Cognitive Chemical Manufacturing

Dial-a-Molecule Annual Meeting 2018: Enabling Synthesis

9-10th July

i-HUB, Imperial College, White City Campus

Dr Tom Chamberlain & Dr Federico Galvanin

What is "cognitive chemical manufacturing"?

- **Cognitive chemical manufacturing** is an **information framework** where data across chemical systems, equipment and processes are utilised to derive actionable insight across the entire value chain from design through manufacture to support.
- Cognitive manufacturing drives at **key productivity improvements** in quality, efficiency, and reliability of the manufacturing environment.
- It employs **cognitive technologies**, including
  - **Intelligent assets and equipment**: utilizing connected sensors, analytics, and cognitive capabilities to sense, communicate and self-diagnose issues in order to optimize performance and reduce unnecessary downtime
  - **Cognitive processes and operations**: analyzing a variety of information from workflows, context, process, and environment to drive quality, enhance operations and decision-making
  - **Smarter resources and optimization**: combining various forms of data from individuals, location, usage, and expertise with cognitive insight to optimize and enhance resources such as labor, workforce, and energy

Cognitive Chemical Manufacturing

- £2.5M Project using Machine Learning to Optimise Chemical Manufacturing starting July-Sept 2018
- EPSRC call on 'Digital Manufacturing Potential'
- Led by IPRD Leeds (PI: Richard Bourne)
- Academic Partners: University College London, University of Nottingham, Hartree Centre
- Industrial Support: IBM, AstraZeneca, Swagelok and Promethean Particles
- 4 year project with 14 years of PDRA time











Partner Roles

Swagelok
Reactor Design

Lab-Bot Design
Pilot-Bot Design
Integration of External Algorithms
Organic Synthesis Experiments
Cognitive Systems
Pilot Demonstration (Alfa Laval)

iPRD
UNIVERSITY OF LEEDS

University of Nottingham
UK | CHINA | MALAYSIA
Nanoparticle Synthesis

IBM
Bayesian Optimisation
Algorithm
Cloud-based
Experimental
Marketplace

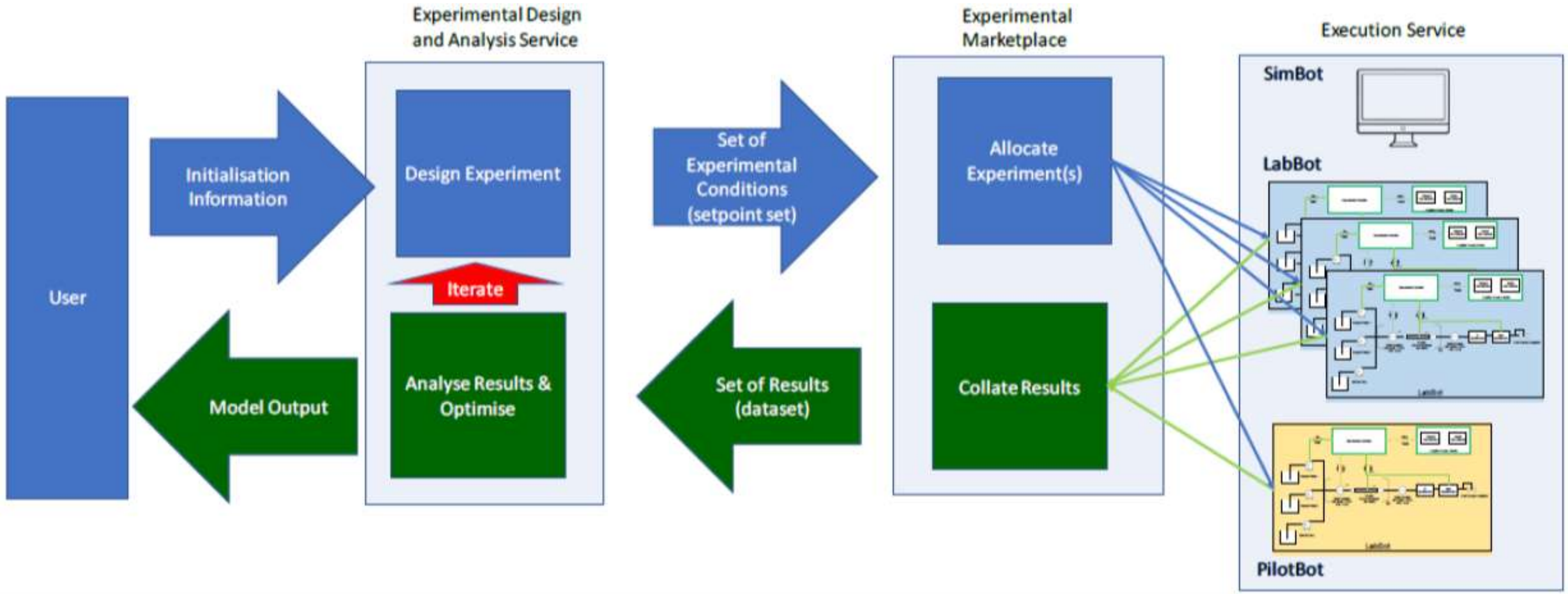
AstraZeneca
Industrial Demonstration
Model Case Studies

