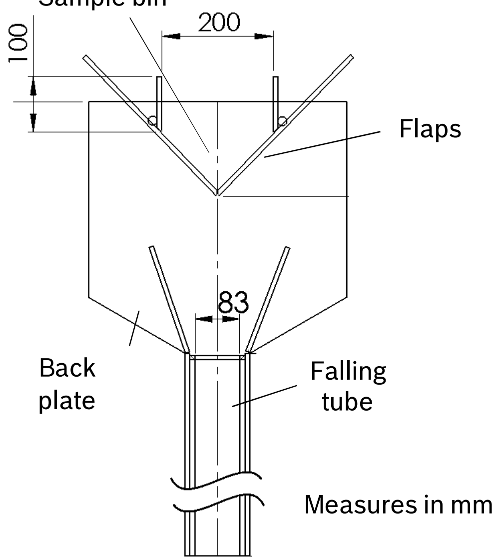
b)



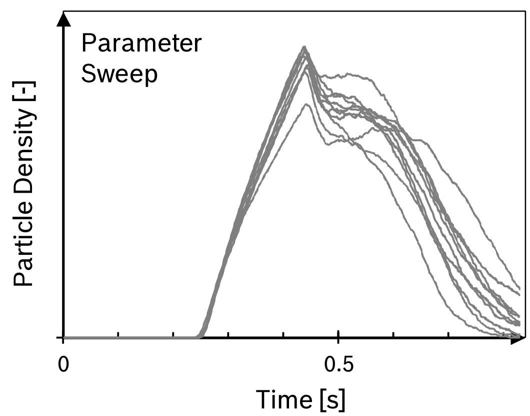
+ Lots of data available in postprocessing
+ Fully automatic refinement
- Initial considerations about MOP algorithm necessary

Calibration with Optislang – Calibration Trial

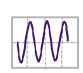
Calibration + **Validation**



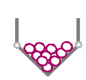
Drop test[1]



Sources for noise:

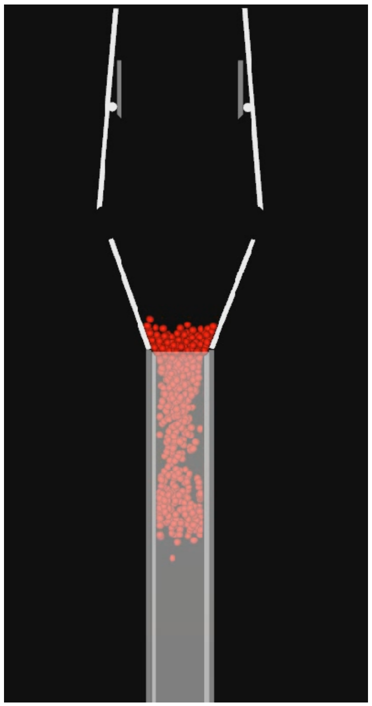


Numerical Noise



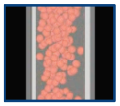
Random Initial Condition

Comp. Cost ↑



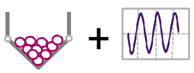
[1] Kirsch et al., 2018, Simulation of Vertical Filling Processes of Granular Foods for typical Retail Amounts

