

A Holistic Approach for the Model-based Control of Crystal Size, Shape and Purity in Integrated Batch and Continuous Crystallization - Wet Milling Systems

Botond Szilagyi, Zoltan K. Nagy

**School of Chemical Engineering
Purdue University, West Lafayette, IN**

PURDUE
UNIVERSITY

Outline

Project objectives

... and main deliverables



Progress summary

... in a nutshell



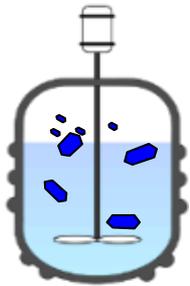
Next steps

... given what we know, what could we do



Project objectives

- Many technology and economic drivers
- 70% of all solid products & 90% of APIs involve a crystallization step
- Control of crystalline properties (CSD, shape, polymorphic form, purity, etc.) important
 - Product effectiveness (dissolution, bio-availability, tablet stability)
 - Efficient downstream operations (filtration, drying)



Crystallization

Downstream processes

Final product

Control of crystal properties is critical for product functionality and operational efficiency



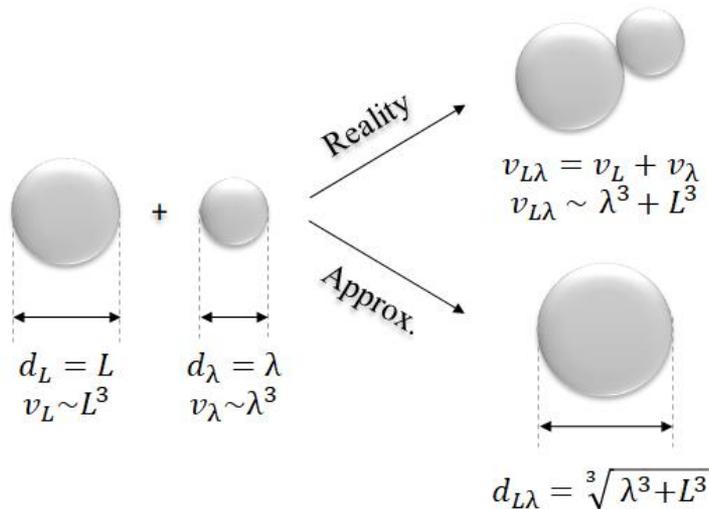
1D agglomeration and breakage models and solvers

Agglomeration modeling in crystallization (1D)

- Agglomeration often spontaneously occurs during crystallization.
- “Forced agglomeration”: spherical agglomeration.
- Granulation processes fully governed by agglomeration.

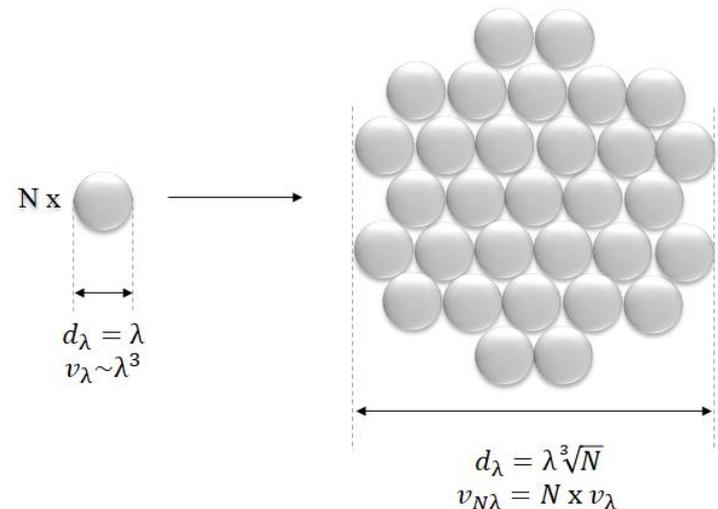
Agglomeration of two primary particles

- Volume conservation
- No shape conservation. Modeling practice: sphere equivalent diameter



Agglomeration of multiple particles

- Volume conservation
- Quasi shape-conservation. Modeling practice: sphere equivalent diameter



Agglomeration modeling in crystallization (1D)

The agglomeration population balance model-equation:

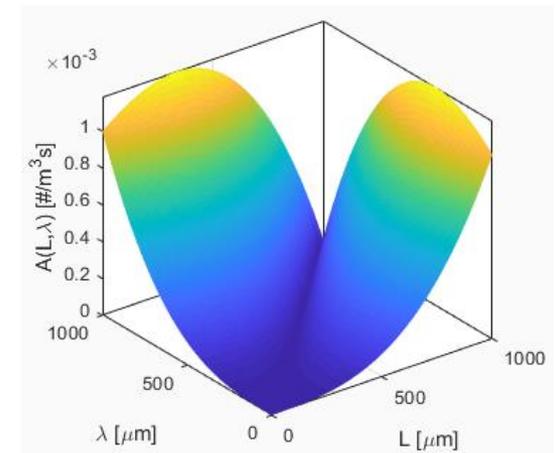
$$\frac{\partial n(L, t)}{\partial t} = \frac{L^2}{2} \int_0^L \frac{\beta[(L^3 - \lambda^3)^{1/3}, \lambda]}{(L^3 - \lambda^3)^{2/3}} n((L^3 - \lambda^3)^{1/3}, t) n(\lambda, t) d\lambda - n(L, t) \int_0^{L_{max}} \beta(L, \lambda) n(\lambda, t) d\lambda$$

Birth rate of L -size particles by agglomeration

Death rate of L -size particles by agglomeration

$\beta(L, \lambda)$: agglomeration kernel. Implemented:

Name	$\beta(L, \lambda)$
Constant	k_{ag}
Brownian motion	$k_{ag} \frac{(L + \lambda)^2}{L\lambda}$
Sum	$k_{ag}(L^3 + \lambda^3)$
Hydrodynamic	$k_{ag}(L + \lambda)^3$
Differential force	$k_{ag}(L + \lambda)^2 L - \lambda ^2$



Differential force ($k_{ag} = 10^{-12}$)

Breakage modeling in crystallization (1D)

- Attrition often occurs during crystallization processes.
- Fragmentation might also occur.
- Wet milling: governed by particle breakage.
- Breakage: volume conserving. Not shape conserving (there are exceptions, as high aspect-ratio crystals)

The breakage population balance model-equation:

$$\frac{\partial n(L, t)}{\partial t} = \int_{\lambda}^{L_{max}} b(L|\lambda)n(\lambda, t)S(\lambda)d\lambda - S(L)n(L, t)$$

Birth rate of L -size particles by breakage

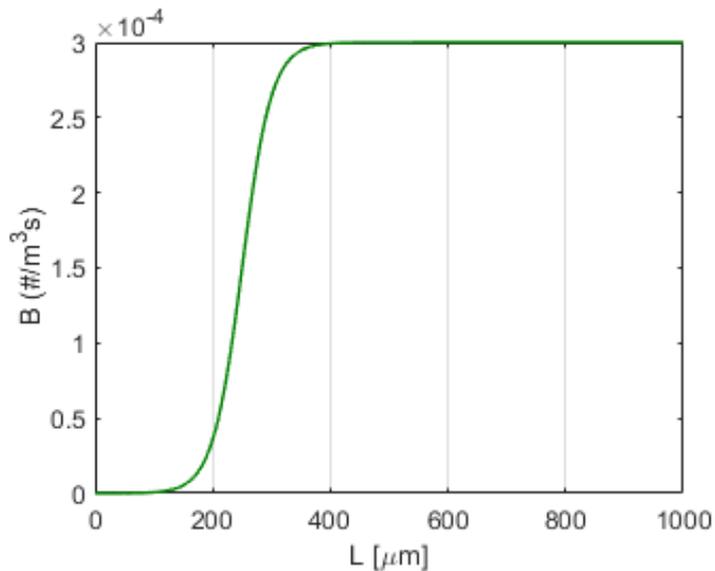
Death rate of L -size particles by breakage

Breakage modeling in crystallization (1D)

Breakage selection function ($S(L)$)

- Probability that an L size crystal breaks up
- Numerous functions. Implemented: constant, power-law and hyperbolic tangent

$$S(L) = k_{br} \frac{1}{2} (\tanh(k(L_c - L)) + 1)$$

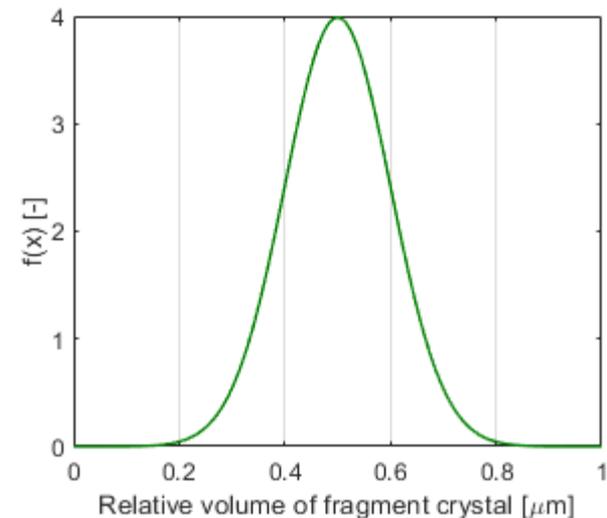


Parameters: $k_{br} = 0.0003$; $k = 0.02$; $L_c = 250 \mu\text{m}$

Fragment distribution function ($b(L|\lambda)$)

