



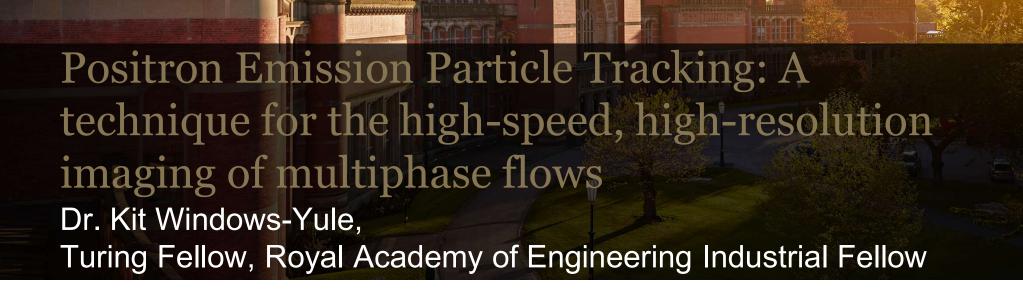




Engineering and Physical Sciences Research Council



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# **Overview & Motivation**



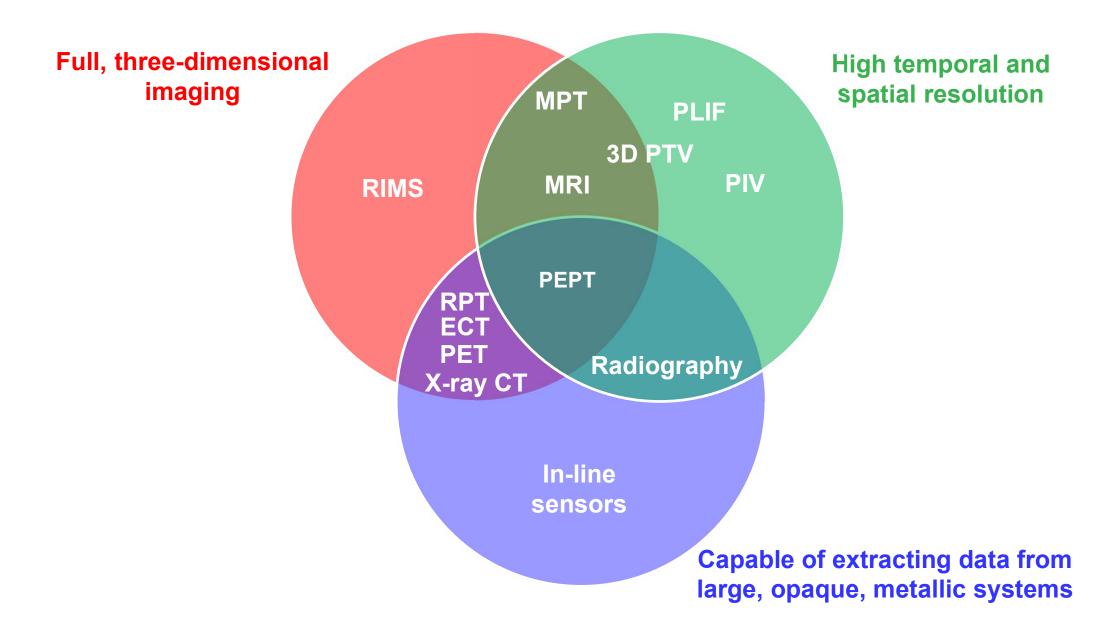
### How do we better understand industrial systems?

- Understanding the dynamics of multiphase flows is crucial to the optimisation of diverse process equipment
- ...but these large, metal systems are near-impossible to accurately image using conventional methods



How do we better understand industrial systems?

- Numerical methods (DEM, CFD, MP-PIC...) can provide insight
- But without experimental validation, simulations may be misleading
- → We still need to find a way to experimentally investigate these large, opaque systems!



Talk Overview







I) An Introduction to PEPT

II) Case Study

III) The Synergy of PEPT and Numerical Simulation





# 

# I. An Introduction to PEPT

## Positron Emission Particle Tracking (PEPT)

Uses highly-penetrating gamma radiation to **directly track** the three-dimensional motion of particulate, fluid and multiphase systems, with **high temporal and spatial resolution**.

Uses highly-energetic gamma rays, capable of penetrating opaque media, including aluminium and steel

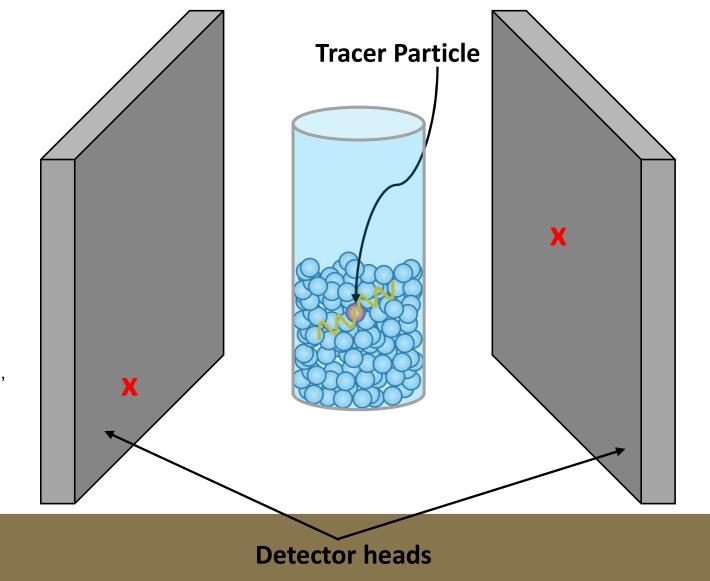
In essence, PEPT allows us to 'see inside' opaque systems.



## How does it work?

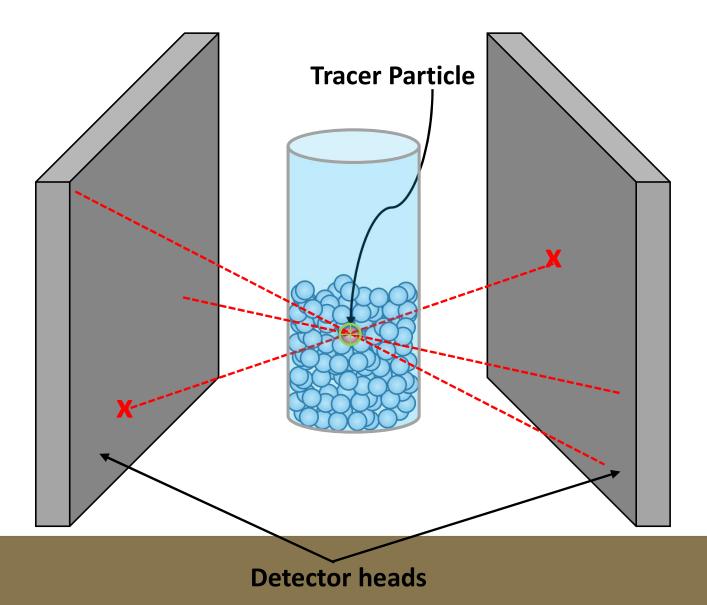
Windows-Yule, C. R. K., Seville, J. P. K., Ingram, A., & Parker, D. J. (2020).
Positron Emission Particle Tracking of Granular Flows. Annual Review of Chemical and Biomolecular Engineering, 11.

> UNIVERSITY<sup>of</sup> BIRMINGHAM



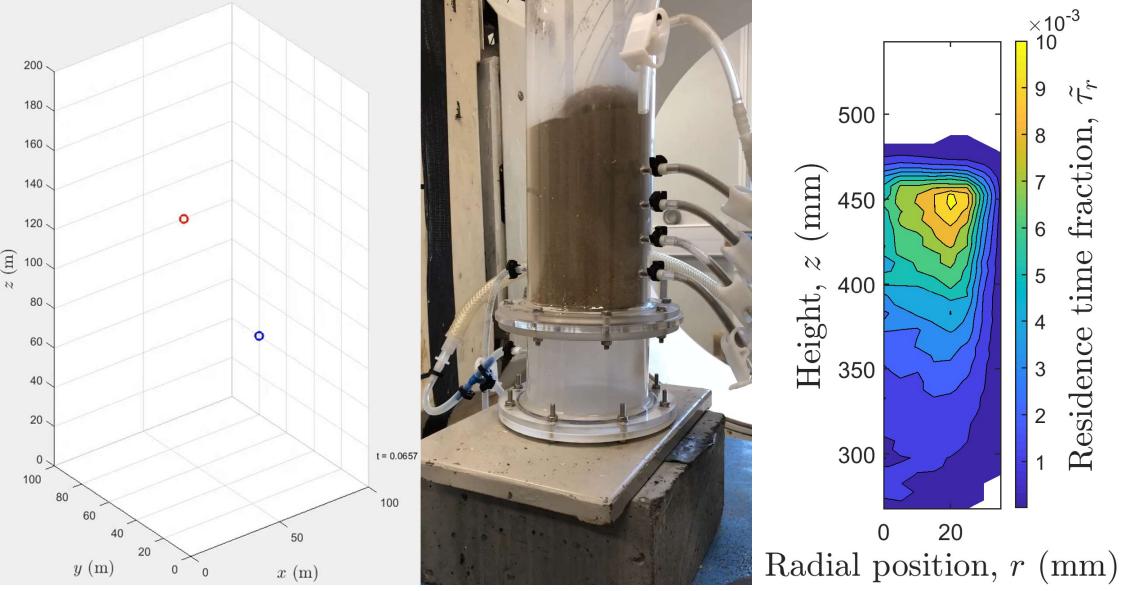
## How does it work?

Windows-Yule, C. R. K., Seville, J. P. K., Ingram, A., & Parker, D. J. (2020).
Positron Emission Particle Tracking of Granular Flows. Annual Review of Chemical and Biomolecular Engineering, 11.





### Example: PEPT imaging of a fluidised bed



# Example: PEPT imaging of a serious fluidised bed



Modular cameras provide additional, flexible imaging area

Main ADAC camera heads

Large, opaque vessel = 300 mm, H > 1 m) (D Solid steel walls

THE

ROYAL

SOCIETY





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# Example: PEPT imaging of a real, industrial fluidised bed



Featured in *Ingenia* magazine:

ACCES



THE

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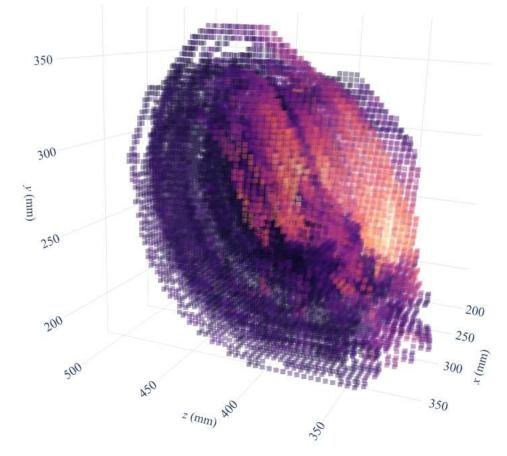




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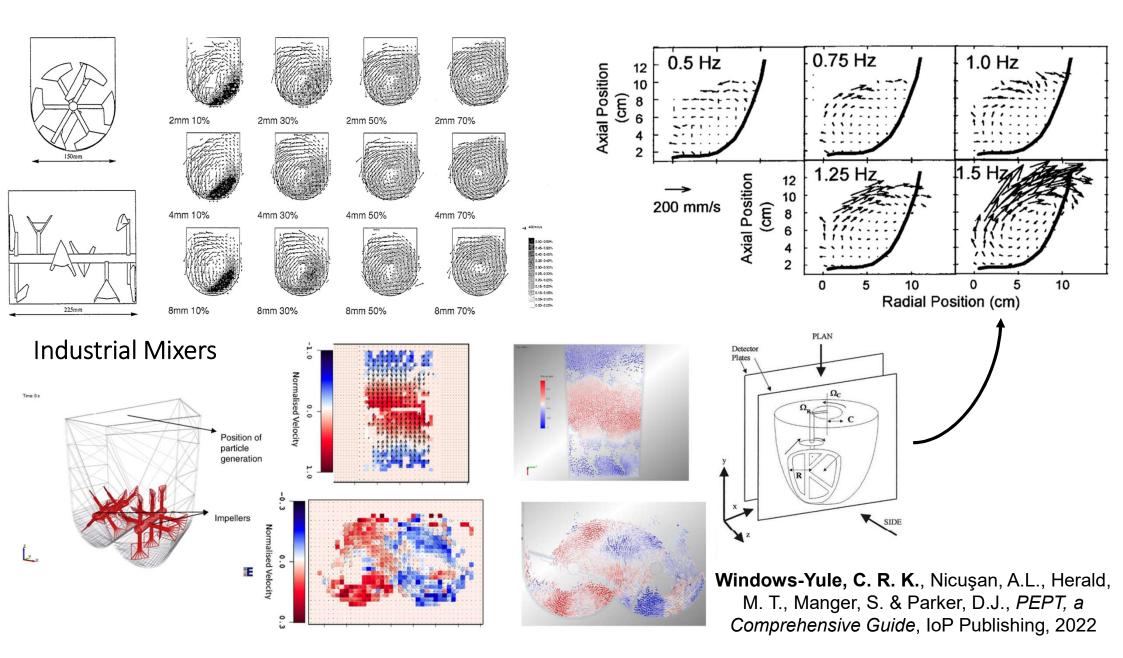