Calibration with Optislang

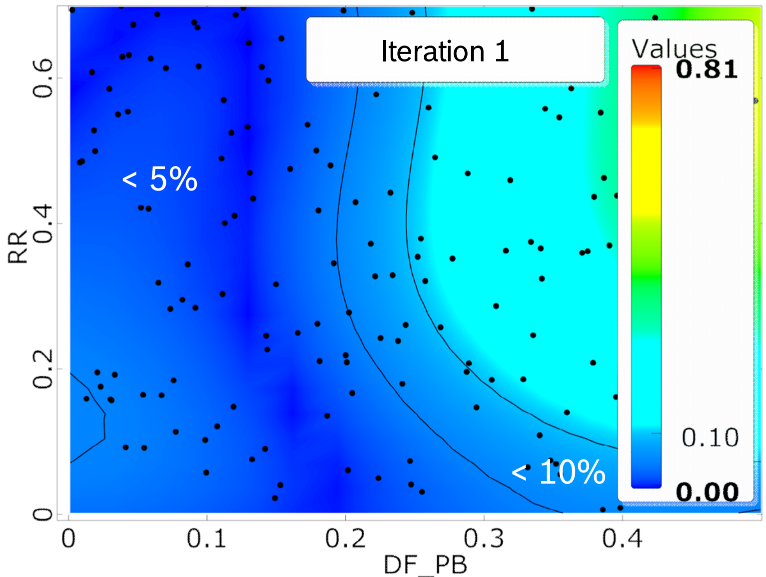


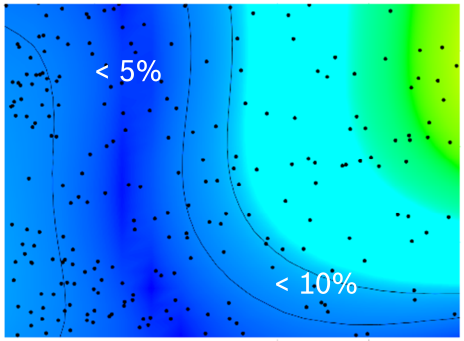
Drop test

Raw Model → AMOP → Optimization on MOP → MOP Validation → Model Validation

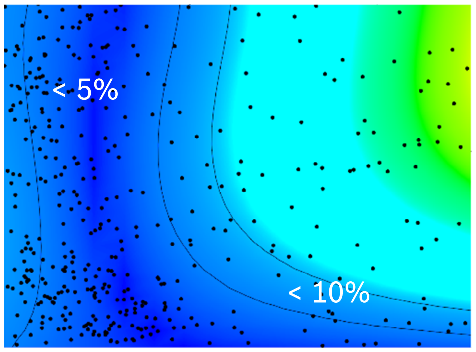


Model error predicted by MOP





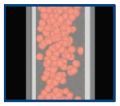
Iteration 3



Iteration 10

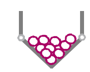
BOSCH

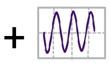
Calibration with Optislang



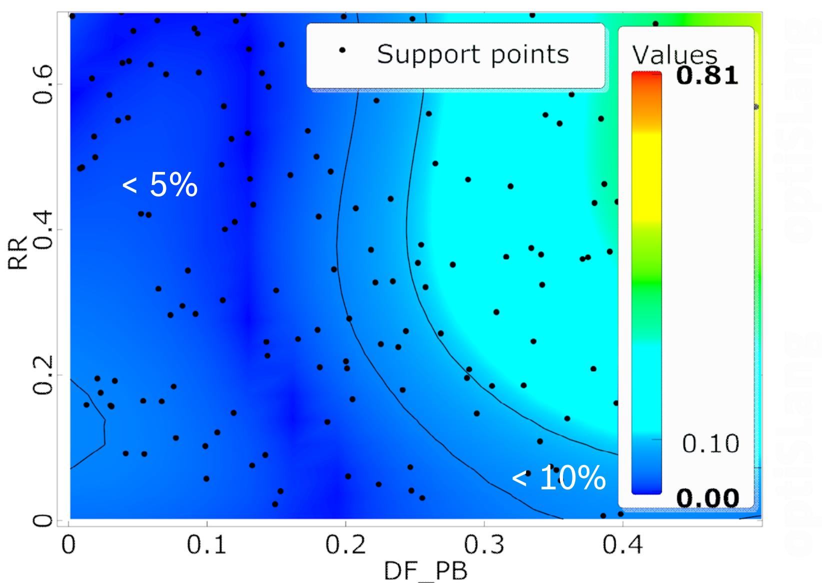
Drop test

Raw Model → AMOP → Optimization on MOP → MOP Validation → Model Validation