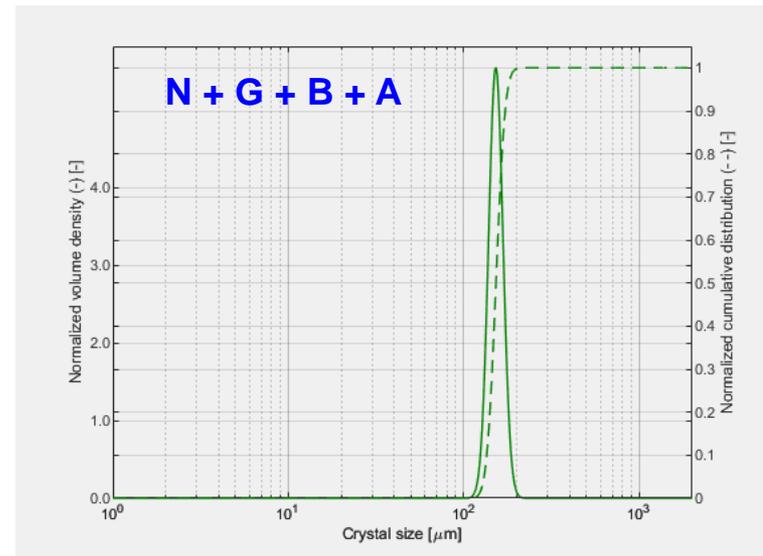
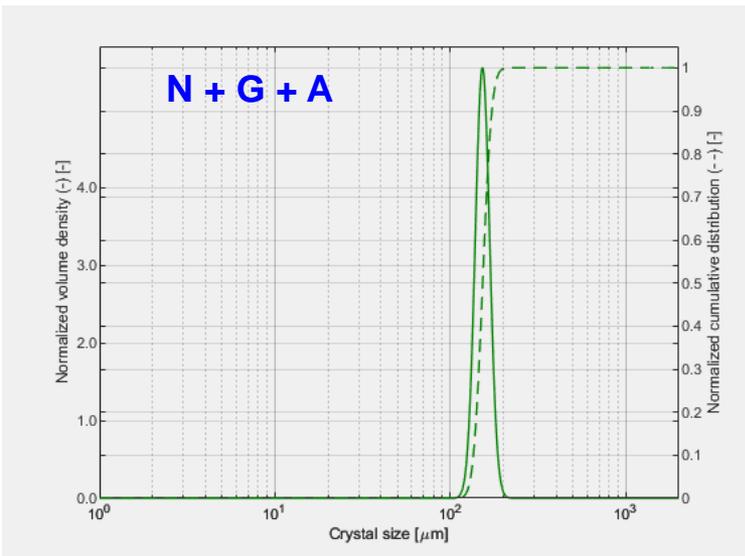
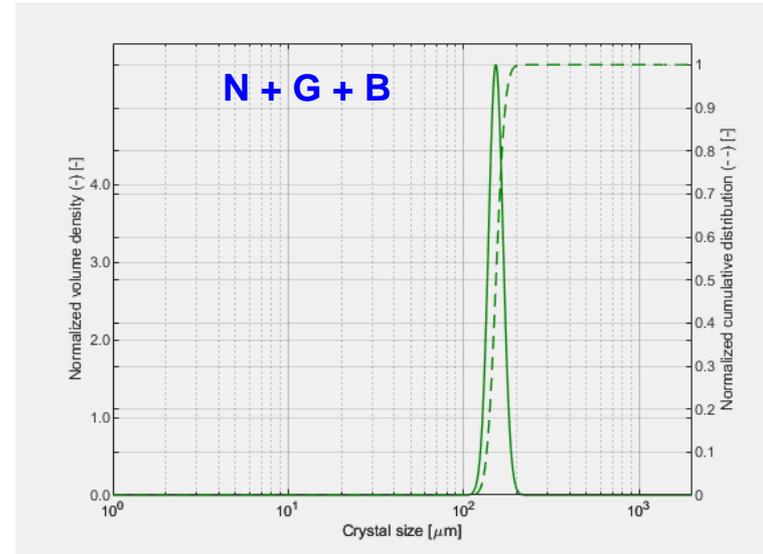
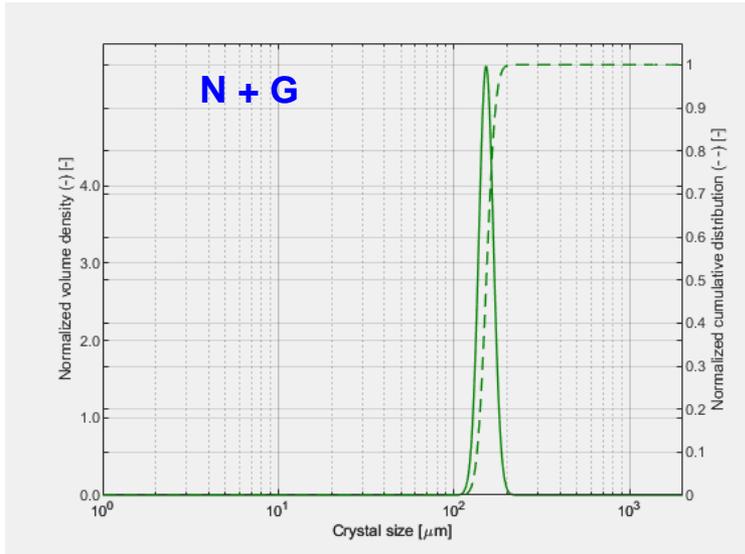
- Probability that L sized crystal is produced from the breakage of a λ size crystal
- Implemented: symmetric fragmentation, uniform distribution, normal distribution

$$b(L|\lambda) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(L - \mu)^2}{2\sigma^2}\right)$$