PrometheanParticles
Formulating solutions with nanomaterials
Industrial Demonstration
Model Case Studies
Pilot Studies

UCL
Kinetic Models and
Parameterisation
Sim-Bot Development

Project Vision

- Experiments are performed by a linked network of multiple reactor systems – like multi threaded computer cores
- Individual reactions are allocated from the cloud based on reactor capability and the efficiency of performing experiments



Synthesis in flow

API synthesis

Lab scale

- Leeds University
- AZ

Plant scale

- Leeds University

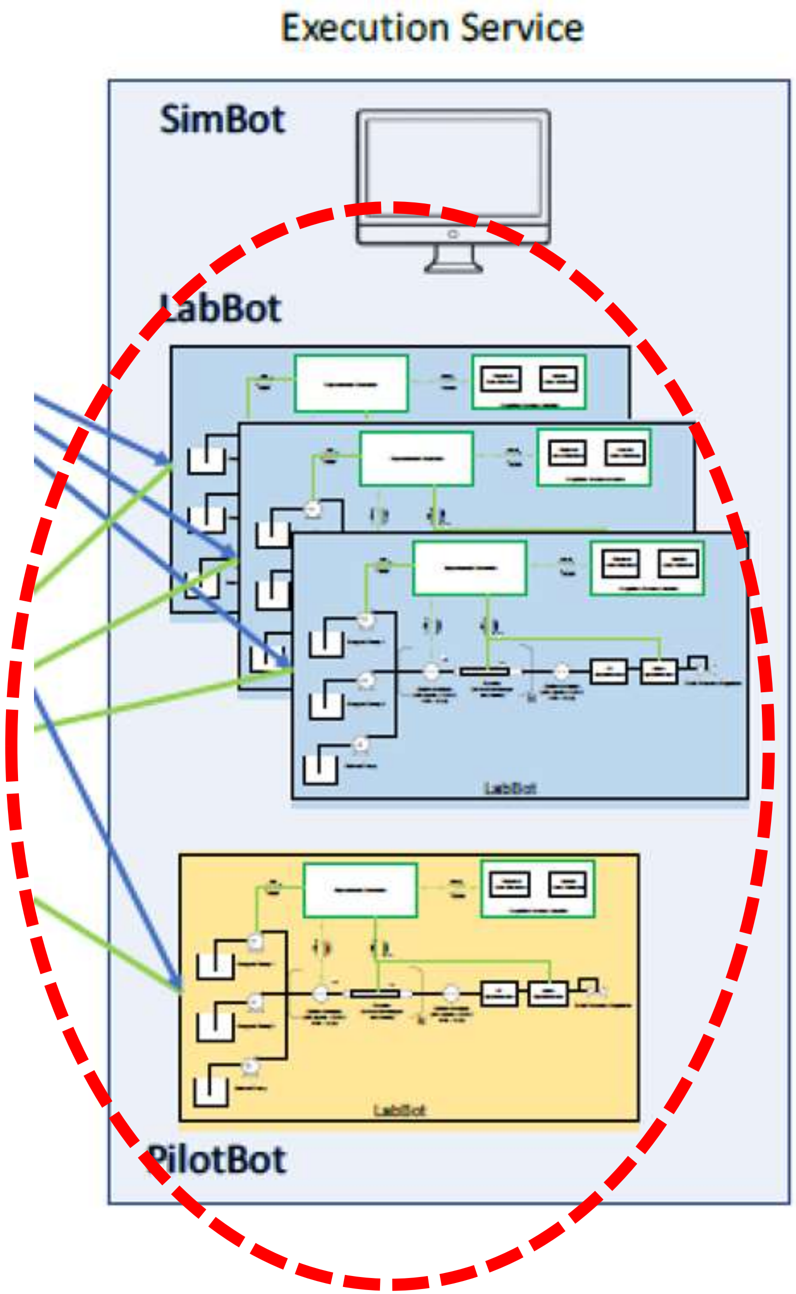
Nanomaterial synthesis

Lab scale

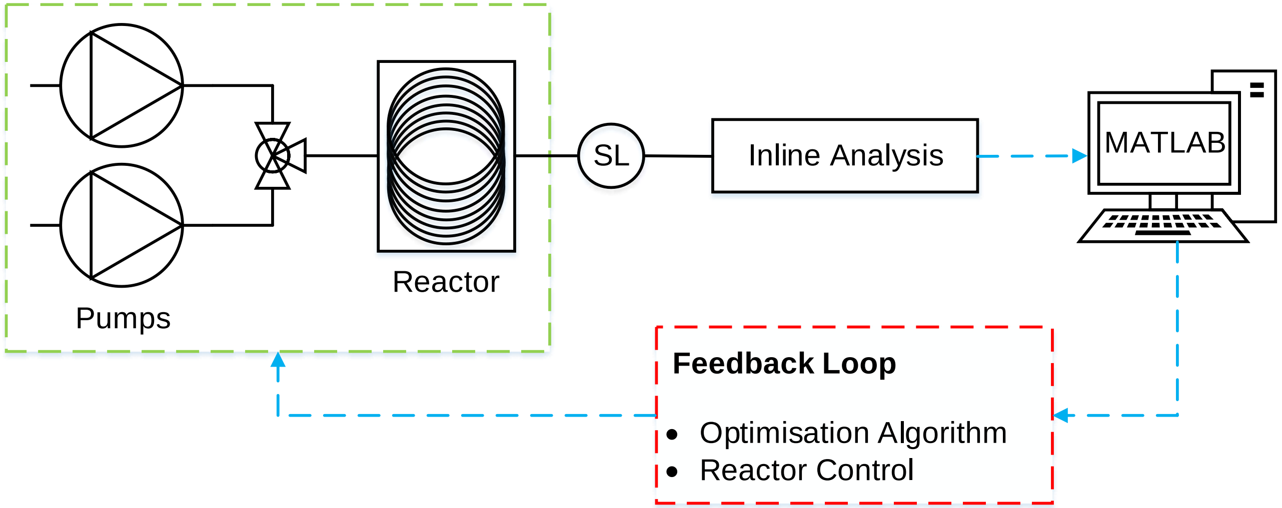
- Leeds University
- Nottingham University