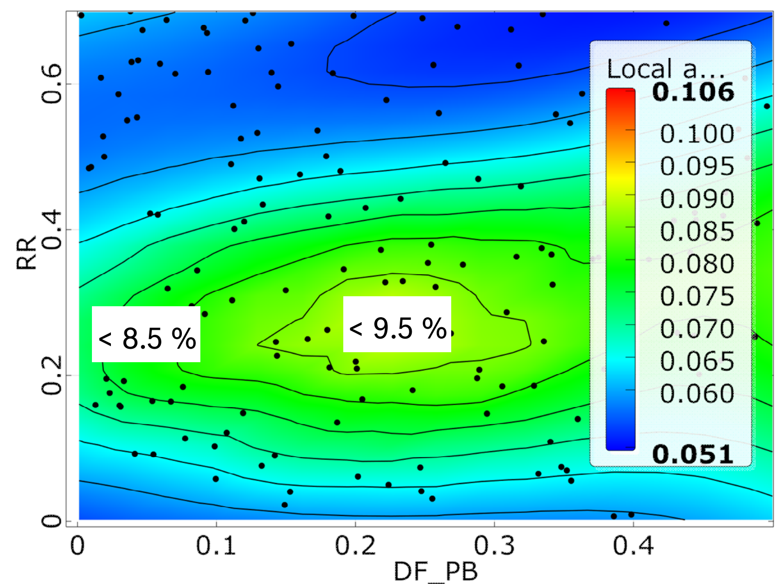


Model error predicted by MOP



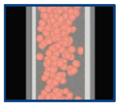
Iteration 1

Estimated absolute MOP error



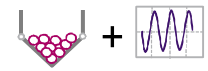
BOSCH

Calibration with Optislang

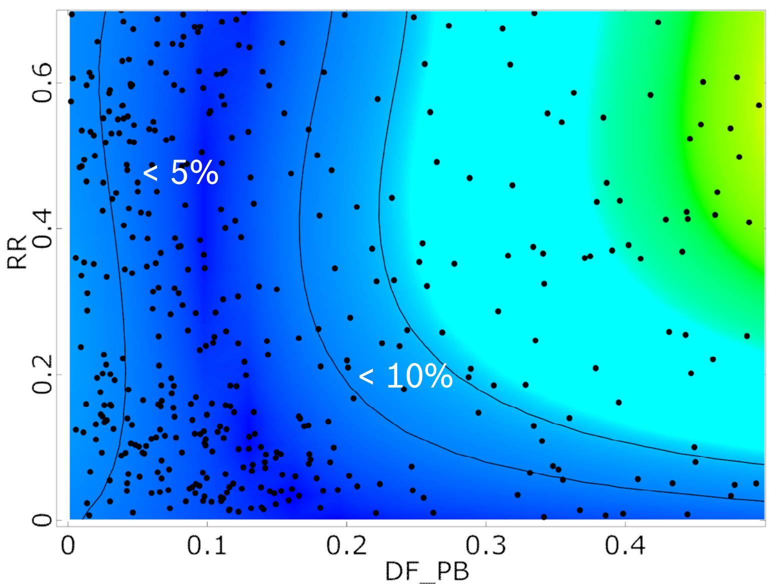


Drop test

Raw Model → AMOP → Optimization on MOP → MOP Validation → Model Validation

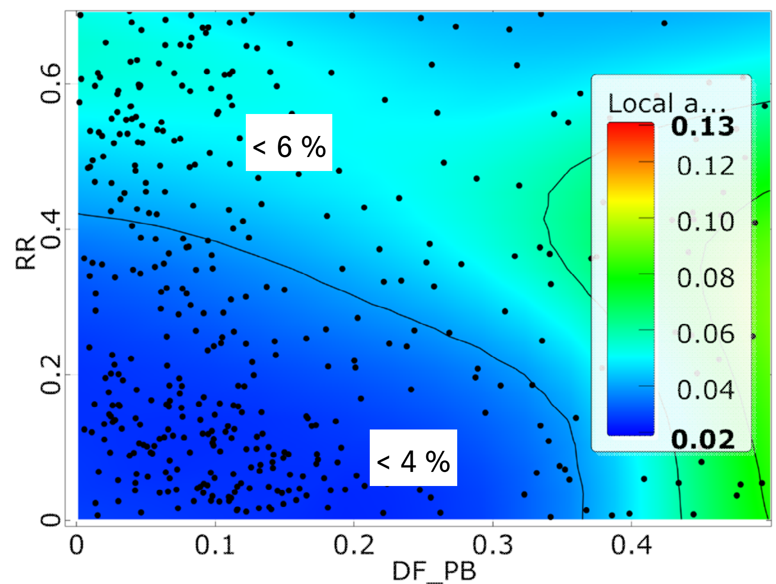


Model error predicted by MOP



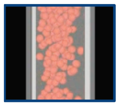
Iteration 10

Estimated absolute MOP error



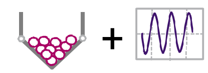
15th Annual Weimar Optimization and Stochastic Days 2018