Parameters: $\sigma = 0.1\lambda$; $\mu = 0.5\lambda$

Implementation in the generic 1D solver

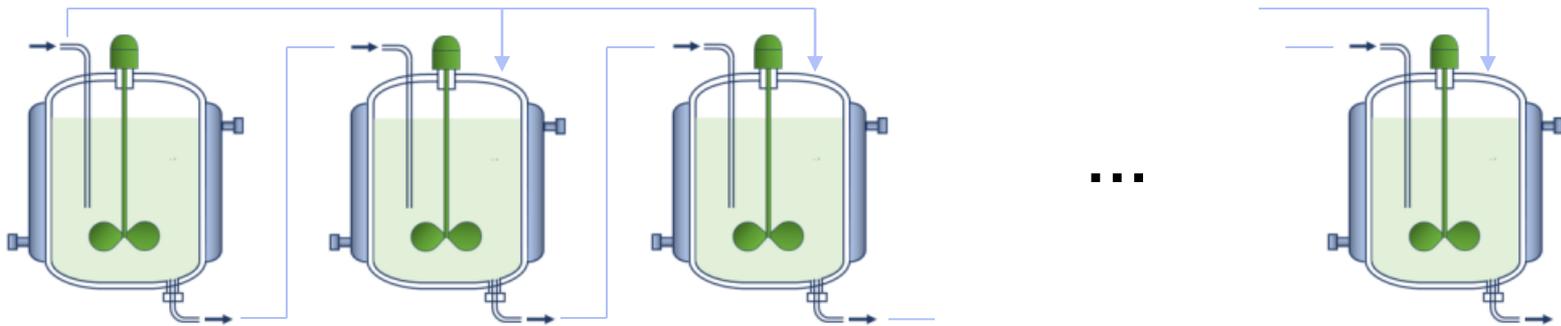




***Integrated system model development: MSMPR
cascade and it's applications***

MSMPR cascades

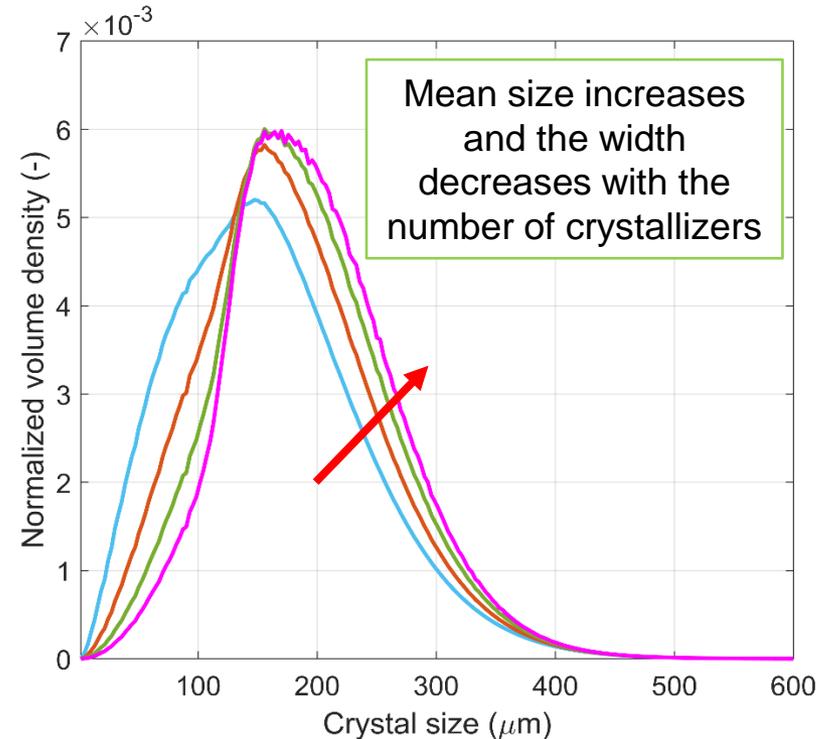
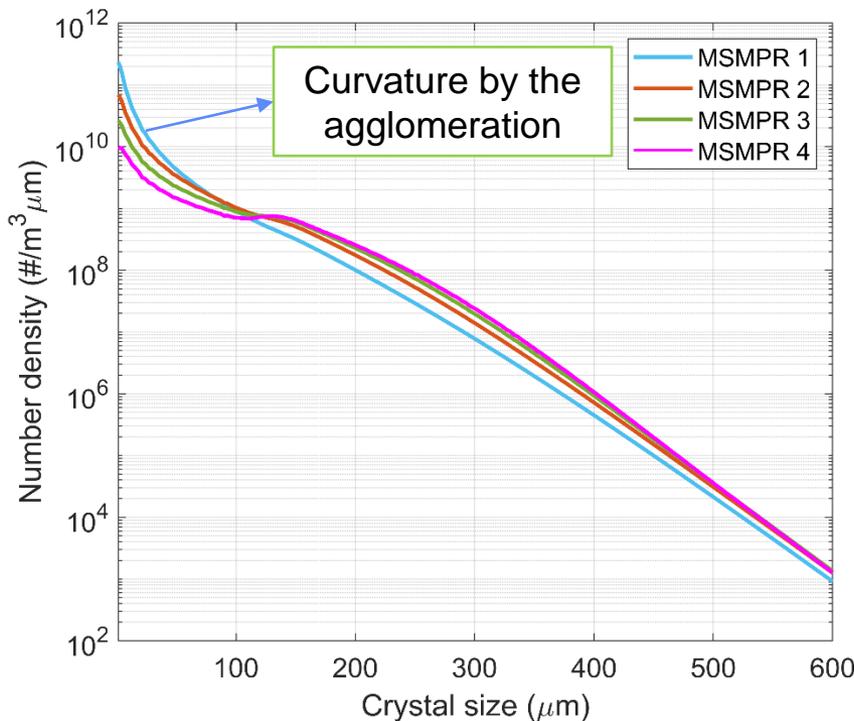
- ❑ First step in the flexible crystallization network development.
- ❑ Mechanisms: 1D nucleation, growth, dissolution, breakage, agglomeration
- ❑ System types: cooling, antisolvent, combined cooling and antisolvent



- ❑ Flexible number of crystallizers (no upper limit)
- ❑ Operating conditions configured individually for each crystallizer

MSMPR cascades: modeling and simulation

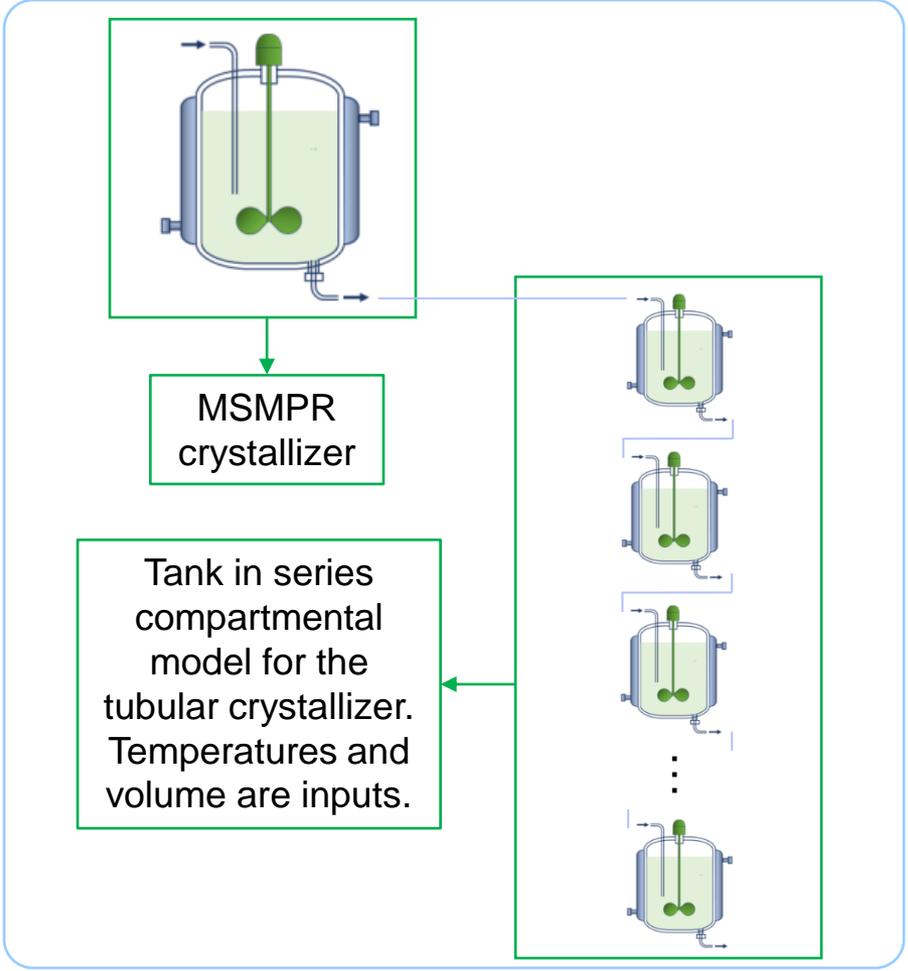
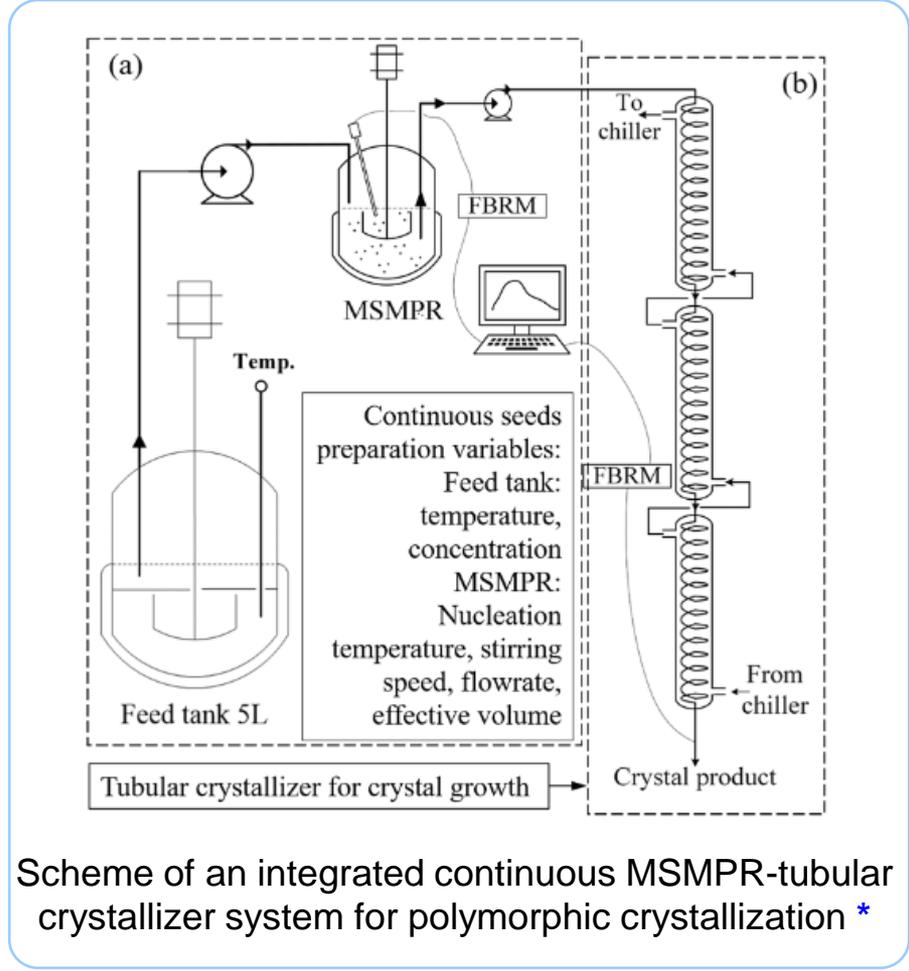
- ❑ Quick example: pure cascade of four MSMPRs. Model-equations were populated and solved automatically for each crystallizer
- ❑ Cooling crystallization with identical yields and mean residence times



Typical MSMPR cascade simulation with nucleation, growth, agglomeration and size dependent breakage (~ 10 s, $3 \mu m$ grid size, $2400 \mu m$ max. size)