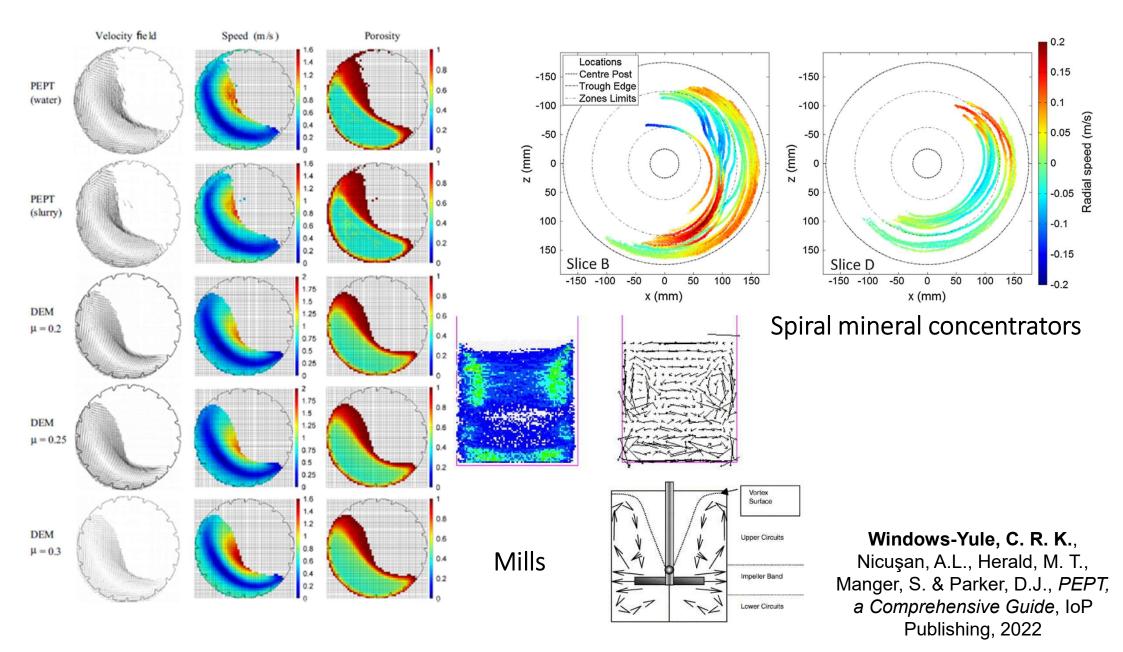
### High-resolution, three-dimensional data

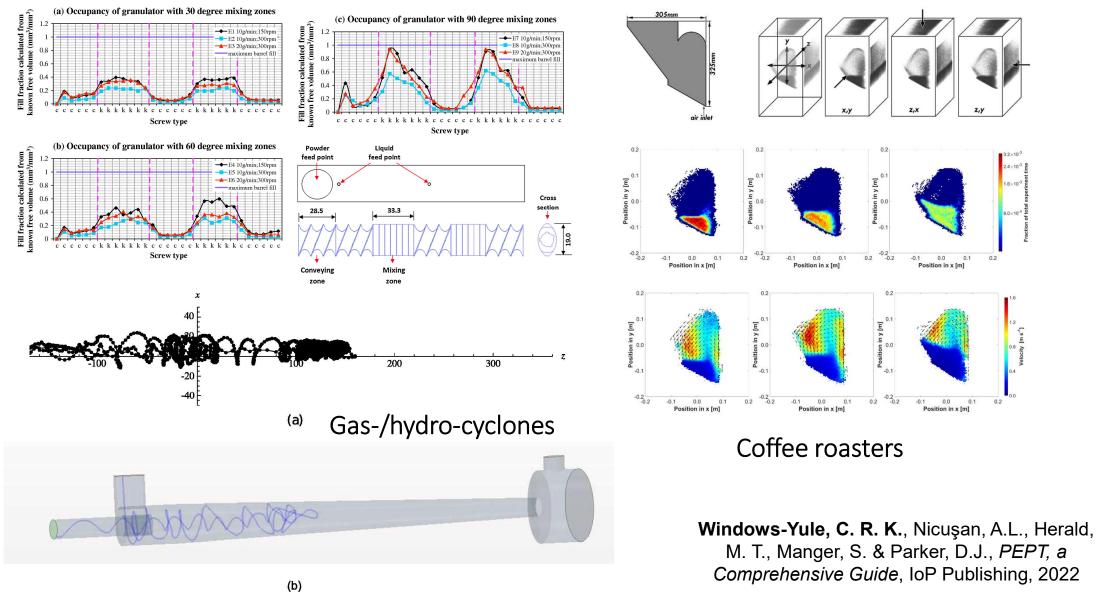


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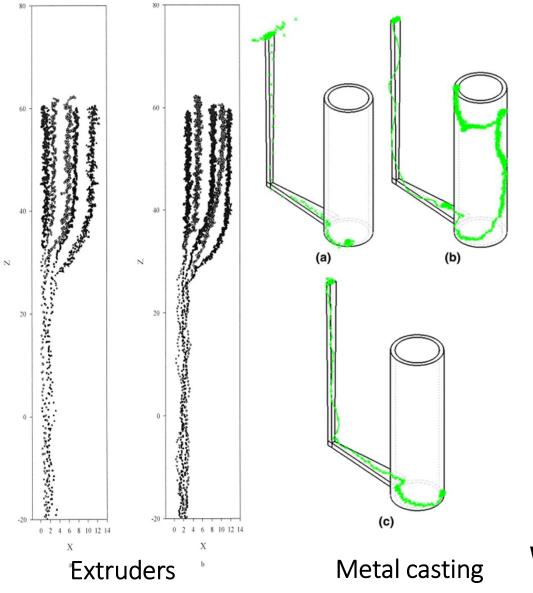


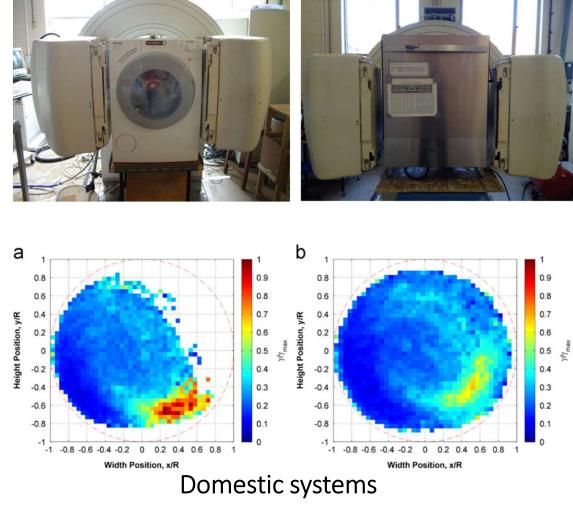






#### Twin screw granulators

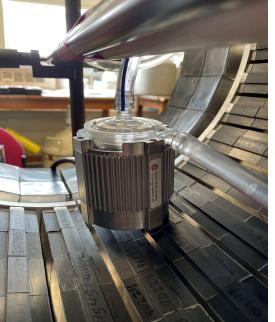


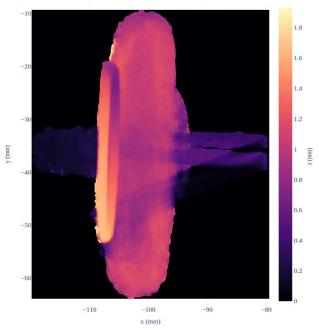


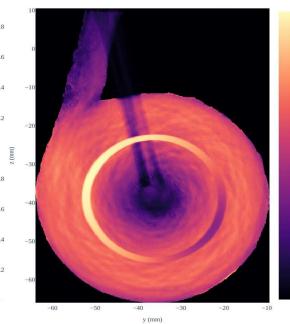
Windows-Yule, C. R. K., Nicuşan, A.L., Herald, M. T., Manger, S. & Parker, D.J., *PEPT, a Comprehensive Guide*, IoP Publishing, 2022