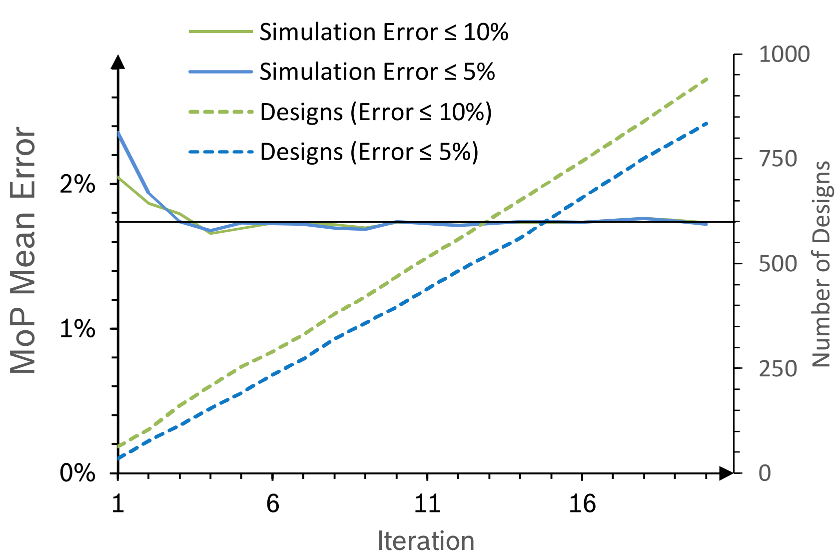
Calibration with Optislang

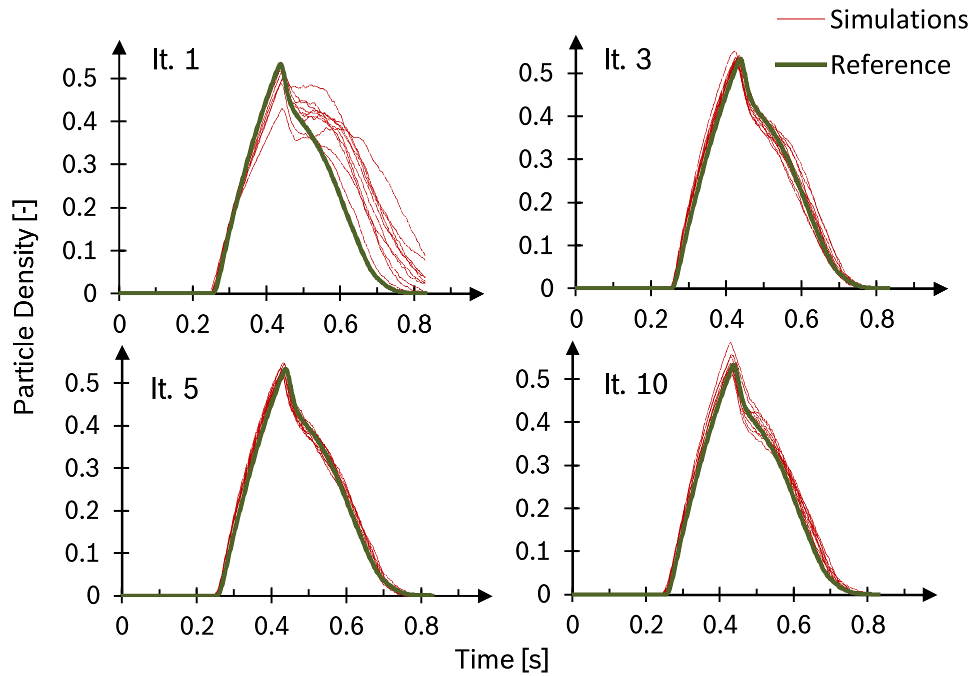


Drop test

Raw Model → AMOP → Optimization on MOP → MOP Validation → Model Validation



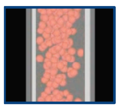




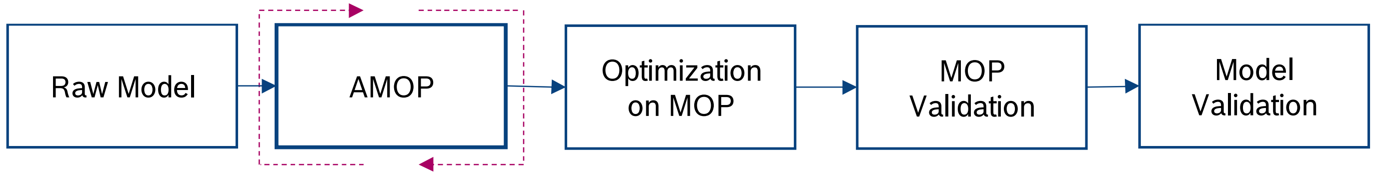
Packaging Technology | PANL/END4 | Stefan Kirsch | 21/06/2018