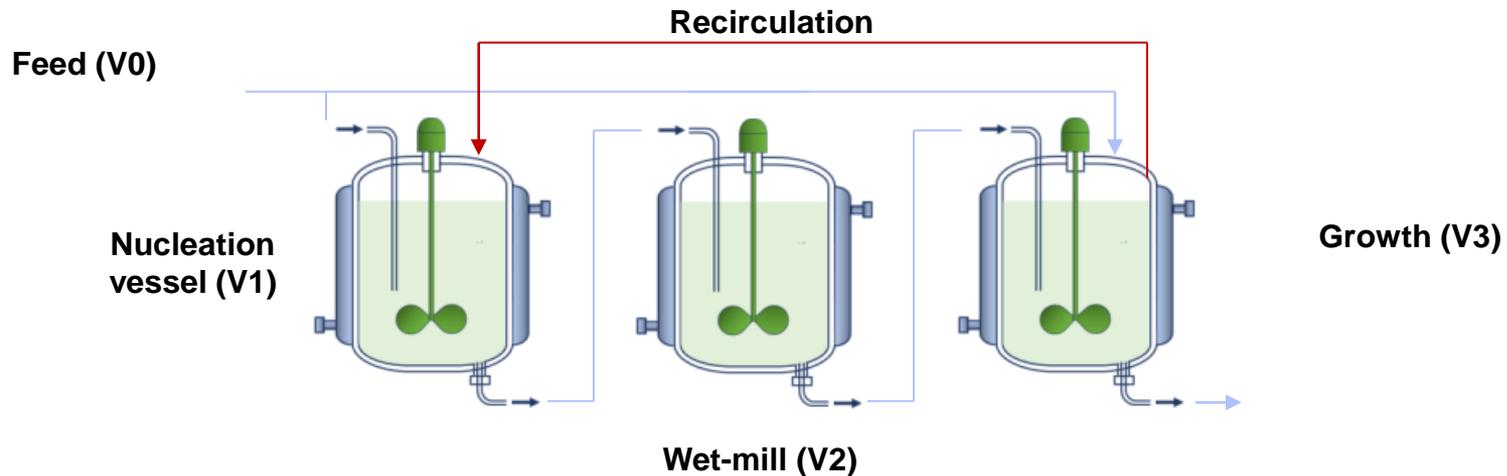
Flexible MSMPR cascade model: further applications

- Integrated MSMPR-tubular crystallizers are promising devices. In MSMPR in-situ seed generation happen.



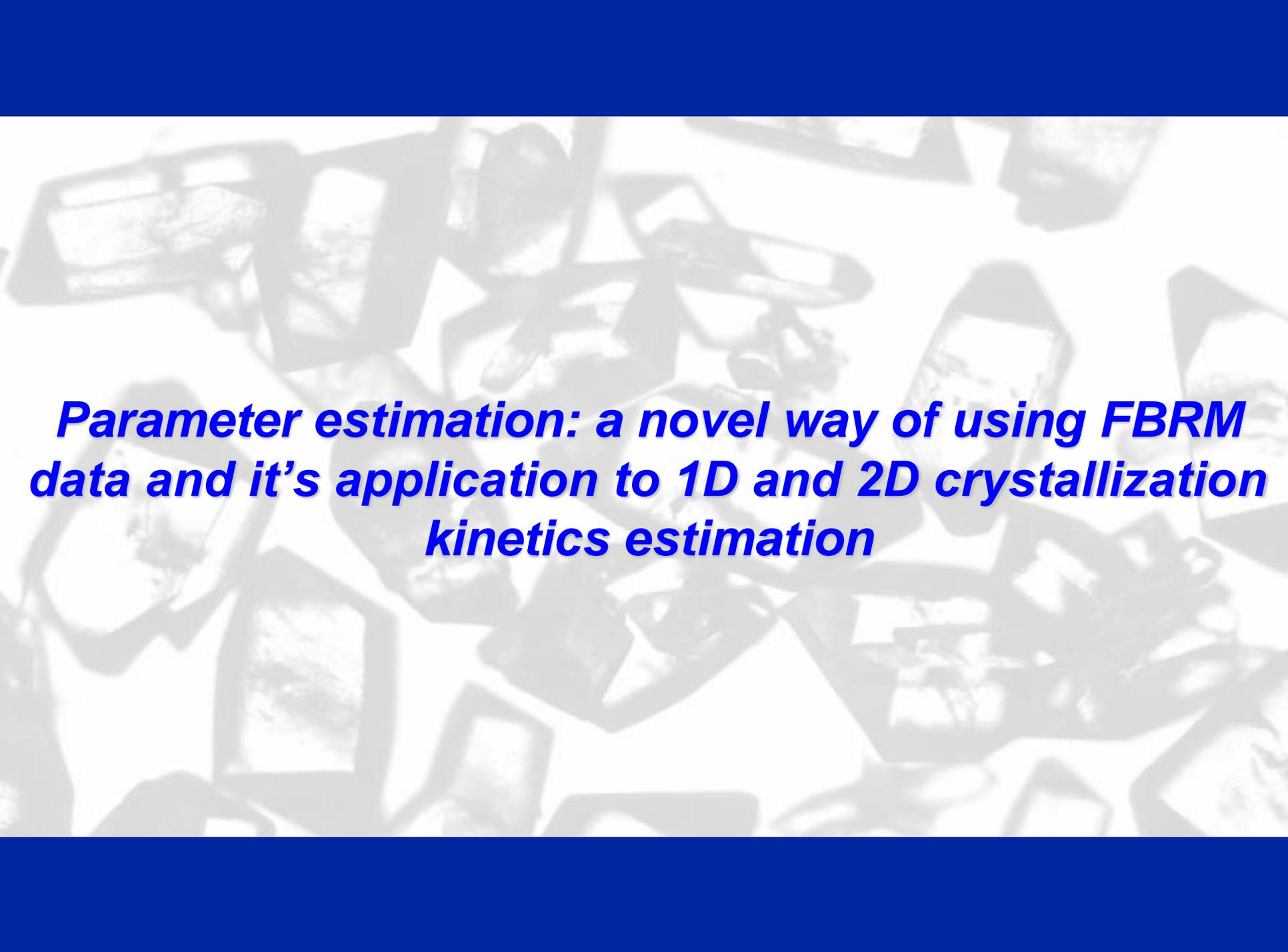
Extension to MSMPR network (in progress)

- ❑ Model-equations populated based on adjacency matrices that defines the connectivity
- ❑ The active crystallization mechanisms set for each MSMPR



	V0	V1	V2	V3
V0	0	1	0	1
V1	0	0	1	0
V2	0	0	0	1
V3	0	1	0	0

- *Example:* definition of connectivity between the MSMPRs
- “1” in a cell means that there is a flux from the crystallizer in the given line to the crystallizer of the given column
- Similar adjacency matrices are applicable for the definition of other operating conditions (e.g. flowrates)

The background of the slide is a grayscale micrograph showing a dense collection of various crystalline particles. These particles exhibit a wide range of shapes, including rectangular, hexagonal, and irregular forms, some with distinct facets and sharp edges. The particles are scattered across the field of view, with some appearing larger and more prominent than others. The overall appearance is that of a complex, multi-phase crystalline material.

Parameter estimation: a novel way of using FBRM data and its application to 1D and 2D crystallization kinetics estimation

How to use the FBRM count data for PE?

Repeating question, because:

- FBRM became routine tool in crystallization monitoring
- Great for qualitative measurements, indirect feedback control on particle size (DNC)
- Difficult to quantify
- Inaccurate CSD-CLD transformations
- Generally not used for PE

$$O(KP) = f(\Delta C) + wf(\Delta D) + uf(\Delta N)$$

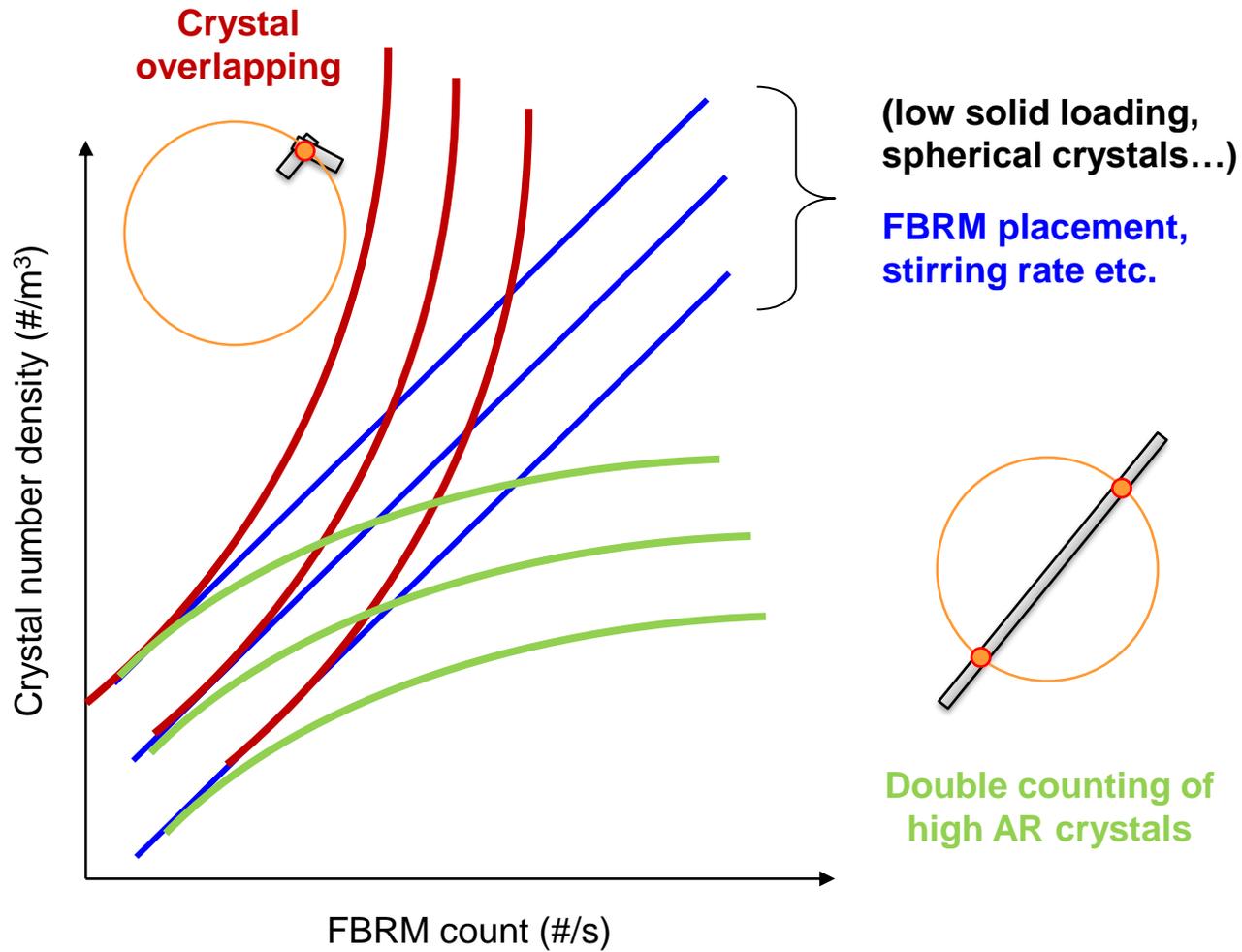
ΔC sum-squared error of concentrations

ΔD sum-squared error of CSDs

ΔN FBRM term (generally not used)



Correlation between count and number density?