#### The human body?









1.6



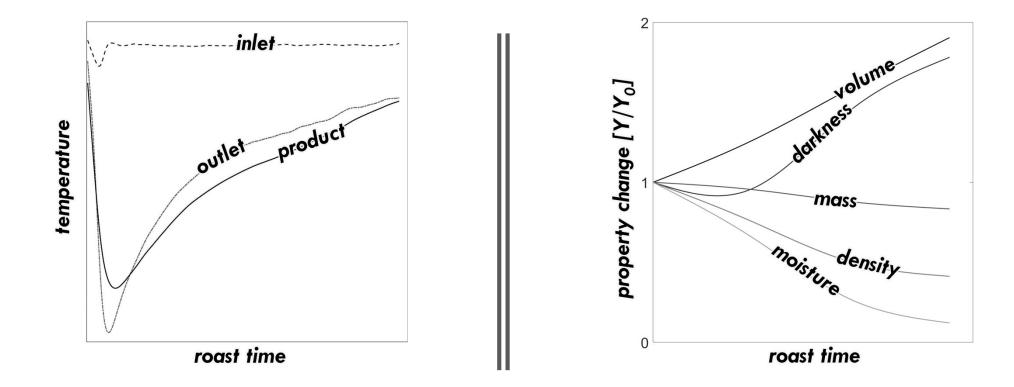


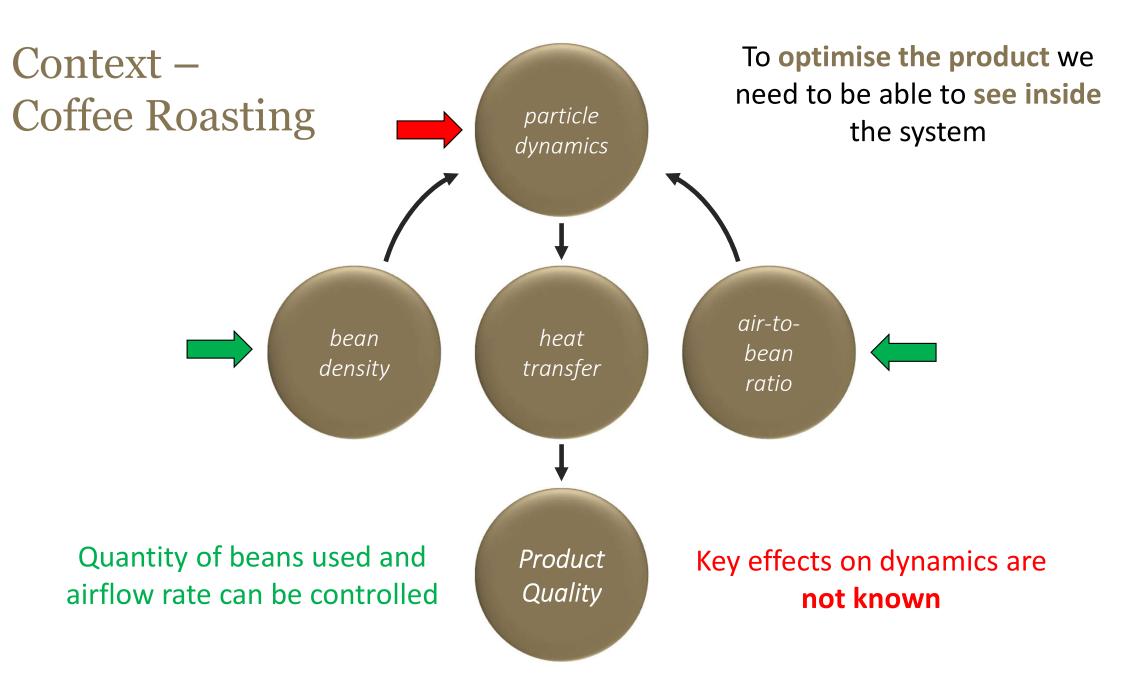


II. Case Study: Spouted Bed Coffee Roaster (Jacobs Douwe Egberts)

# Context – Coffee Roasting

Transformations during roasting



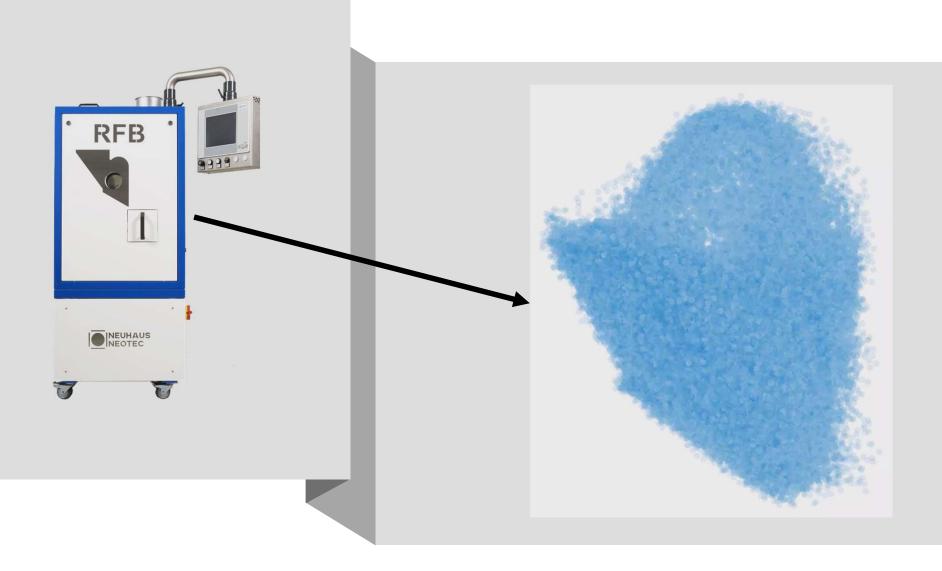






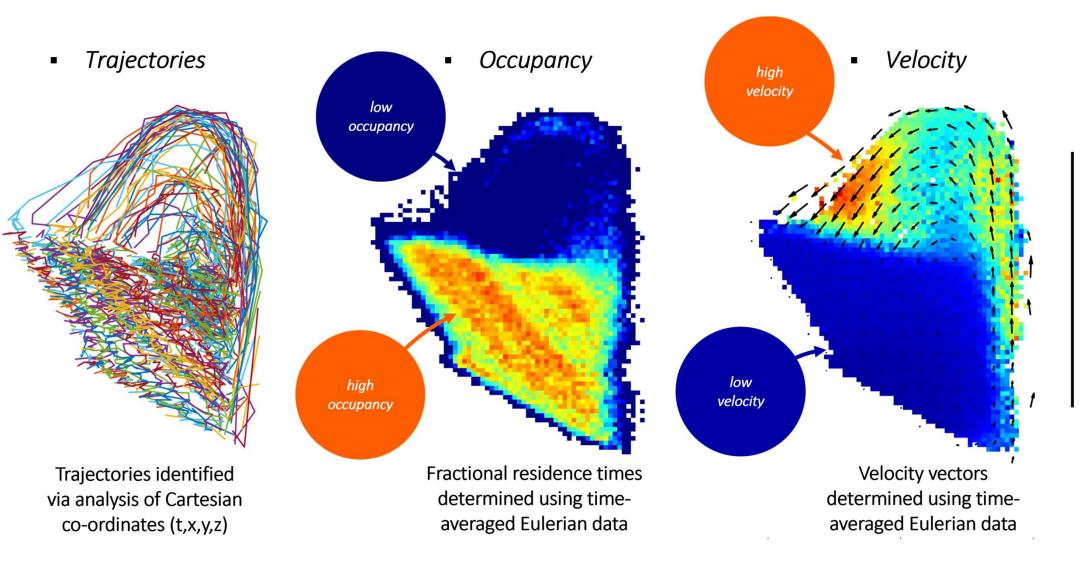


# Experimental set-up



# **Extracting Data from PEPT**

Al-Shemmeri, **Windows-Yule**, *et al.* (2021). Coffee bean particle motion in a spouted bed measured using Positron Emission Particle Tracking (PEPT). *Journal of Food Engineering*, 110709.

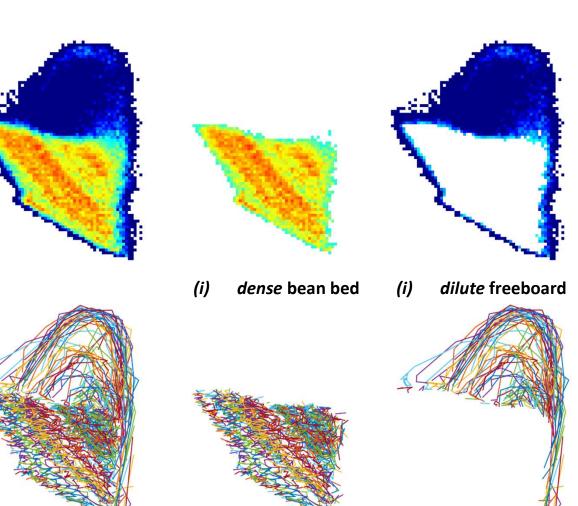


20cm

# **Extracting Data from PEPT**

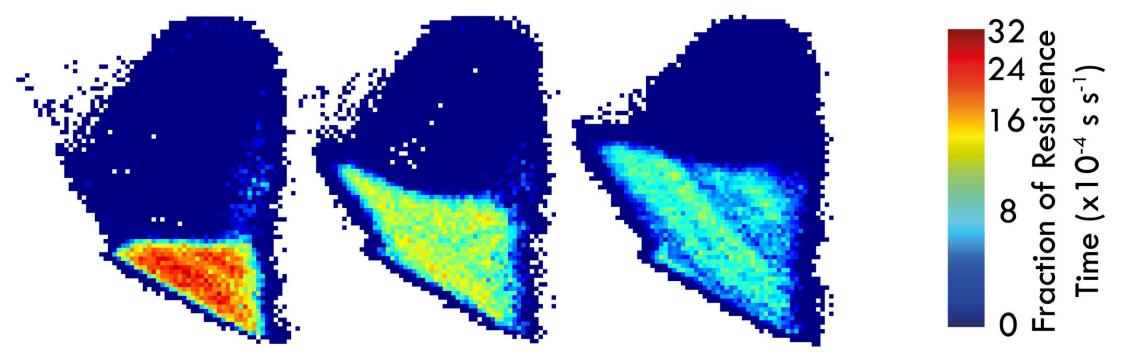
- Bean bed delineation
- Defined via Otsu method threshold
- Revealed Two distinct regions
  - (i) dense bean bed
    - □ Low velocity, high occupancy
    - Convective heat transfer limited
    - Lower temp. & heat transfer
  - (ii) dilute freeboard
    - □ high velocity, low occupancy
    - Convective heat transfer dominant
    - Higher temp. & heat transfer

Al-Shemmeri, **Windows-Yule**, *et al.* (2021). Coffee bean particle motion in a spouted bed measured using Positron Emission Particle Tracking (PEPT). *Journal of Food Engineering*, 110709.



## Results – Effect of batch size

Increasing batch size

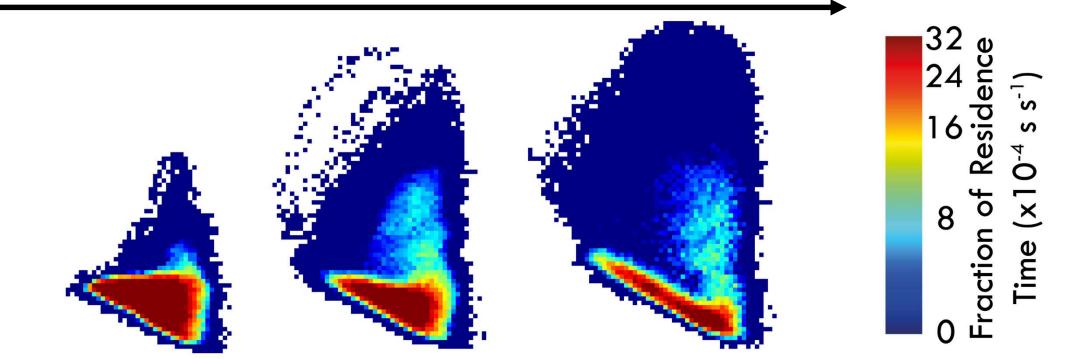


roasted coffee with an air velocity of 7.2 m s<sup>-1</sup>

Larger batch  $\rightarrow$  larger bed  $\rightarrow$  reduced heat transfer

# Results – Effect of batch size

Increasing air velocity



200g batches of green coffee roasted coffee with an air velocity of 7.2 m s<sup>-1</sup>

Higher air flow  $\rightarrow$  smaller bed  $\rightarrow$  improved heat transfer



# The Commercial Dilemma

#### Larger batch size

- Increased throughput
- Decreased heat transfer

#### **Increased** air flow

- Increased heat transfer
- Increased energy requirements

A complex optimization problem!



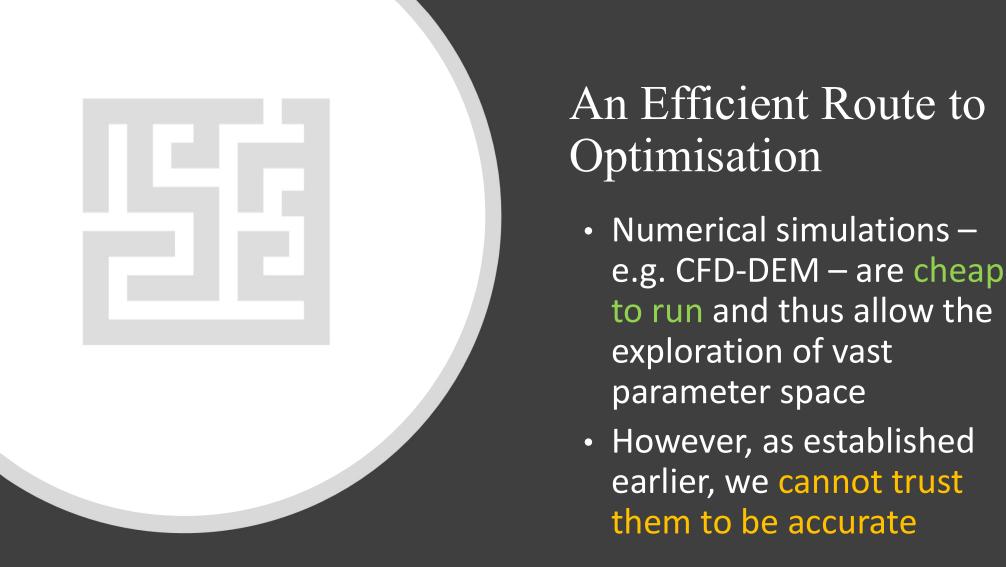


III. The Synergy of PEPT and Numerical Modelling



# An Efficient Route to Optimisation

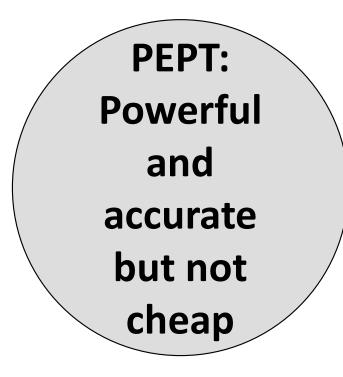
- Solving an optimisation problem requires a detailed exploration of the relevant parameter space
- (Lots of experiments!)
- Though powerful, PEPT facilities are rare, and thus oversubscribed – and the technique is costly to run