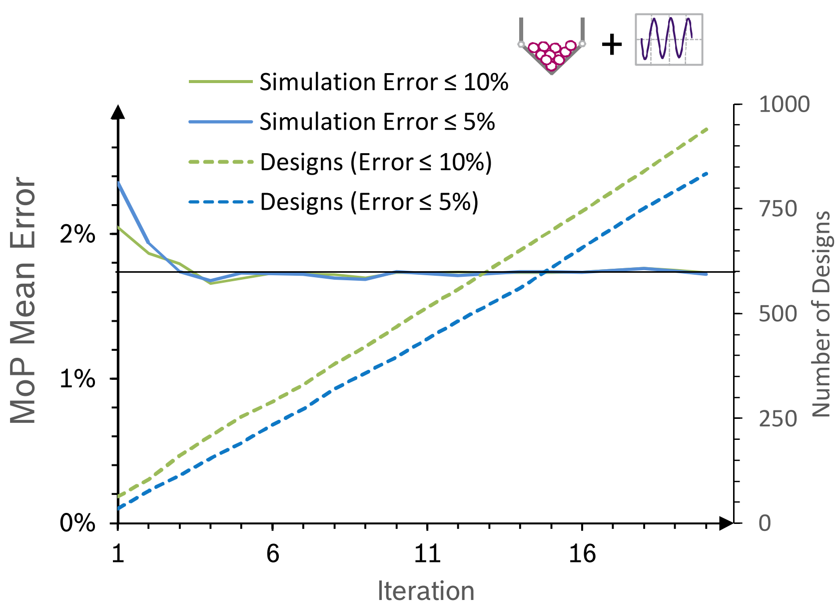
BOSCH

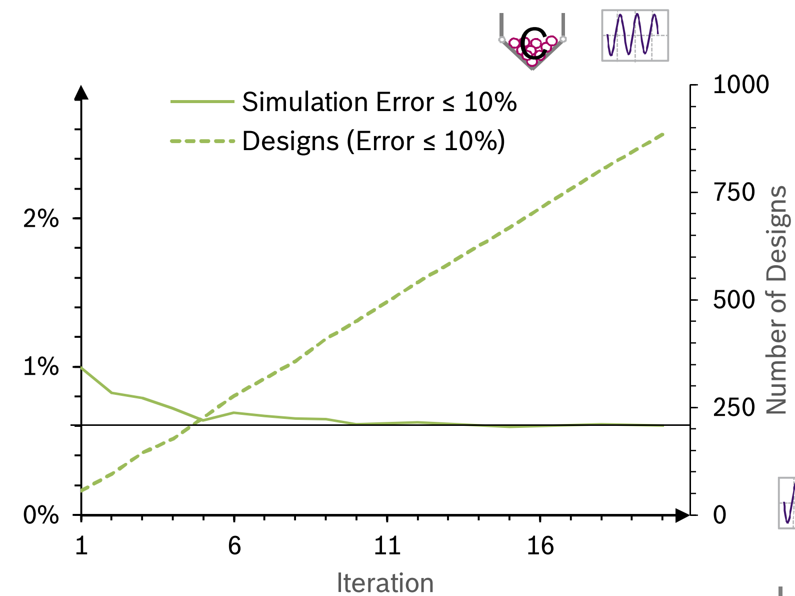
Baseline noise is much lower with constant initial condition