How to use the FBRM data for PE?

Repeating question, because:

- FBRM became routine tool
- Great for qualitative measurements
- Hard to quantify
- Inaccurate CSD-CLD transformations
- Generally not used for PE

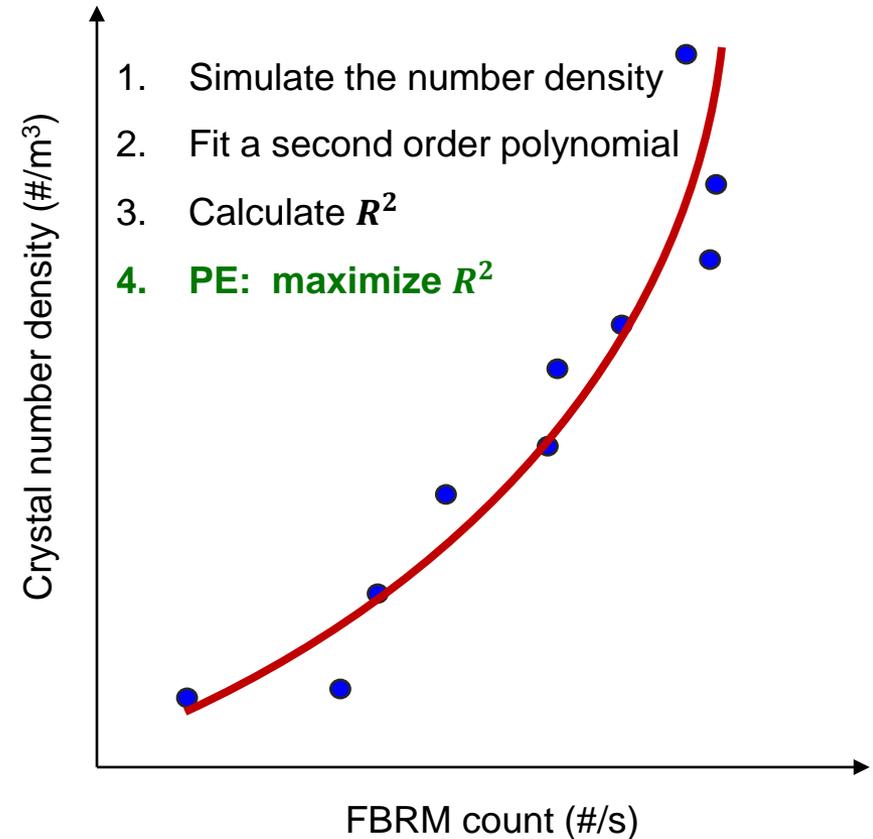
$$O(KP) = f(\Delta C) + wf(\Delta D) + uf(\Delta N)$$

ΔC sum-squared error of concentrations

ΔD sum-squared error of CSDs

ΔN FBRM term (generally not used)

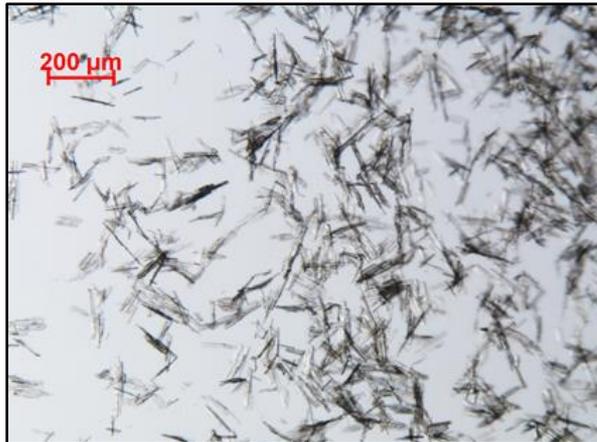
$$\Delta N = -R^2$$



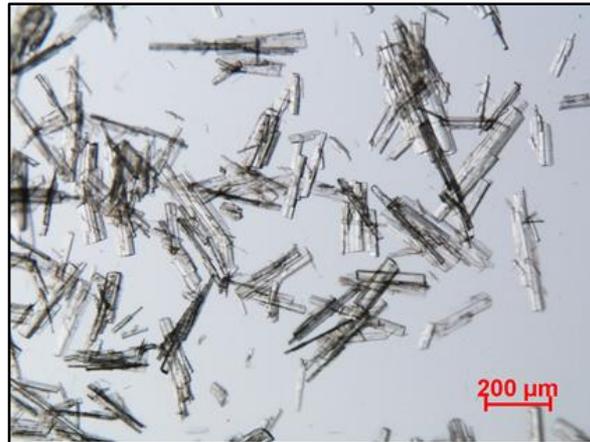
New assumption: The FBRM count correlates with the true number density, which can be captured with a second order equation

Crystallization kinetics of a model API: 1D case

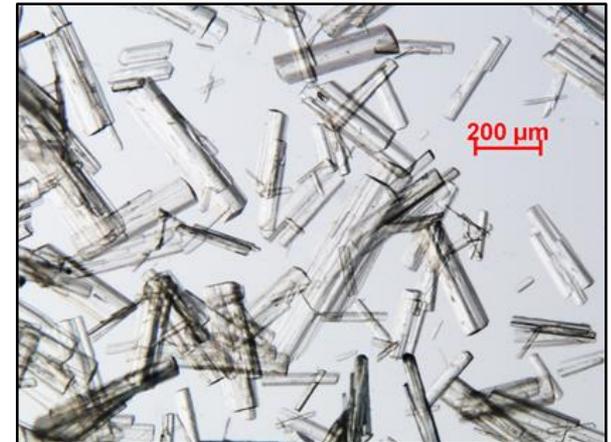
- ❑ 1D demonstration to introduce a novel size dependent growth expression and the count correlation based parameter estimation.
- ❑ Model API (“Compound A”, real API candidate).
- ❑ Slow-growing high aspect ratio crystals, nucleation-dominated process.
- ❑ Temperature cycles are required to obtain sufficiently large crystals.
- ❑ The model would enable direct optimization and *in-silico* DOEs



Linear cooling *



One temperature cycle *



Three temperature cycles *

Numerical solution: 2D HR-FVM

□ 1D PBM with nucleation and growth

$$\frac{\partial n(L, t)}{\partial t} + \frac{\partial G(S)n(L, t)}{\partial L} = B(S)\delta(L - L_n)$$

□ Numerical solution: HR-FVM on non-uniform grid

□ The kinetics (fitting parameters)

$$B = k_b \sigma^b V_c$$

$$D = k_d \sigma (1 + d_d L)^{-d_e}$$

$$G = k_g \sigma^g \exp\left(-\frac{E_A}{RT}\right) G(L)$$

Size dependent growth models
generally used to fit steady-state
MSMPR CSD data

Model 1: $G(L) = (1 + c_1 L)^{c_2}$

Model 2: $G(L) = 1 - \exp(-c_1(L + c_2))$

Model 3: $G(L) = 0.5(\tanh(c_1(L - c_2)) + 1)$

Model 4: $G(L) = 0.5(\tanh(c_1(L - c_2)) + 1)(1 + c_3 L^{c_4})$

Size dependent growth
models proposed in this case
to capture size dependency in
the Kolmogorov scale

Crystallization kinetics of a model API: 1D case

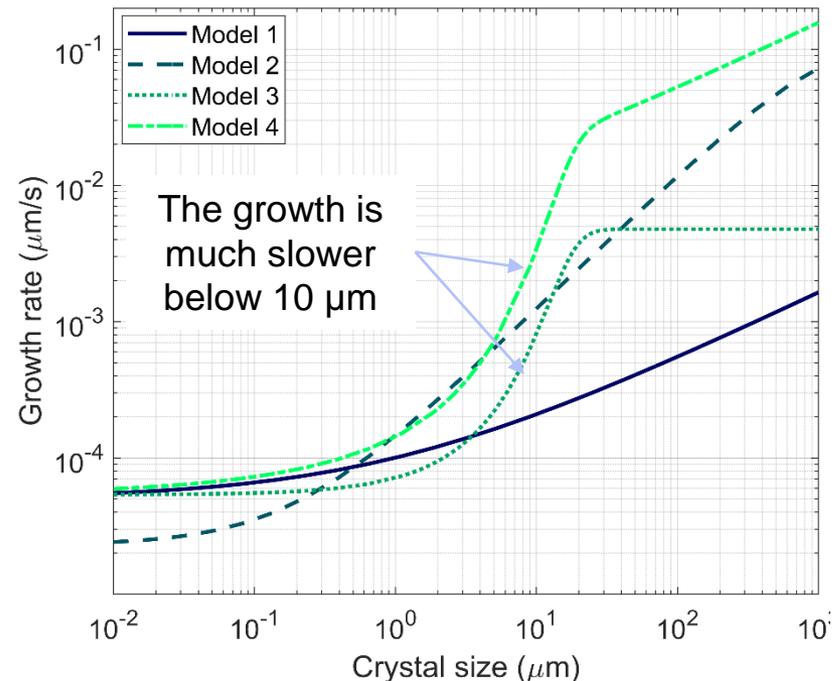
- PE using 6 calibration and 2 validation experiments.