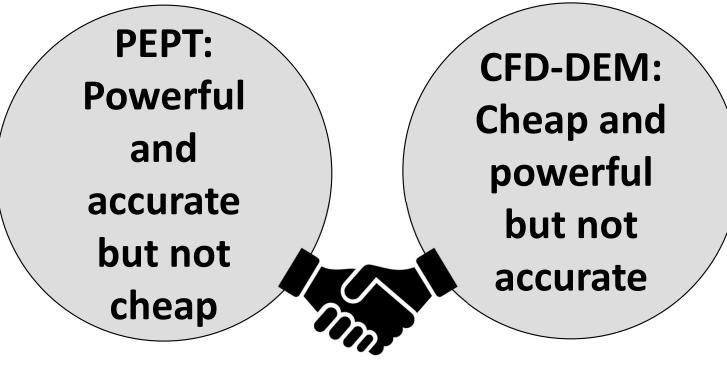
## PEPT as a Validation Tool

- PEPT can provide identical outputs to DEM, MP-PIC, CFD...
- → Facilitates detailed, multi-point comparison
   between experiment and simulation, considering local
   variations in key
   fields at all points in space
- → Uniquely comprehensive validation

# **Experiment** 0.02 -0.02 -0.04 Simulation



CFD-DEM: Cheap and powerful but not accurate

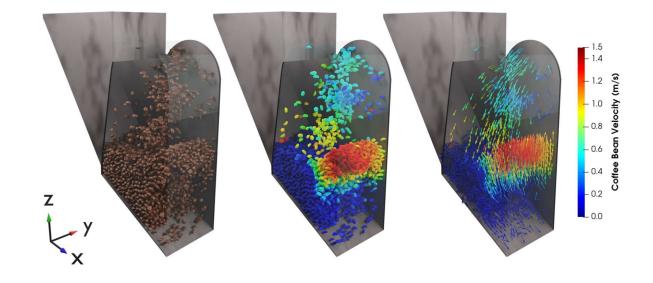


# **PEPT + CFD-DEM:** Powerful, accurate, and cost-effective

# Back to our Case Study



- CFD-DEM model of roaster
- 3D velocity & occupancy fields produced for both PEPT and CFD-DEM
- PEPT data and CFD-DEM data discretised on the same three-dimensional mesh



### **Comparing PEPT & CFD-DEM**

Occupancy:

Che, **Windows-Yule**, et al. (2023). PEPT validated CFD-DEM model of aspherical particle motion in a spouted bed. *Chemical Engineering Journal*, *453*, 139689.

2E-3 Solid velocity: 2.0 m/s0 **CFD-DEM** PEPT **CFD-DEM CFD-DEM CFD-DEM** Model 3 Model 4 Model 1 Model 2

Cell-by-cell comparison of multiple three-dimensional fields  $\rightarrow$  detailed, highly-rigorous validation of models used  $\rightarrow$  aid model choice.

# Rigorous, Quantitative Validation

Che, **Windows-Yule**, et al. (2023). PEPT validated CFD-DEM model of aspherical particle motion in a spouted bed. *Chemical Engineering Journal*, *453*, 139689.

Occupancy: 0.02 0.02 0.02 0.01 0.01 0.01 0.01 0.00 0.01 0.02 0.00 0.00 0.01 0.02 0.01 0.02 0.00 0.00 0.01 0.02 Solid velocity: 1.5 1.5 1.5 1.5 1.0 1.0 1.0 1.0 0.5 0.0 0.0 1.0 1.5 0.00.5 1.0 1.5 0.0 05 1.0 0.5 0.0 1.5 0.5 1.0 1.5 **CFD-DEM CFD-DEM CFD-DEM CFD-DEM** Model 3 Model 4 Model 1 Model 2 Model 2 Model 3 Model 4 Model 1 0.659 0.834 Occupancy 0.7330.867

0.930

0.913

0.903

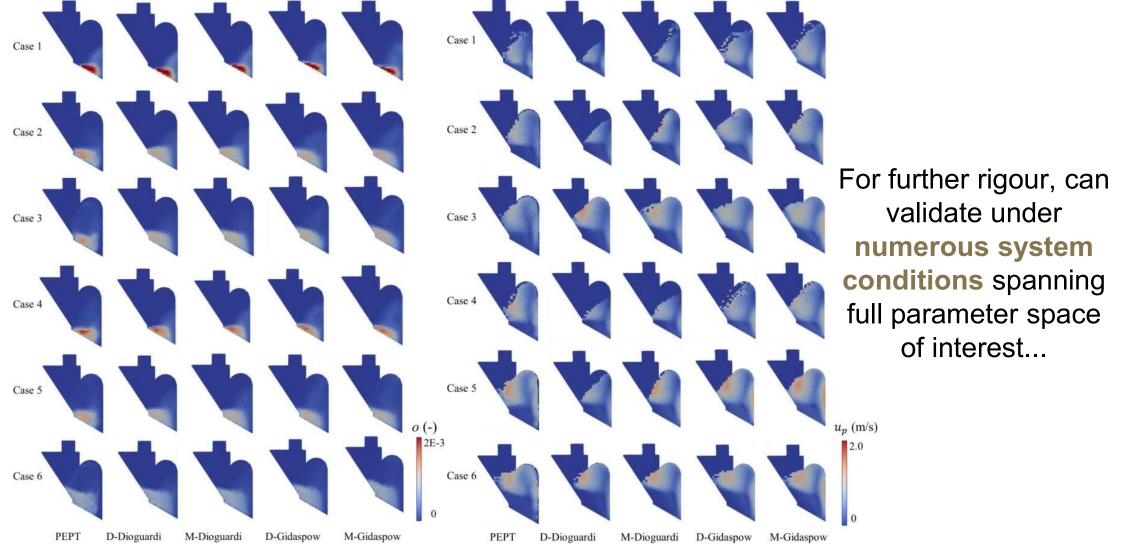
Velocity

0.942

- Simulation accuracy can be **quantitatively assessed** through Pearson coefficient (or others statistical measures)
- Pearson coefficient can also be used as a **cost function** for ACCES calibration
- → Skip the characterisation step!

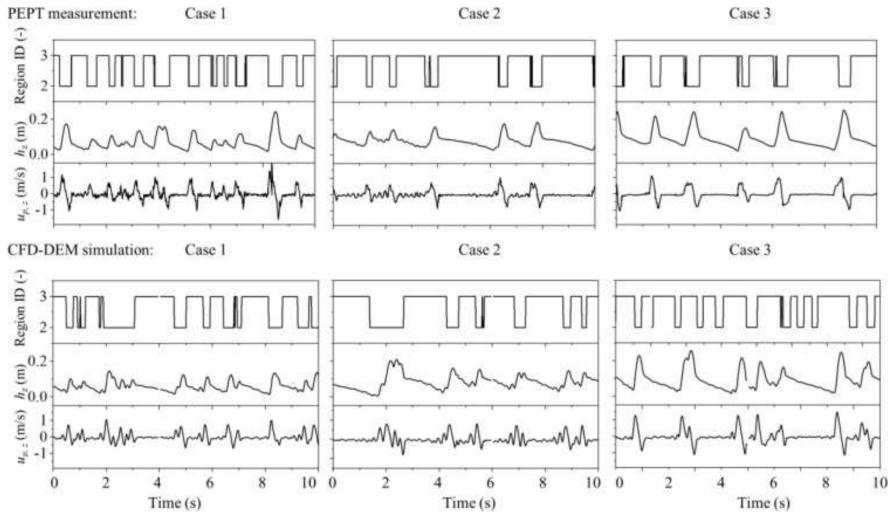
**Rigorous**, Quantitative Validation

Che, Windows-Yule, et al. (2023). PEPT validated CFD-DEM model of aspherical particle motion in a spouted bed. Chemical Engineering Journal, 453, 139689.



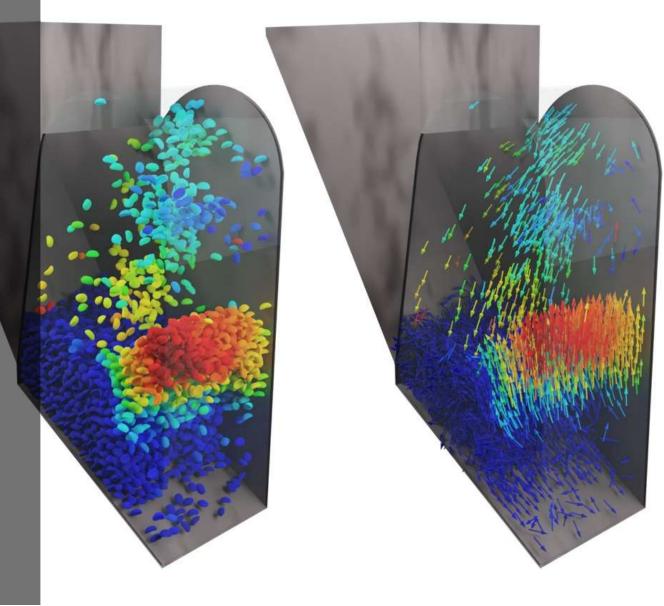
### Rigorous, Quantitative Validation

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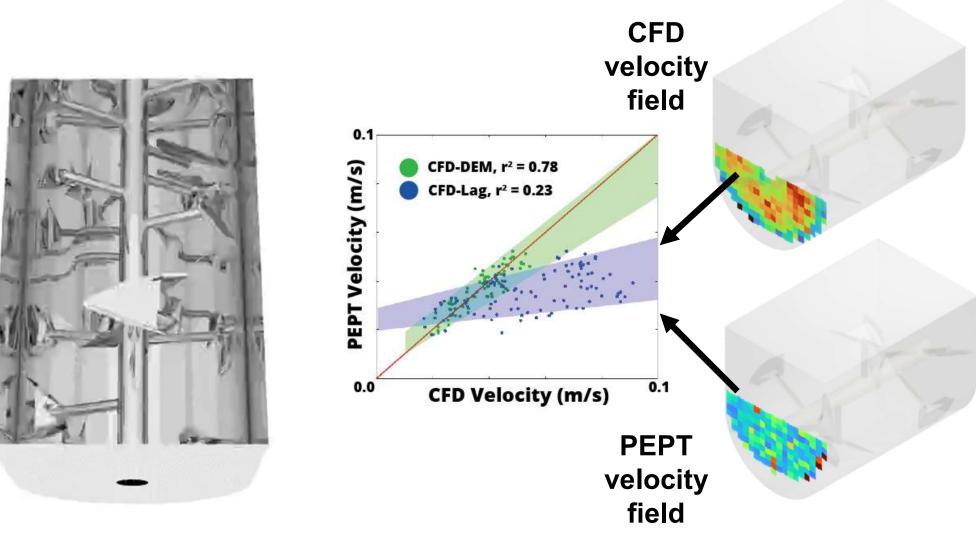


...as well as investigating a diverse array of other (Eulerian & Lagrangian) quantities!

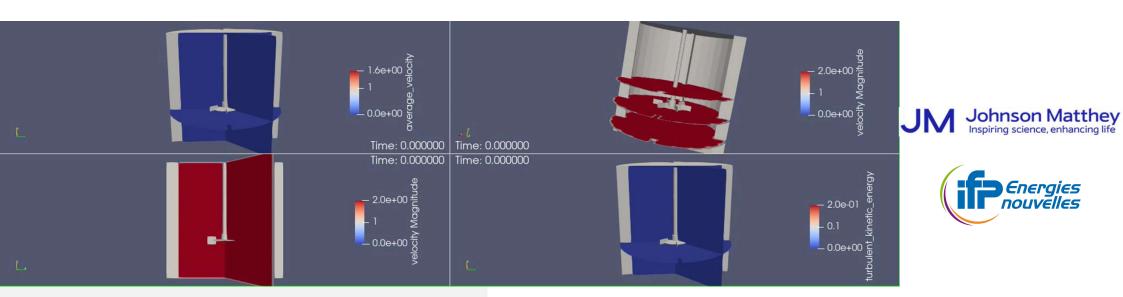
End result: a comprehensively validated numerical model which can be used to easily, efficiently and cheaply gain insight into JDE's systems.