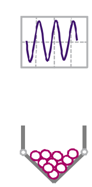


Drop test





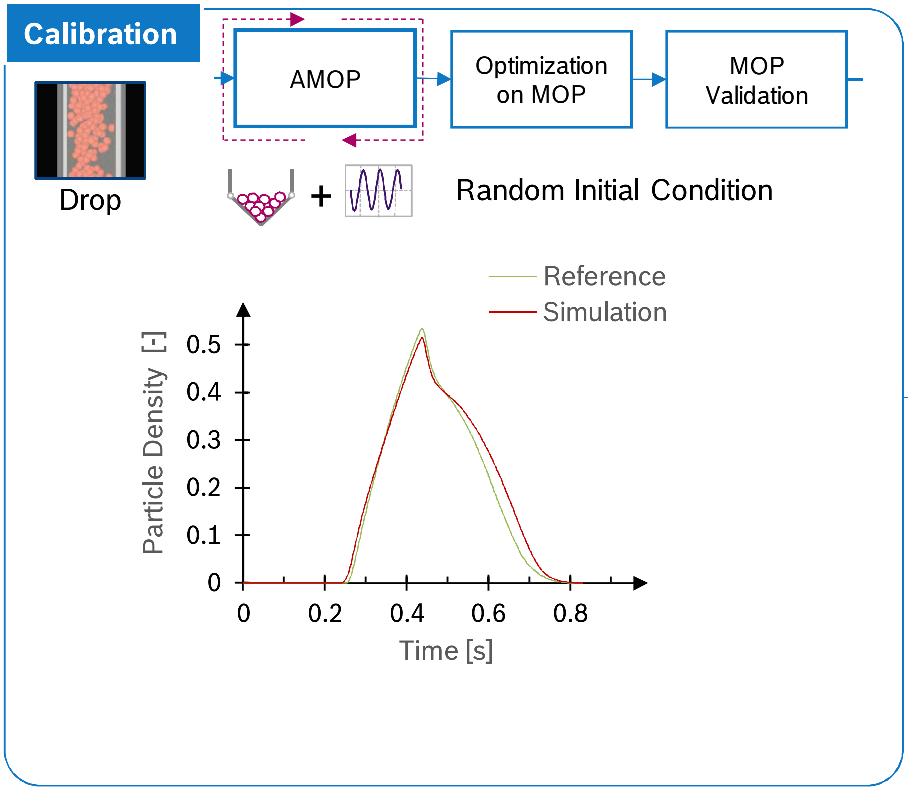


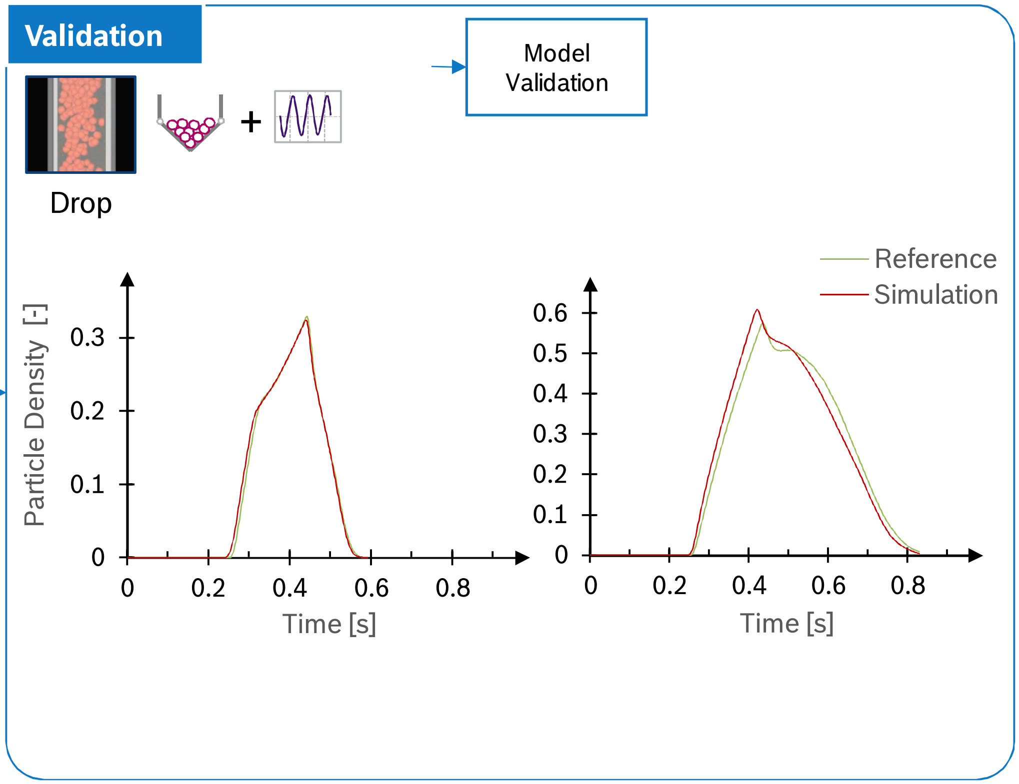