$\min_{P \in \mathcal{R}_+^0} O(P)$	With FBRM data				Without FBRM data			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Calibration	29237.2	2682.7	495.0	232.6	11543.6	1804.3	278.8	129.3
Validation	6018.6	1462.8	212.9	90.0	4593.8	1083.3	145.1	67.1

Much narrower CI-s for Model 4 by FBRM

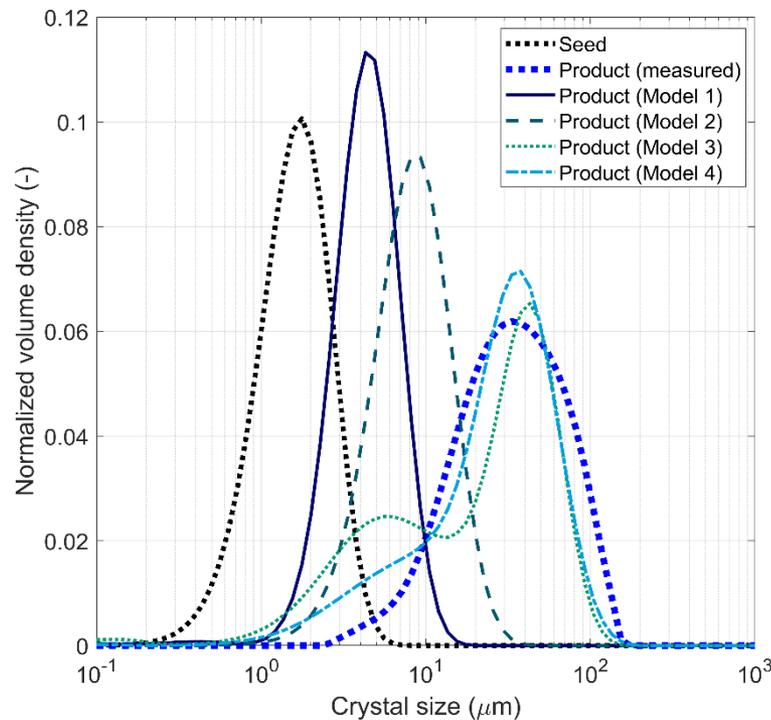
Parameter	Nominal parameters (\pm C.I. limits)	
	W.O. FBRM	W. FBRM
$\log_{10}(k_s)$	-2.77 ± 8.6	-3.06 ± 0.21
s	2.19 ± 14.0	2.25 ± 0.37
$\log_{10}(k_g)$	10.83 ± 53.5	10.79 ± 0.79
g	1.12 ± 4.9	1.04 ± 0.17
$\log_{10}(E_A)$	4.91 ± 2.0	$4.92 \pm 2.4 \cdot 10^{-2}$
$\log_{10}(c_3)$	-0.75 ± 0.74	-0.90 ± 0.39
c_4	0.97 ± 0.17	0.84 ± 0.14
$\log_{10}(c_1)$	$0.77 \pm 7.0 \cdot 10^{-2}$	$0.84 \pm 2.0 \cdot 10^{-2}$
$\log_{10}(c_2)$	Quasi size-independent dissolution	
$\log_{10}(k_d)$	Quasi size-independent dissolution	
$\log_{10}(d_d)$	$-3.10 \pm 2.2 \cdot 10^4$	-3.19 ± 105.6
d_e	$1.2 \cdot 10^{-3} \pm 61.76$	1 ± 237.6

Different SDG shapes in the small range

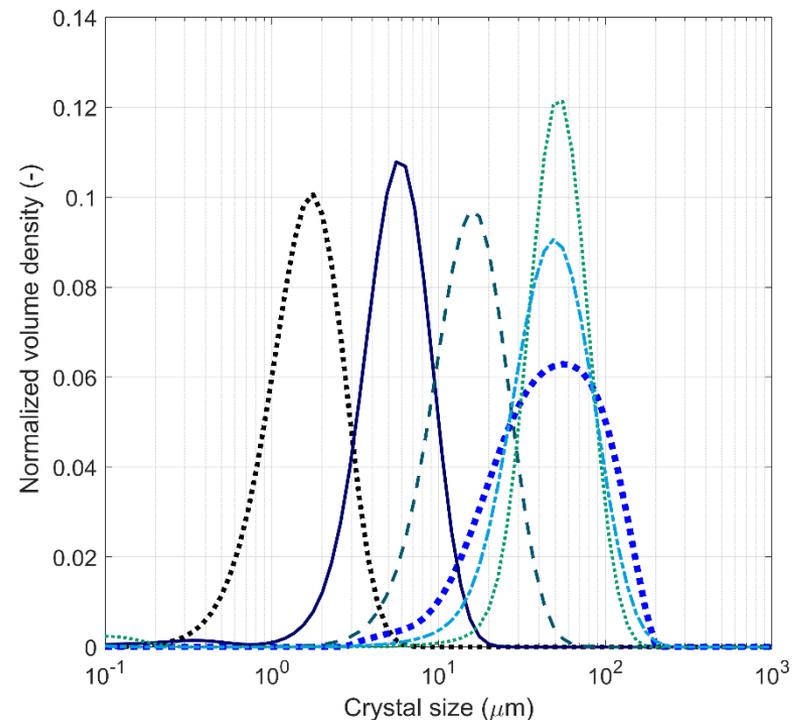


Crystallization kinetics of a model API: 1D case

- ❑ Hyperbolic tangent growth models (Model 3 and Model 4) gave superior performance compared to the traditional SDG models.
- ❑ Model 1-3 has the same number of parameters (no over-fitting).



Validation experiment # 1: simulated and measured product CSDs



Validation experiment # 2: simulated and measured product CSDs

The need for a 2D model in this case

Mean aspect ratio of product crystals obtained in different experiments.

There is a strong variation.

Expt. #	Seed type	Product mean AR
1	Type 1	7.78
2		7.33
3		4.81
4		6.25
5	Type 2	4.79
6		4.41
7		4.48
8	Type 3	3.62
9		4.91
10		5.44

Nucleation:

$$B = k_b \sigma^b V_c$$

The growth rate equation:

$$G_i = G(L_1, L_2) k_{g,i} \sigma^{g_i} \exp\left(-\frac{E_A}{RT}\right)$$

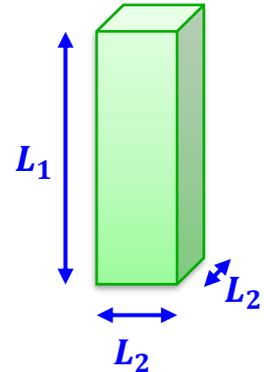
$$G(L_1, L_2) = 0.5(\tanh(c_1(D_e - c_2)) + 1)(1 + c_3 D_e^{c_4})$$

$$D_e = \frac{6}{\pi} \sqrt[3]{k_v L_1 L_2^2}$$

Dissolution:

$$D_i = D(L_1, L_2) k_{d,i} \sigma$$

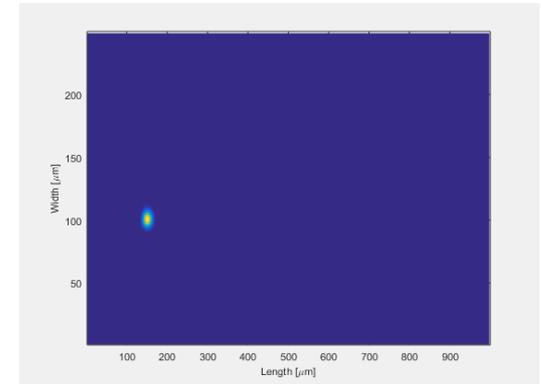
$$D(L_1, L_2) = \frac{1}{(1 + d_d D_e)}$$



Numerical solution: 2D HR-FVM

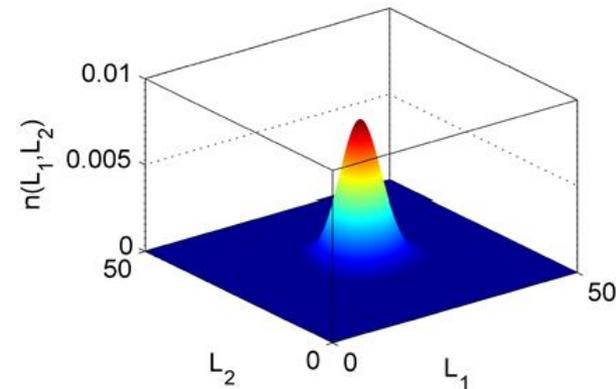
2D PBM with Nucleation and Growth

$$\begin{aligned} & \frac{\partial n(L_1, L_2, t)}{\partial t} + \frac{\partial G_1(S)n(L_1, L_2, t)}{\partial L_1} \\ & + \frac{\partial G_2(S)n(L_1, L_2, t)}{\partial L_2} \\ & = B(S)\delta(L_1 - L_{1n})(L_2 - L_{2n}) \end{aligned}$$