Plant scale

- Promethean Particles

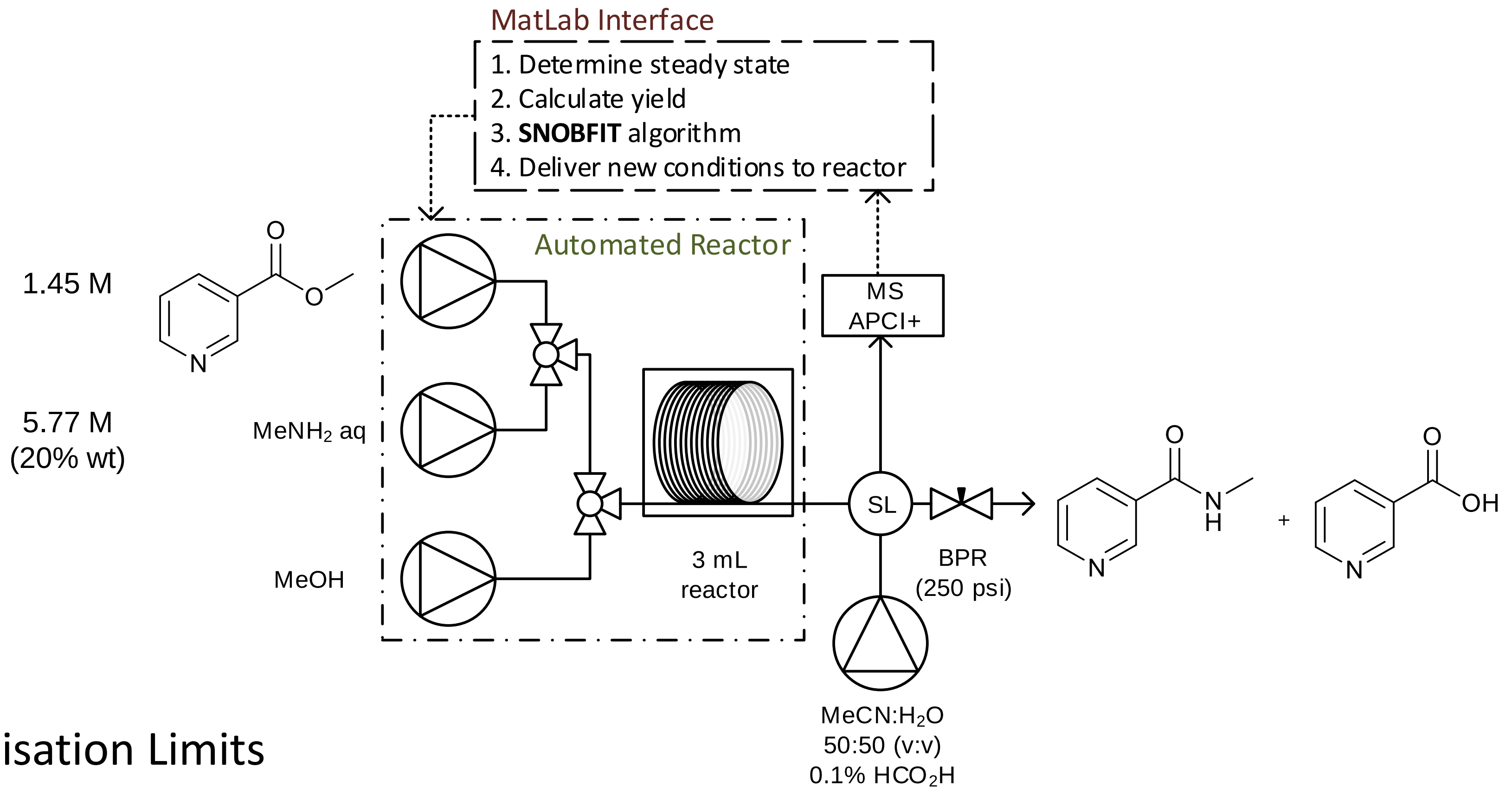


Self-Optimising Lab-Bot



- Algorithmic approach to optimising chemical reactions.
- New experiments generated based on previous results *via* a feedback loop (from the cloud).
- Optimum is verified by experiment.