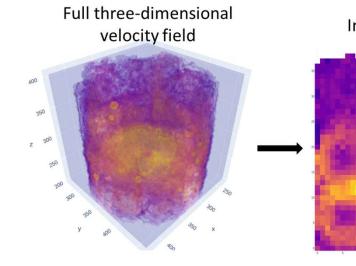


Not just spouted beds, not 'just' particles

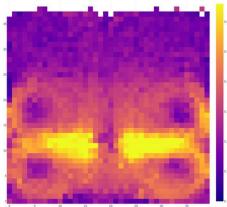


Not *just* spouted beds, not *'just'* particles

•••

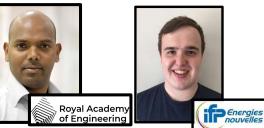


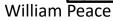
Individual 2D "slice"





### The Team













Zoe Chu



Matthew Herald





Khizra Abdul Wadood

Swapna Kudal



• GRANU TOOLS



**Owen Jones-**Salkey



Leonard Nicuşan







Rk Niklas Adio

GCRF Engineering and Physical Science Research Counci

**Dominik Werner** 



Issa Munnu



Dan Weston





Dan Rhymer









# IV. PEPT as a Calibration Tool





### Autonomous Calibration using Evolutionary Algorithms

- Calibration is an infamously slow and difficult task And one too often overlooked in the literature!
- As well as simply *validating* existing algorithms, PEPT can be used to *calibrate* simulations
- Specifically, it can be used to provide detailed objectives for evolutionary algorithms



ACCES: Autonomous Characterisation & Calibration using Evolutionary Simulation



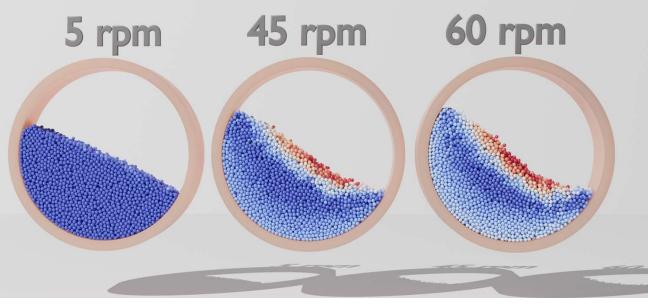
- I. Choose experimental system to model
- II. Define a cost function to quantify difference between experiment & simulation
- III. Choose a suitable optimiser
- IV. Set goal to minimise error function (i.e. maximise agreement between simulation and experiment)
- V. Iterate towards minimum (i.e. find 'true' DEM parameters)

# I. Choosing a system

To illustrate ACCES in an accessible manner, let us consider a simple system to model: Granutools *GranuDrum* 

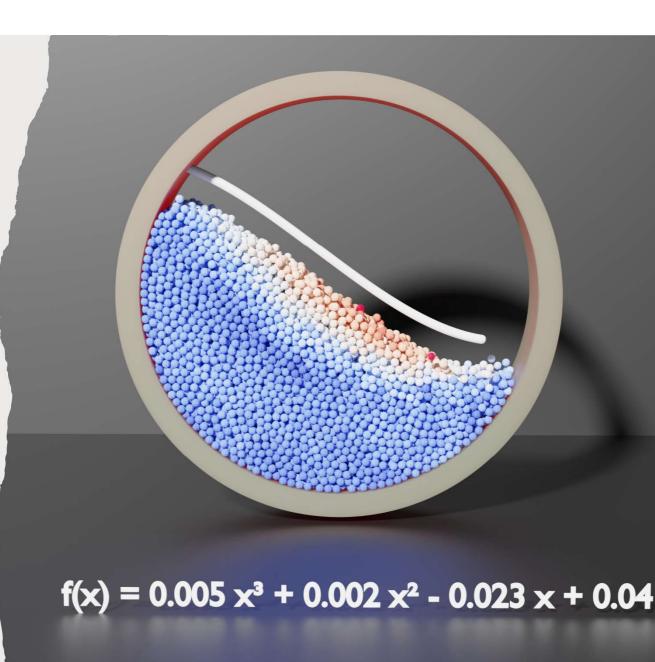
- Simple
- Industrially relevant
- Diverse phenomenology





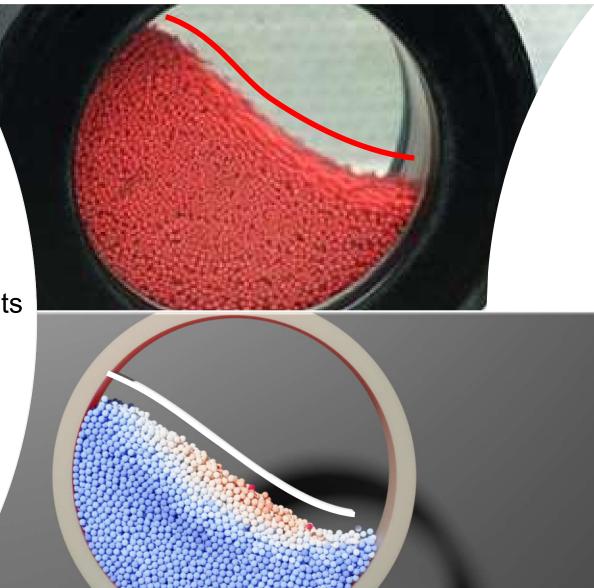
# II. Defining a cost function

- Cost function can relate to practically any quantity
  - Mean system velocity
  - Velocity distribution
  - Density distribution
  - Granular temperature...
- Precise choice depends on goals of calibration
- In this example we want to obtain values for sliding & rolling friction
- →Free surface shape as cost function



# II. Defining an error function

- Free surface can be characterised by a 3<sup>rd</sup> order polynomial
- Compare simulation and experimental fits



# II. Defining an error function

- Free surface can be characterised by a 3<sup>rd</sup> order polynomial
- Compare simulation and experimental fits
- Cost function taken as the integral of the absolute difference between the 2 polynomials

Provides a  $\epsilon = \int |f(x) - g(x)| dx$ simple scalar value that can be used to solve the optimisation problem



#### Evolutionary Optimisation – How it Works

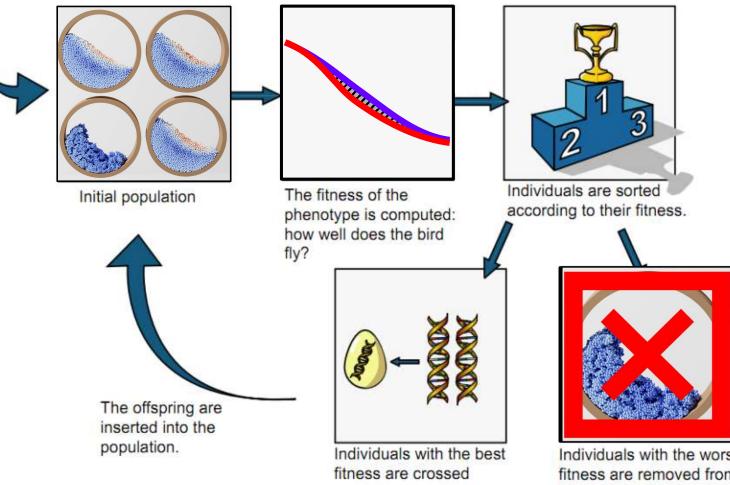
The problem with evolutionary algorithms: lots of function evaluations

**Especially problematic** when coupled to DEM

Utilise state-of-art **CMA-ES** algorithm, which adaptively changes as the spread of the function increases



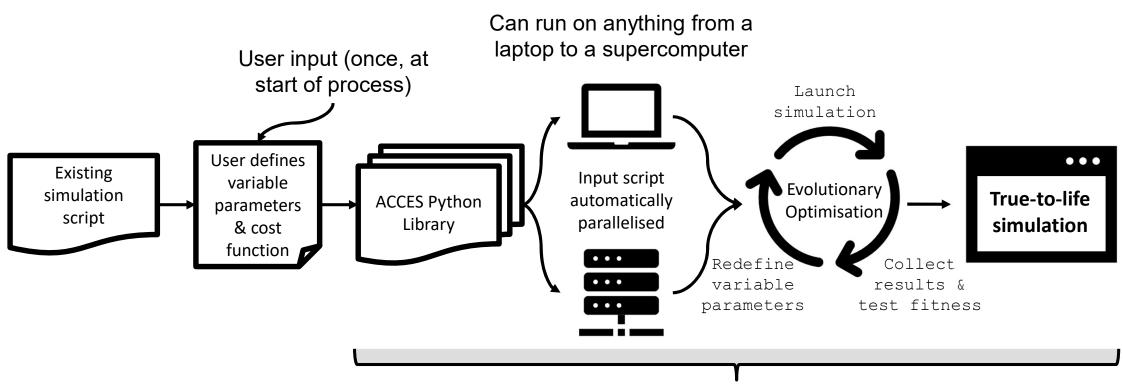
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together; some random mutations in the genotype are added.

Individuals with the worst fitness are removed from the population.

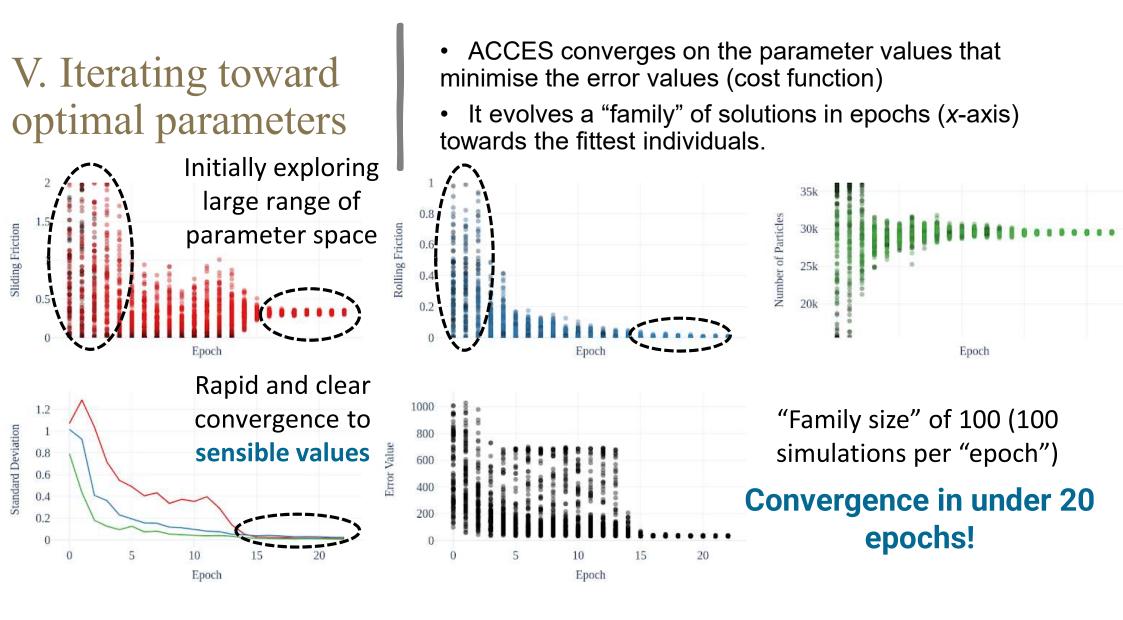
### Evolutionary Optimisation – How it Works in ACCES



#### Absolutely no user input required!

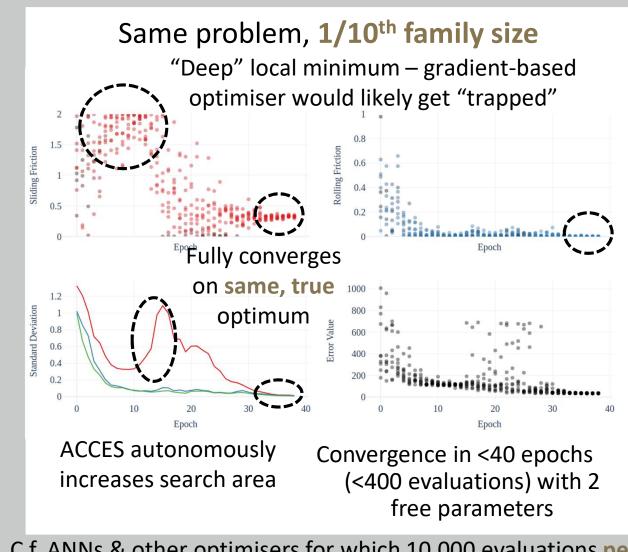


**Metaprogramming** (code that writes code): ACCES takes input scripts, understands them, hacks them, and modifies them to run in fault-tolerant massively parallel environments

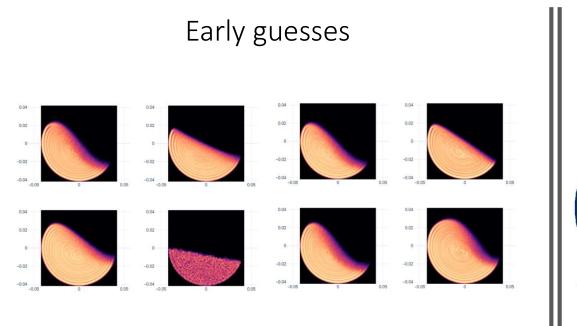


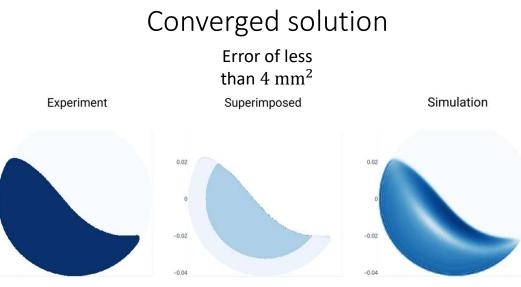
# V. Iterating toward optimal parameters

- What if I don't have 100 CPUs handy?
- "Family size" can be varied at will.
- Larger: more global search, fewer epochs
- Smaller: fewer simulations per epoch, more epochs
- → Fully scalable from HPC to Laptop
- Can still autonomously "escape" false minima and reach true parameter values



C.f. ANNs & other optimisers for which 10,000 evaluations **per parameter** would be considered good!