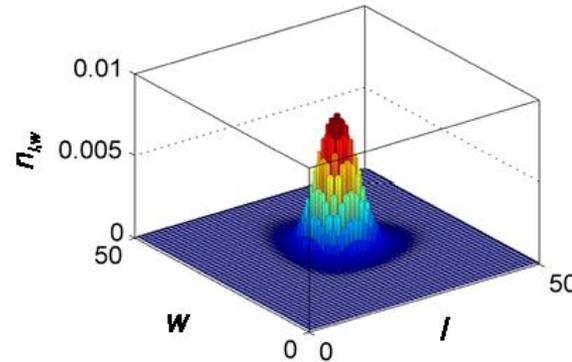


2D CSD dynamics in seeded batch crystallization with N and 2D Growth

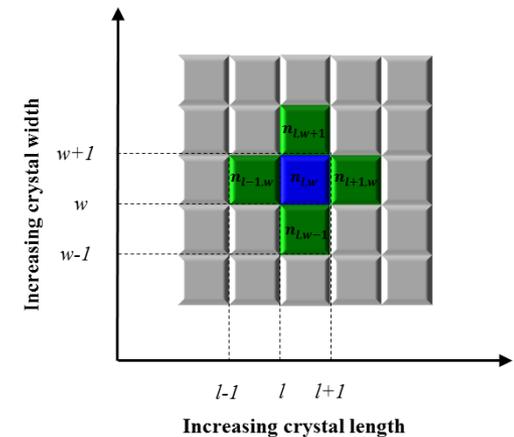
Numerical solution: 2D HR-FVM on GPU



Step 1. Continuous 2D population density function (PDF)



Step 2. Finite volume discretization of the 2D PDF



Step 3. Number balance based on PBM for every cell

Crystallization kinetics of a model API: 2D case

Proposed objective function for 2D parameter estimation

$$O(KP) = f(\Delta C) + wf(\Delta D) + uf(\Delta L) + zf(\Delta N)$$

Concentration
fit

CSD
fit

Shape
fit

Count correlation
maximization

Why these many terms?

$f(\Delta C)$: coupled N , G_1 and G_2 information

$f(\Delta D)$: partly decouples N from G_1 and G_2

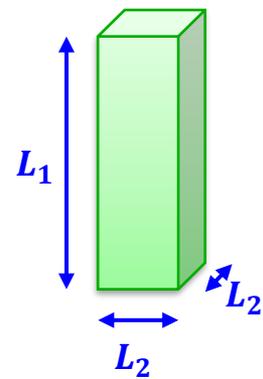
$f(\Delta L)$: provides relative G_1 and G_2 information

$f(\Delta N)$: influenced majorly by N and fines dissolution

However, there is also more sensor-specific error...

Seed CSD approximation

- 2D CSD of seeds must be approximated from 1D size and shape measurement (inverse problem)
- Solved by optimization, assuming sum of 2D correlated normal distributions

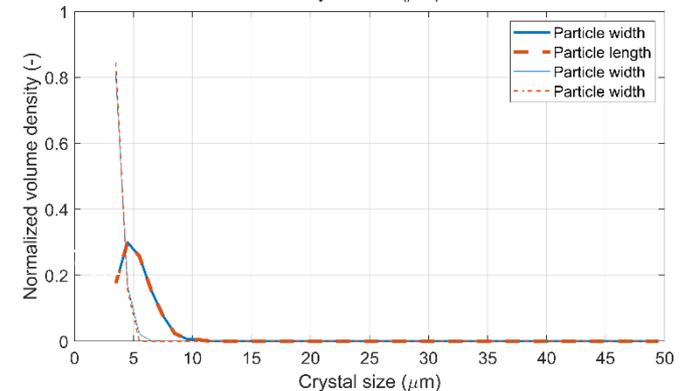
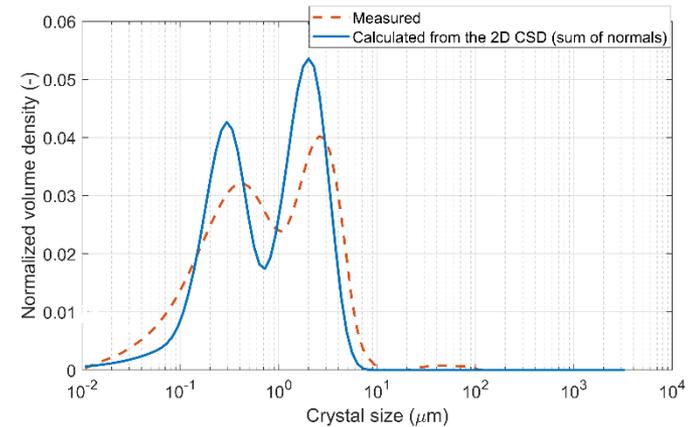
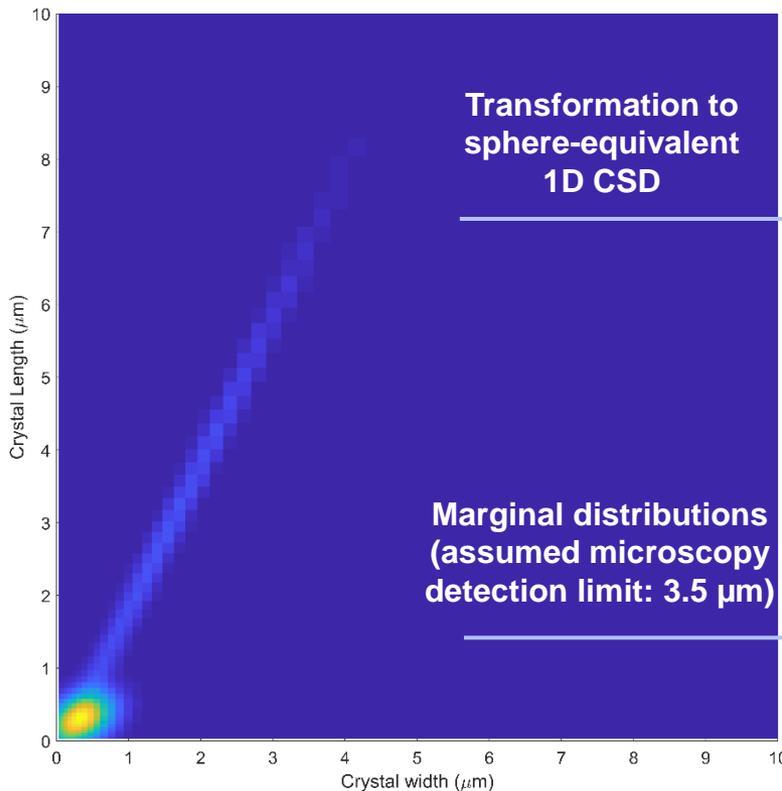


$$V_{Cr} = k_V L_1 L_2^2$$

$$n_0 = n_{0,1} + w n_{0,2}$$

$$k_V = 0.153$$

$$w = 4.98$$



2D case, intermediate results

- 2D crystallization kinetics: dissolution and size dependent growth along the length and with was considered in the first step
- Under extension to nucleation rate model

The considered size dependent growth rates:

$$G_i = G k_{g,i} \sigma^{g_i} \exp\left(-\frac{45000}{RT}\right)$$

$$G = 0.5(\tanh(c_1(D_e - c_2)) + 1)(1 + c_3 D_e^{c_4})$$

D_e is the sphere-equivalent diameter:

$$D_e = \frac{6}{\pi} \sqrt[3]{k_v L_1 L_2^2}$$

The considered size independent dissolution rates:

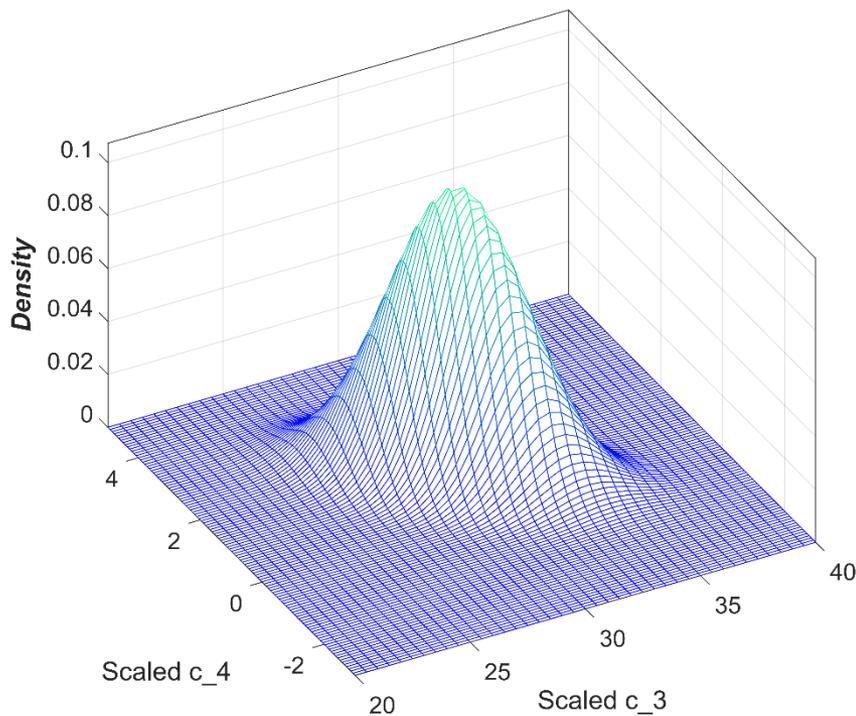
$$D_i = k_{d,i} \sigma$$

Nominal values and 95 % confidence interval limits *

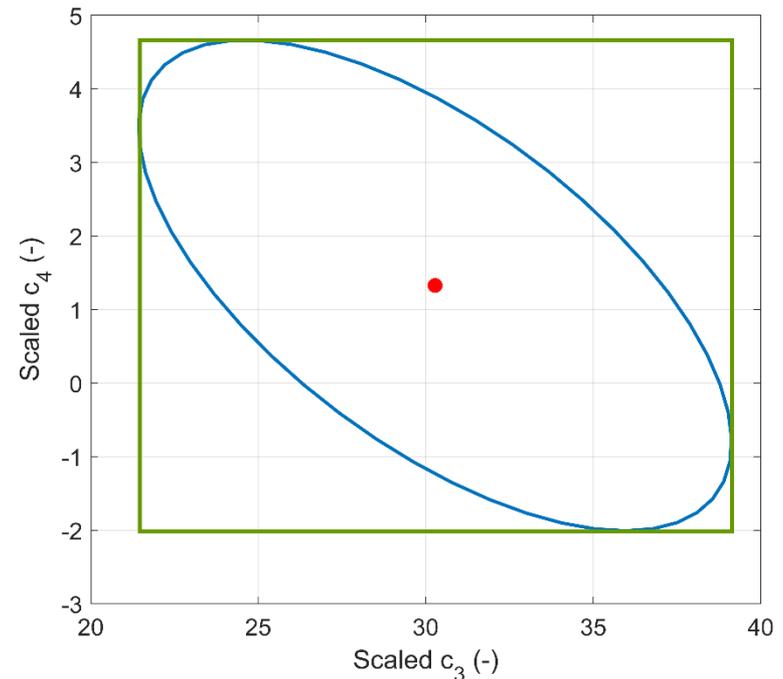
P	Nom.	L.B.	U.B.
$k_{g,1}$	110420	37229	327480
$k_{g,2}$	24429	5218	114370
g_1	1.80	1.34	2.25
g_2	1.42	0.98	1.86
$k_{d,1}$	0.032	0.02	0.51
c_1	0.072	0.054	0.097
c_2	14.02	9.60	20.47
c_3	2.99	1.25	7.16
c_4	0.807	0.51	1.14

2D case, intermediate results

- ❑ Basic uncertainty analysis (as we have many fitting parameters)
- ❑ Monte-Carlo sampling of kinetics assuming multivariable correlated normal CSD (left hand side figure). 150 random kinetic parameter combinations

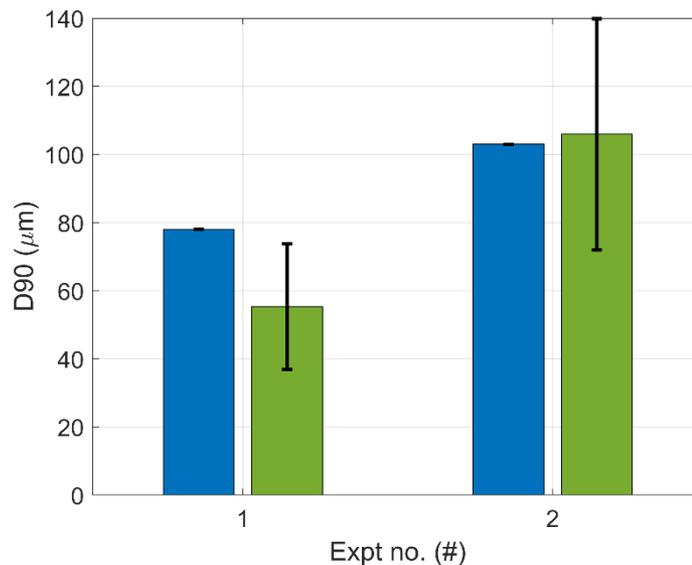
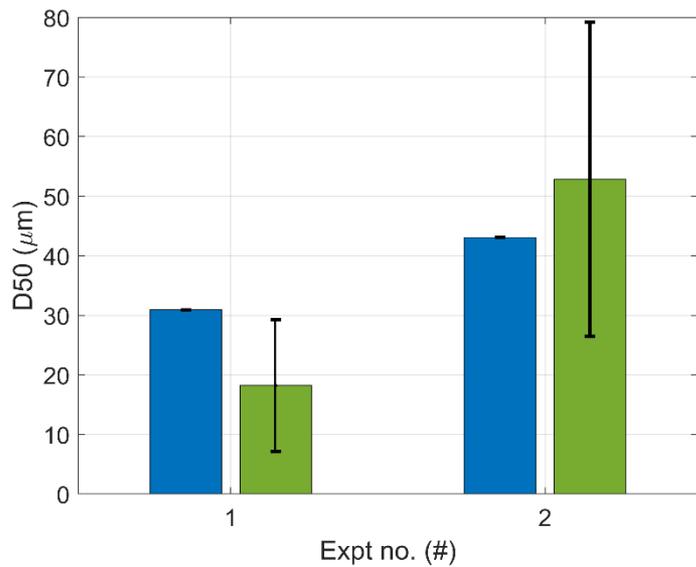
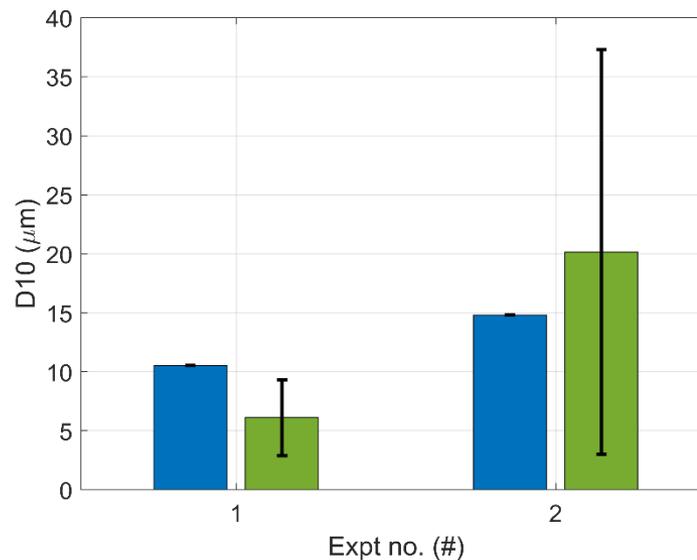
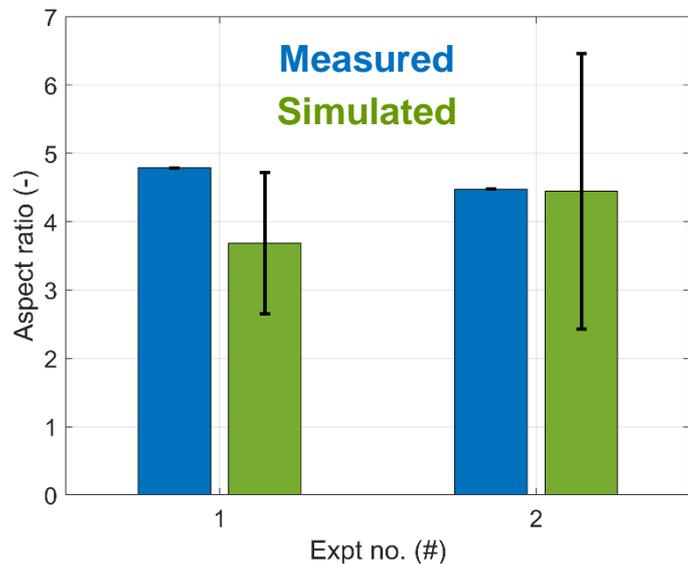


Correlation between c_3 and c_4



Nominal value, confidence ellipsoid and box (confidence intervals)

2D case, intermediate results. Validation runs



Short term plans (~1 year)

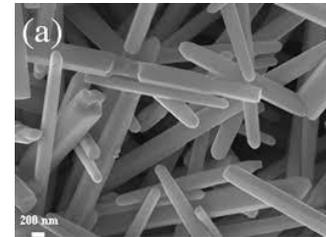
Flexible MSMPR network

... with dedicated wet-mills and recirculation streams



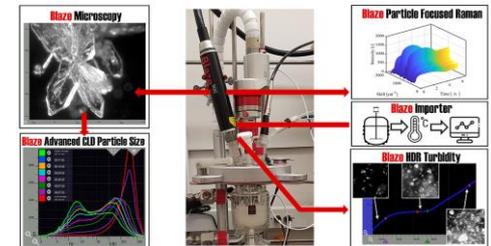
2D crystallization

... Finishing the 2D parameter estimation



Blaze probe acquisition

... and comparing it to the Metler's EasyViewer probe



A Holistic Approach for the Model-based Control of Crystal Size, Shape and Purity in Integrated Batch and Continuous Crystallization - Wet Milling Systems

Botond Szilagyi, Zoltan K. Nagy

**School of Chemical Engineering
Purdue University, West Lafayette, IN**

PURDUE
UNIVERSITY