BOSCH

RESULTS AND CONCLUSION

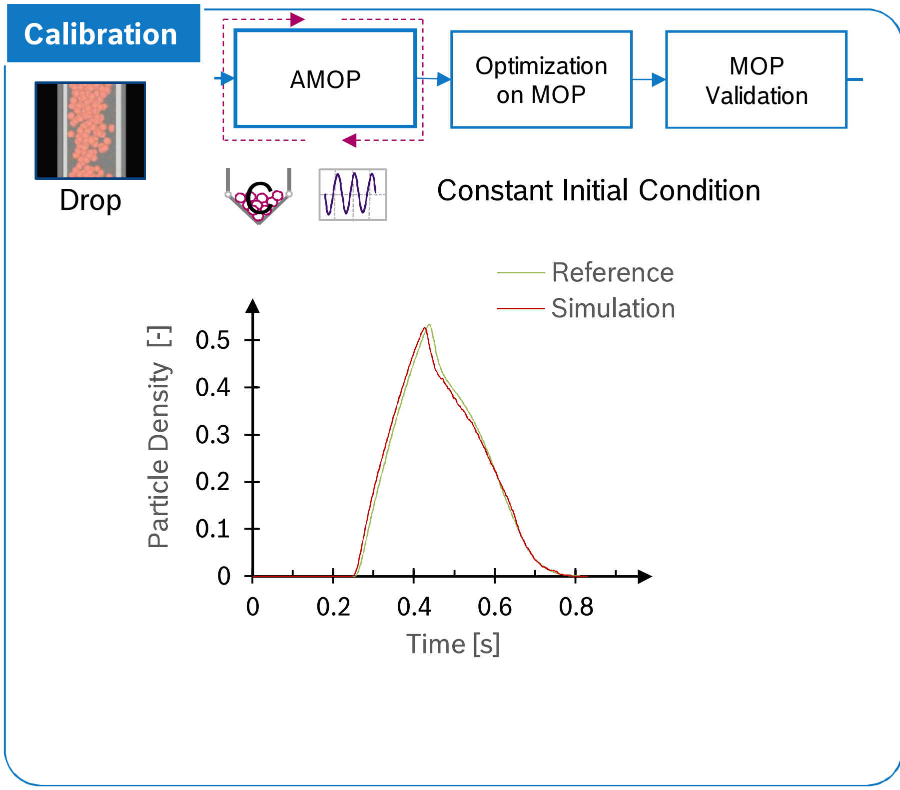
Validation proofs predictive quality of calibrated model