# Example solution

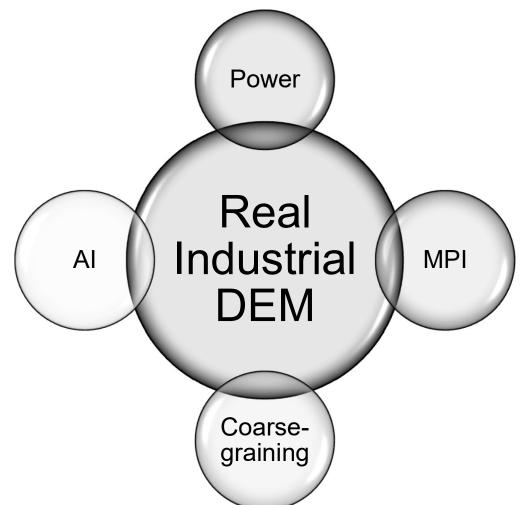
#### Summary

- PEPT facilitates the detailed, 3D imaging of particulate, fluid, and multiphase media, even in large, opaque systems.
- Diverse array of quantities extracted from PEPT facilitates deep insight into the internal dynamics of both scientific and industrial systems
- Synergy between PEPT and numerical methods facilitates an optimal mix of *efficiency* and *accuracy* not achievable using either methodology in isolation



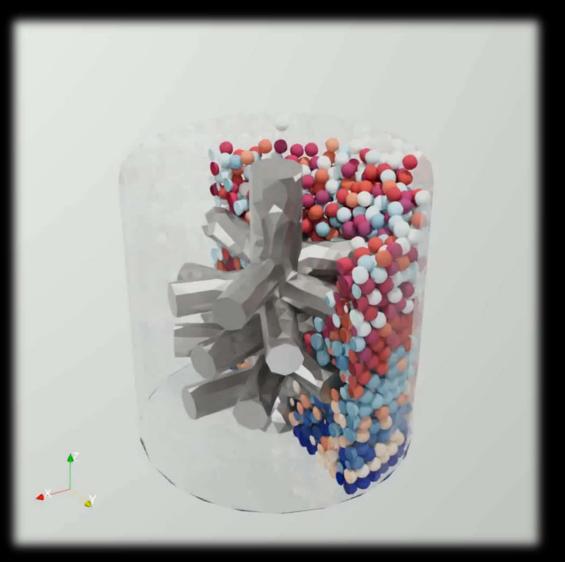
### Why is this talk timely?

- DEM is nothing new but recent advances in computational power, our ability to parallelise code, techniques for upscaling simulations, and advances in Al combined mean that today I can do things with DEM that at the start of my career I could only dream of
- Specifically, things like this:





# "Evolving" the optimal design for a unit operation





# I. Evolutionary Algorithms as a **Calibration Tool:**

Autonomous Characterisation & Calibration using Evolutionary Simulation (ACCES)



Real-world motivation: the need for a better method of calibration international Fine Particle Research Institute

- Leading a 5-year project with IFPRI to investigate current industrial DEM characterisation/calibration strategies
- Detailed interviews with 8 (now 12) multinational companies who use DEM, spanning Agriculture, Chemical, FMCG, Food, & Pharmaceutical sectors
- Goal: to determine a "gold standard" methodology for the calibration of DEM simulations



Real-world motivation: the need ... for a better method of calibration

	Company											
	1	2	3	4	5	6	7	8				
Phase 1												
Phase 2												
Phase 3												
	1											
Key: Char	acterisation	n methods	5									
Shear testing						K	ey: Shape	model				
Angle of repose testing						R	Rolling friction					
Impact testing						G	lued spher	re				
Microtribometry						Su	iperquadr	ic				
Ramp rolling friction testing						Pe	Polyhedral					
						N	one					
Laser diffra	action											
Microscopy	$\prime$ / Optical i	imaging										

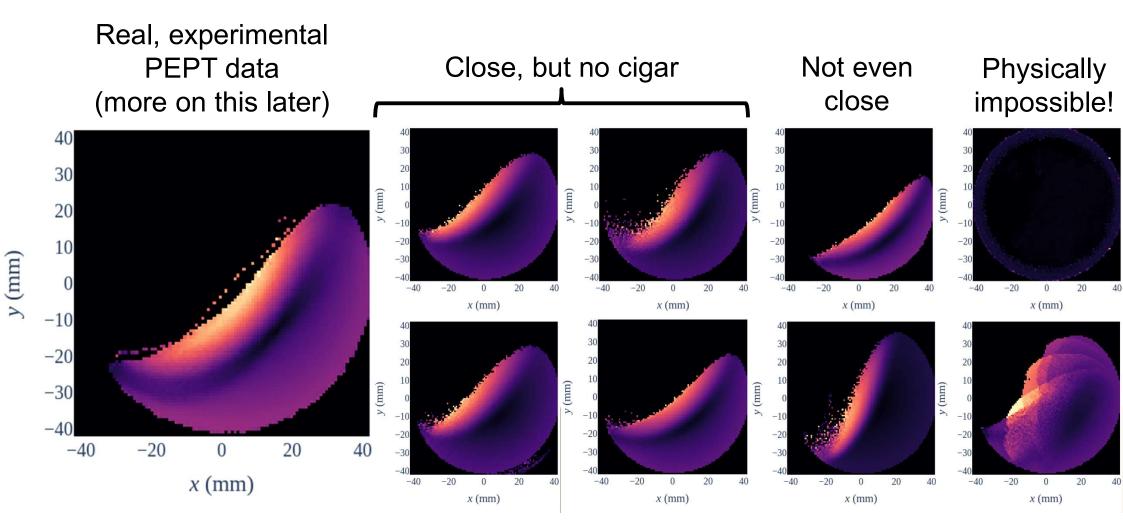


- No two companies adopted the same procedures, equipment, or geometric models
- Most produced different values for same materials
- The result?

	Company											
	1	2	3	4	5	6	7	8				
Phase 1												
Phase 2												
Phase 3												

# Real-world motivation: the need for a better method of calibration



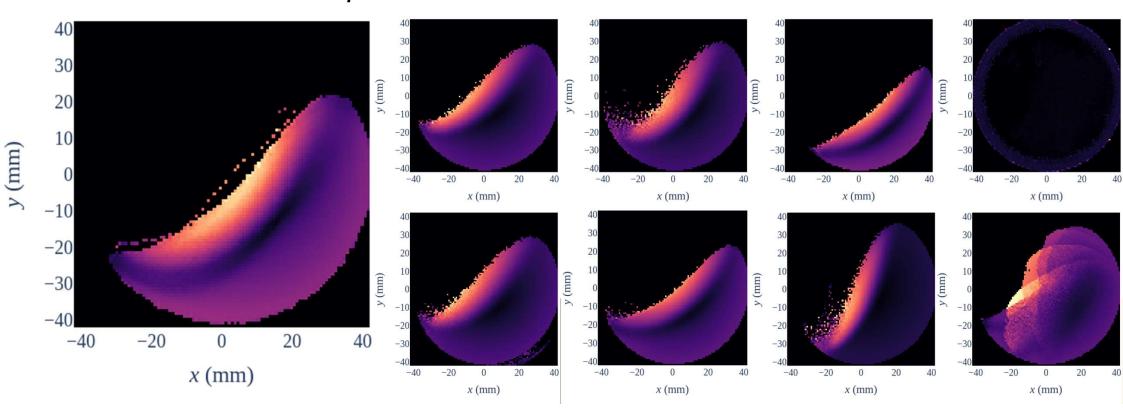


# Real-world motivation: the need for a better method of calibration



The scary<br/>part(s):1) These<br/>method<br/>real con

1) These are *real methods* used by *real companies* 



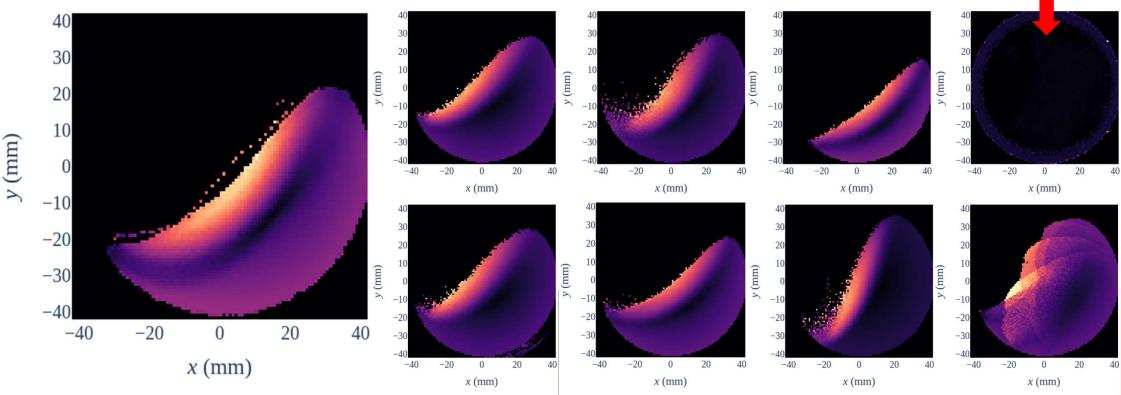
Real-world motivation: the need for a better method of calibration

The scary

part(s):



2) While a sensible operator will re-try these... ...without a technique like PEPT, how would we know the others are inaccurate?

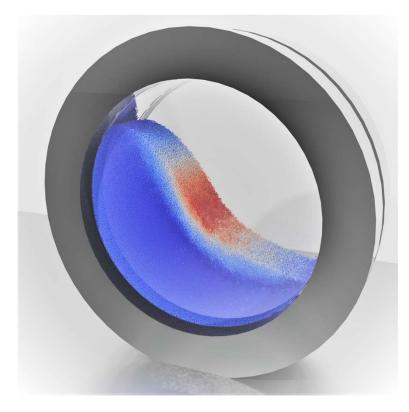


Real-world motivation: the need .:: IFPRI for a better method of calibration



The scary part(s):

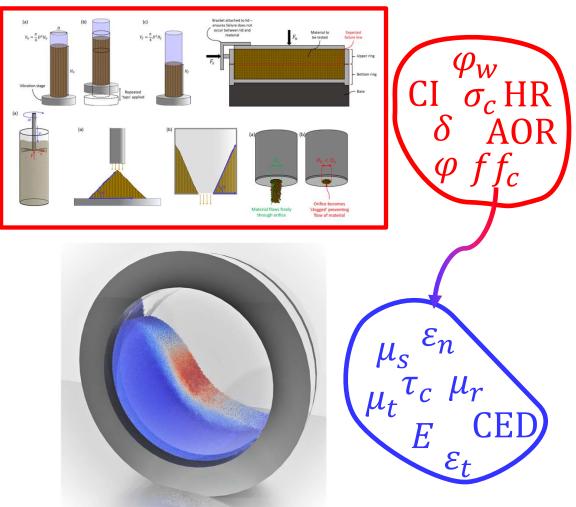
3) This is for a relatively simple, single-phase system containing only spherical particles. How will these methods stand up for more complex cases?





### Problem statement

- Particles' bulk properties are quick and easy to measure using easilyavailable equipment and standardised procedures.
- Measurement of particles' microscopic properties... is none of the above
- → We need a quick, easy and reliable way to map bulk measurements to microscopic properties

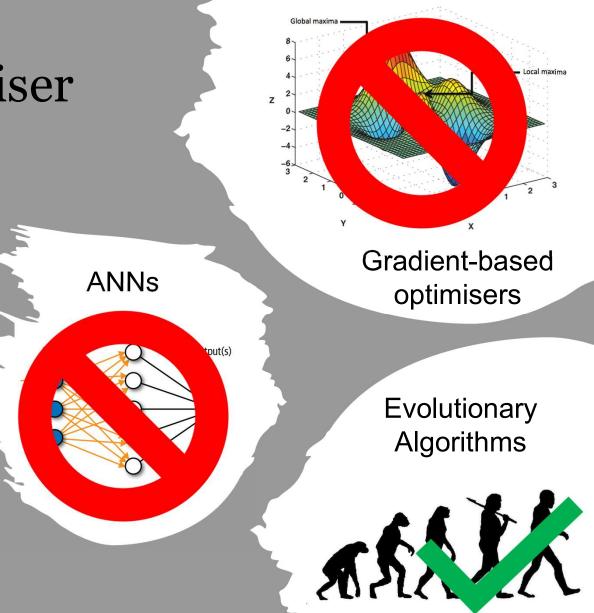




# III. Choosing an Optimiser

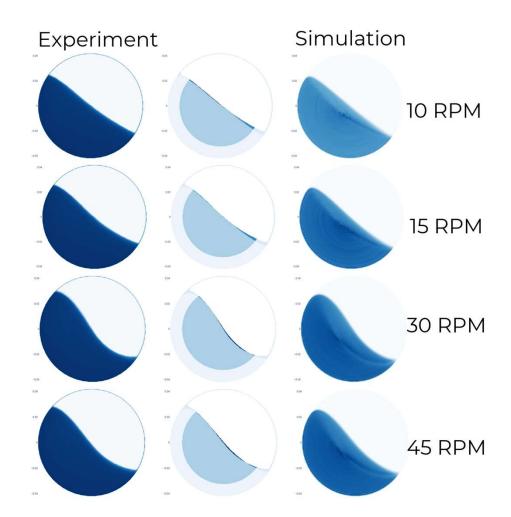
Error function can be very non-convex (local minima) and very non-smooth (lots of "jiggle")  $\rightarrow$  cannot trust gradient!

→ Evolutionary algorithms are the only logical choice for calibration-by-optimisation



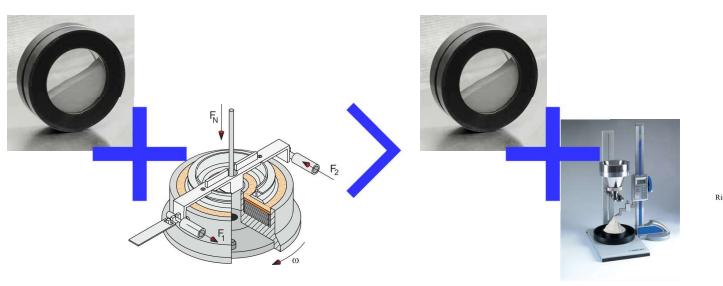
#### Calibrating Multiple Parameters

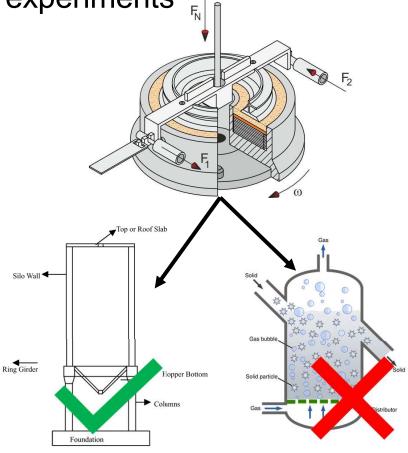
- Mathematically, to solve for N unknowns we need N closure relations
- → Calibrating 5 parameters against a single measurement is ill-defined
- But this does not mean we need 5 instruments!
- E.g. a GranuDrum's free surface shape can be fitted by a 3rd order polynomial → 3 outputs!
- ACCES can calibrate against multiple measurements – e.g. GranuDrums at different RPMs, Shear Cells, FT4...
- → Drum can (hypothetically) calibrate 3N parameters by running at N distinct RPM



### Final thought on ACCES: A tool is only as good as its user

- Easy to make ACCES seem "too good to be true"
- In reality, though the process is fully automated, human intelligence is still required in the initial design of calibration experiments ACCES can only work with what we give it!
- IFPRI project has highlighted importance of:
  - 1) Matching the calibration device to the "real" system
  - 2) When using multiple tools, choosing **distinct** tools









# II. Evolutionary Algorithms as an H∆?₽₽ Optimisation Tool:

Highly-Autonomous Rapid Prototyping for Particle-handling Processes (HARPPP)

#### Beyond calibration

- We have used ACCES to perfectly calibrate a simulation of (say) a mill
- So what next?
- For industry, typically:
- Improve efficiency
- Improve productivity
- Reduce waste
- → Improve green credentials
- $\rightarrow$  Increase profit
- In other words, we have optimised calibration, now we want to optimise the system itself



#### Optimising a Mill

Two main options:

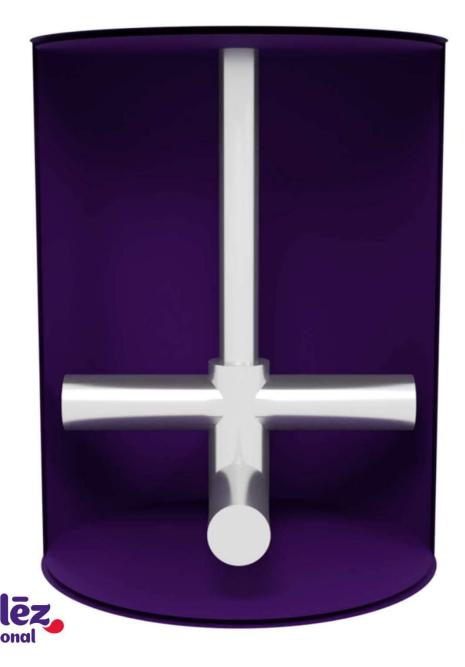
#### 1. Optimise *process parameters* (e.g. attritor RPM, fill level...)

(Relatively) simple, easy to achieve both in "real life" and in simulation.

#### 2. Optimise geometry

Highly costly in real life. Timeconsuming, labour-intensive and "hit and miss" both in real life & DEM.

Can we 1) remove the element of chance and 2) remove the need for human input?

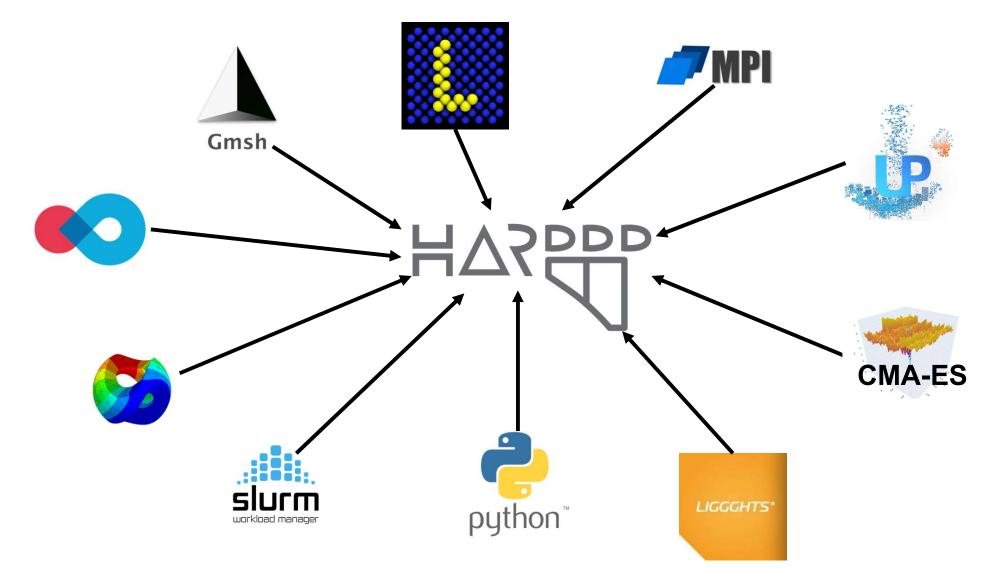


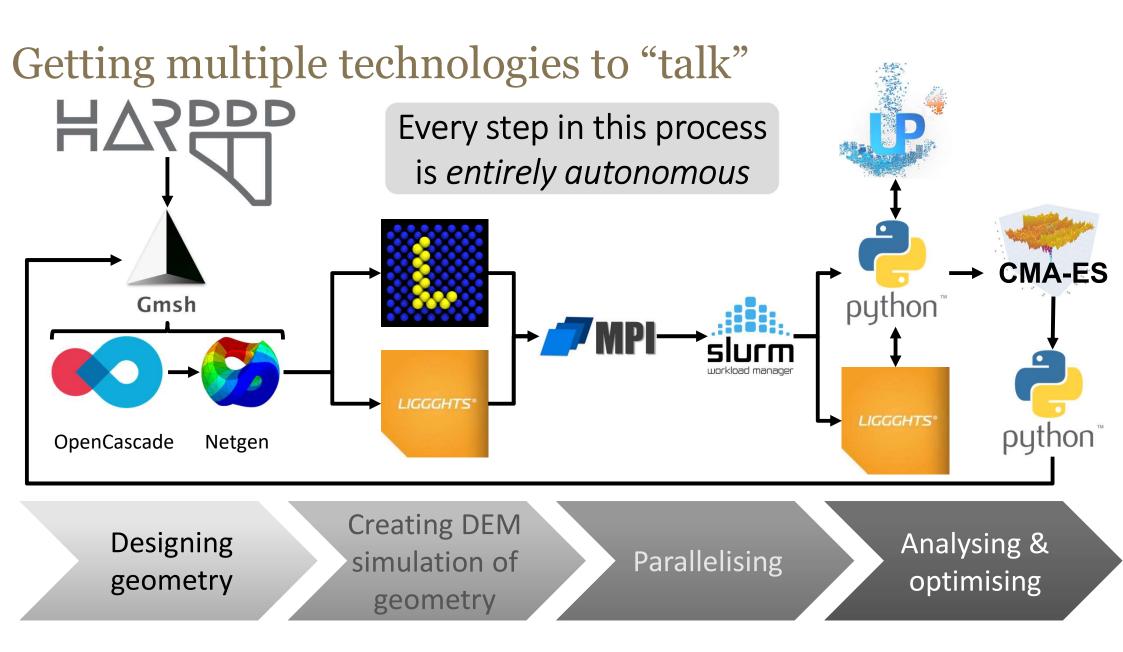
## Highly Autonomous Rapid Prototyping for Particulate Processes (HARPPP)

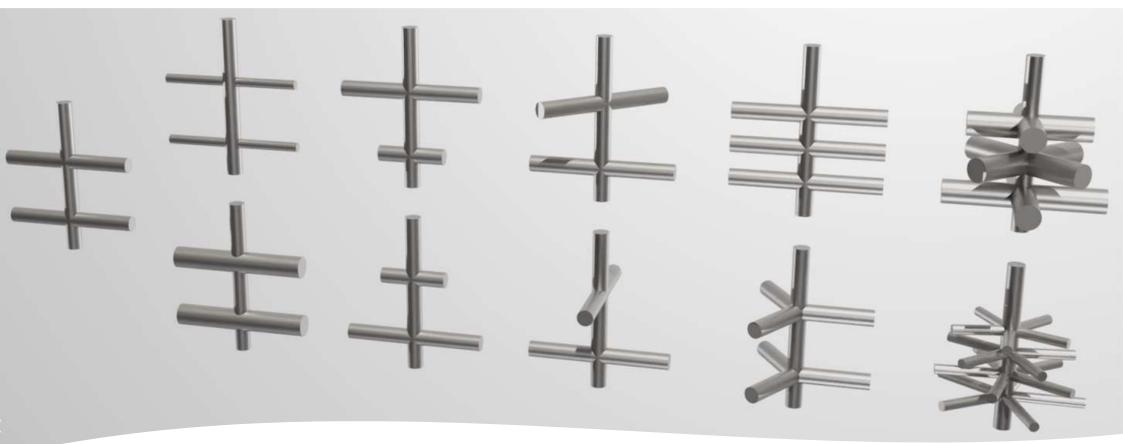


- Applying the evolutionary approach of ACCES to "real" optimisation
- Metaprogramming allows not only alteration of simulation scripts, but also the autonomous design and implementation of entirely novel geometries
- <u>Not</u> a simple task!