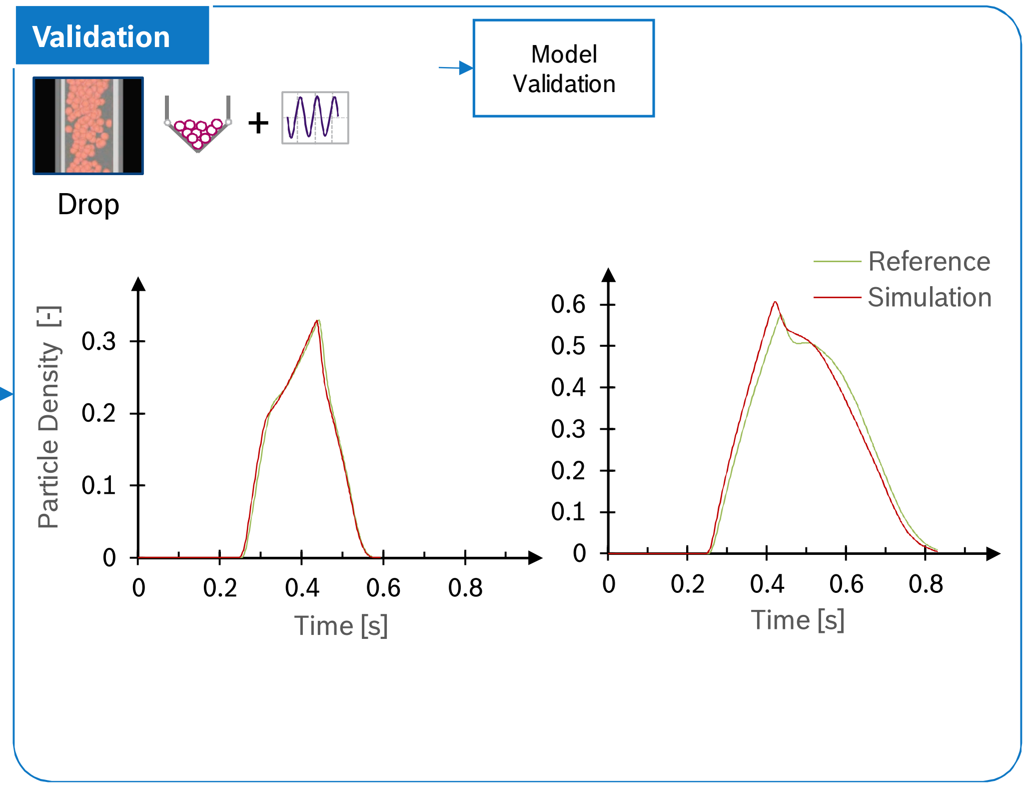




15th Annual Weimar Optimization and Stochastic Days 2018

Validation proofs predictive quality of calibrated model





BOSCH

Conclusion

Summary

Goal

- Improve predictability of filling process
- Find generalized approach for parameter identification

Results

- AMOP approach is an efficient method to localize low-error hotspots
- For sample product & scenario, model has high accuracy
- Noise due to initial conditions does not affect accuracy of calibration

Outlook

- Expand approach to more products