#### Getting multiple technologies to "talk"

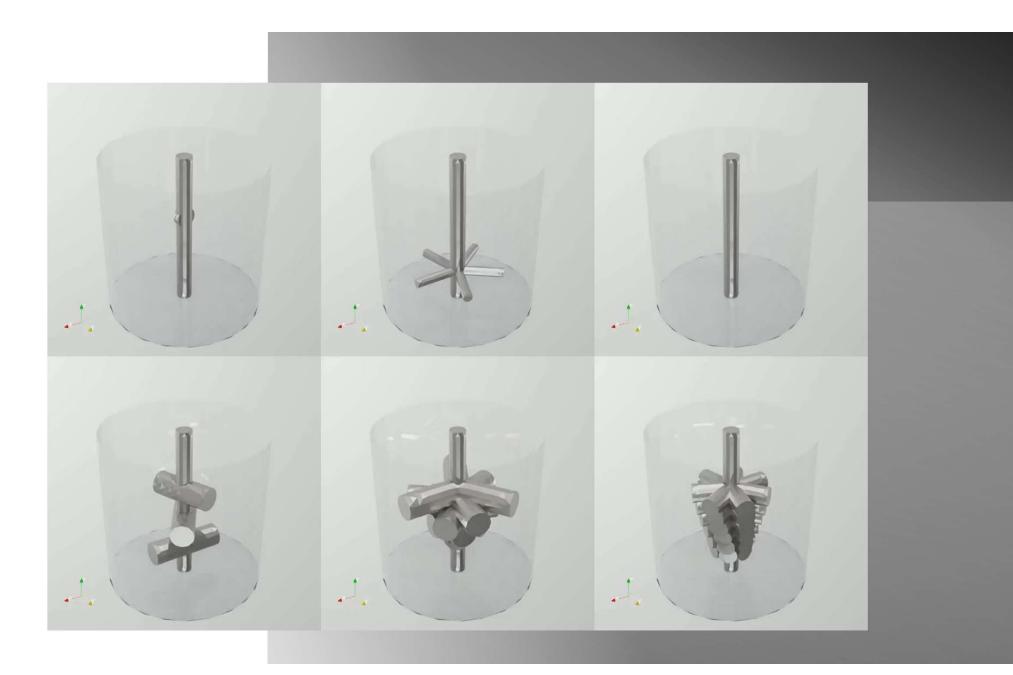






#### Case Study

- Optimising a simple attritor mill
- Give HARPPP the ability to vary pin length, pin diameter, pin number (horizontal and vertical), and pin angle
- Set goal to minimise power draw → reduced energy costs, "greener", more sustainable process



## What went wrong?

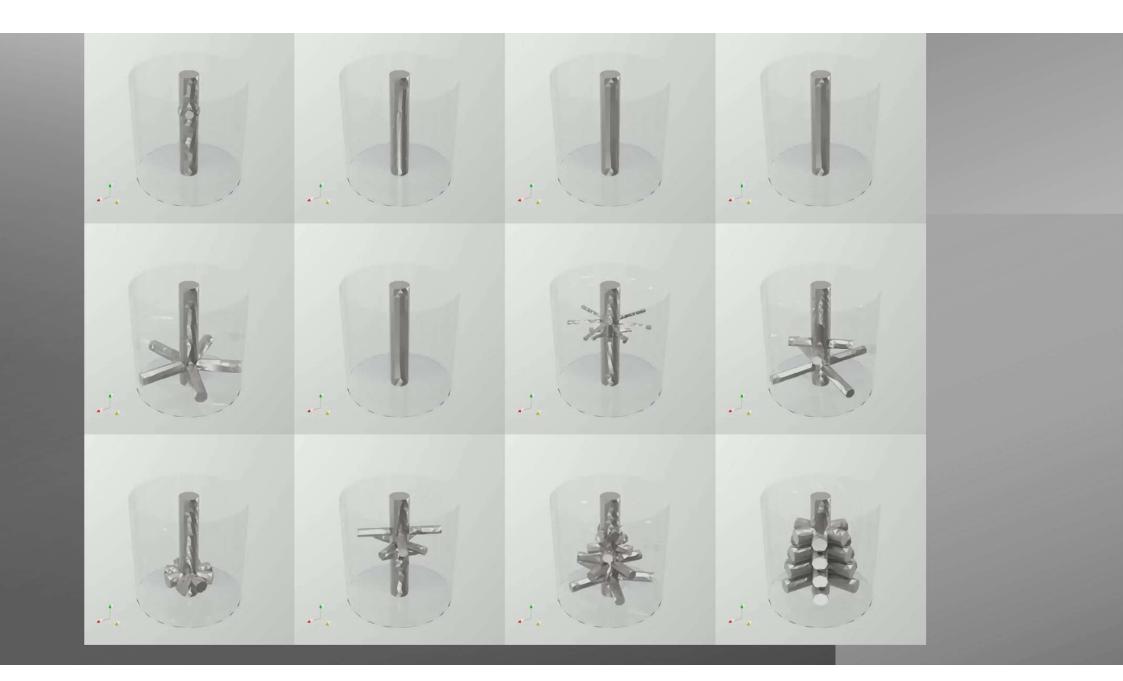
- Technically, nothing
- HARPPP did exactly what we requested and perfectly minimised power draw
- Nonetheless, it is decidedly *not* a good mill!
- Take home point: need to thoughtfully define our objective



### What went wrong?

- Luckily, HARPPP is capable of multi-objective optimization
- Can thus define a more intelligent goal, for example minimize power draw (Objective 1) whilst maintaining a minimum mean pair stress energy (Objective 2)



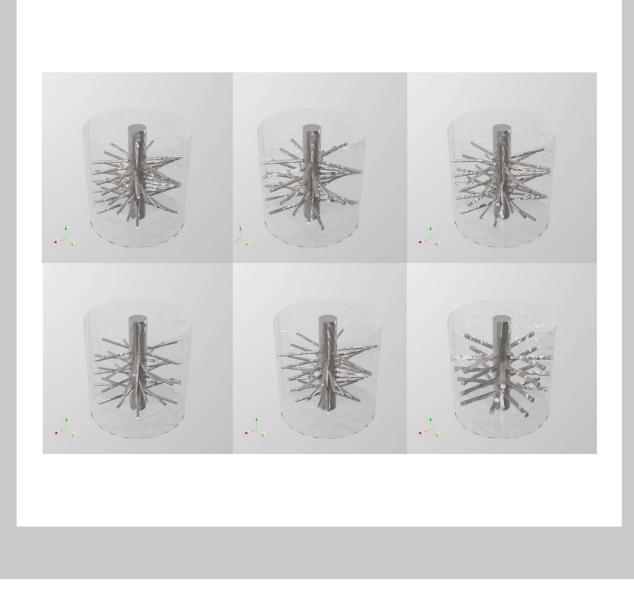


## Results

For different mill geometries, operating conditions and particle properties tested, **energy savings of between 24% and 40%** achieved compared to base model, whilst producing the **same or greater** average pair stress energy

# Can we learn from the machines?

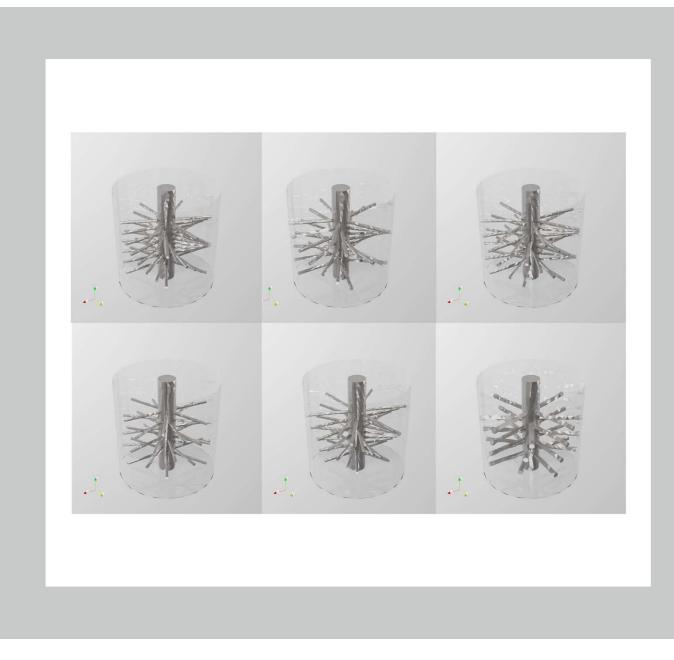
- In later stages of evolution, majority of attritors show certain commonalities, namely large numbers of long, thin, staggered pins
- Indeed, these features remain robust even with mills and particles at different scales!
- Does this suggest some key design principles that we can learn from HARPPP?

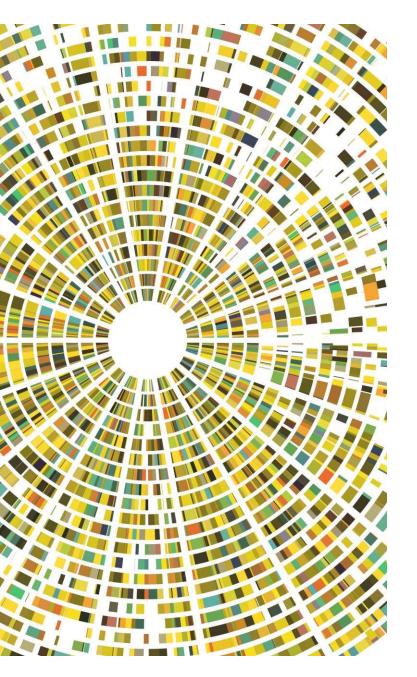


# Can we learn from the machines?

Possible interpretations:

- Long pins → value fairly obvious!
- Thin pins → minimise propensity to simply "push" particles → remove interactions which cause power draw without inducing collision or shear
- Large numbers of closelypacked, staggered pins → redirect particle motion → improve axial transport, induce "chaos"



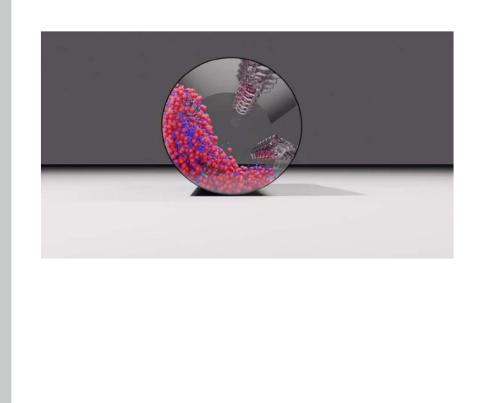


#### Only the tip of the iceberg

- A good proof of concept, but still relatively simple.
- Many additional factors which can be included:
- Lower-bound on pin size to ensure robustness?
- More complex goals specific force *distribution*? Optimise both collision and shear?
- More complex geometric variations?
- User can define arbitrary number of objectives & constraints dependent on their system, and their goals.
  - HARPPP can also, of course, optimise much more than just mills!

## Not just mills...

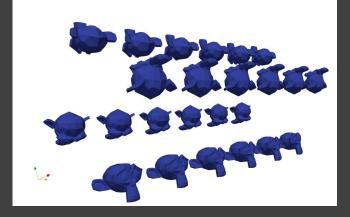
- Rotating drum system with particles of differing size & density
- In standard form, significant segregation
- Goal: design baffles
   to optimize mixing

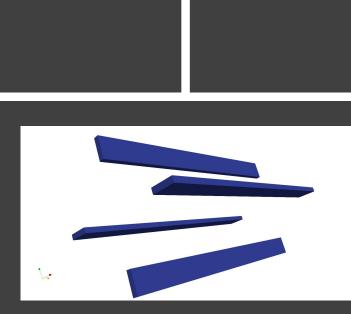


# 

Optimise width, thickness, number and axial position

Optimise size, number & position constrain shape to monkey





Optimise width and thickness, constrain number and shape



Optimise width, thickness, number radial position & shape

Optimise width, thickness, & local angle