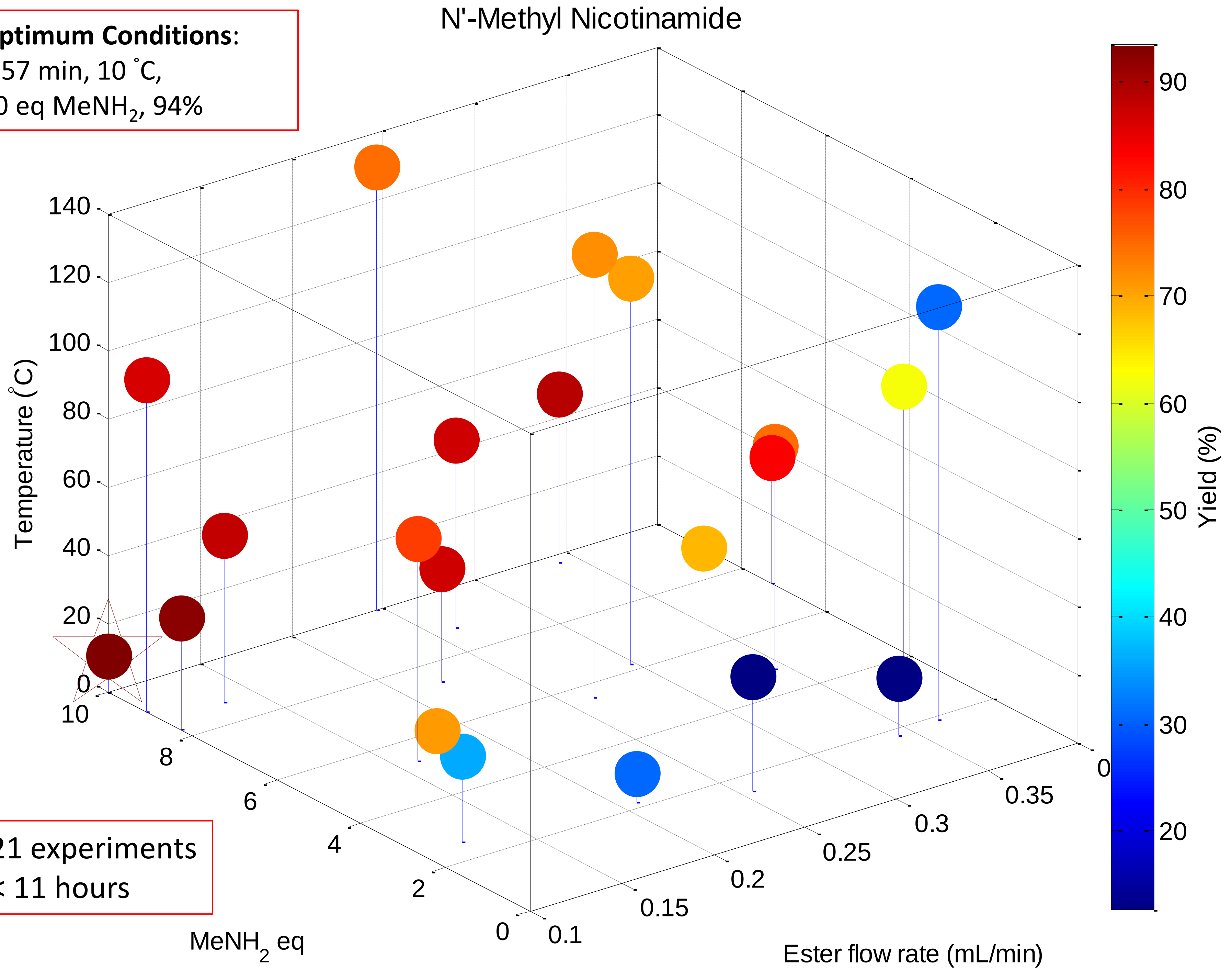
Self-Optimisation - LabBot



Optimisation Limits

	Ester flow	$MeNH_2$	Temperature
Lower	0.1 mL/min	1 eq	0 °C
Upper	0.4 mL/min	10 eq	130 °C

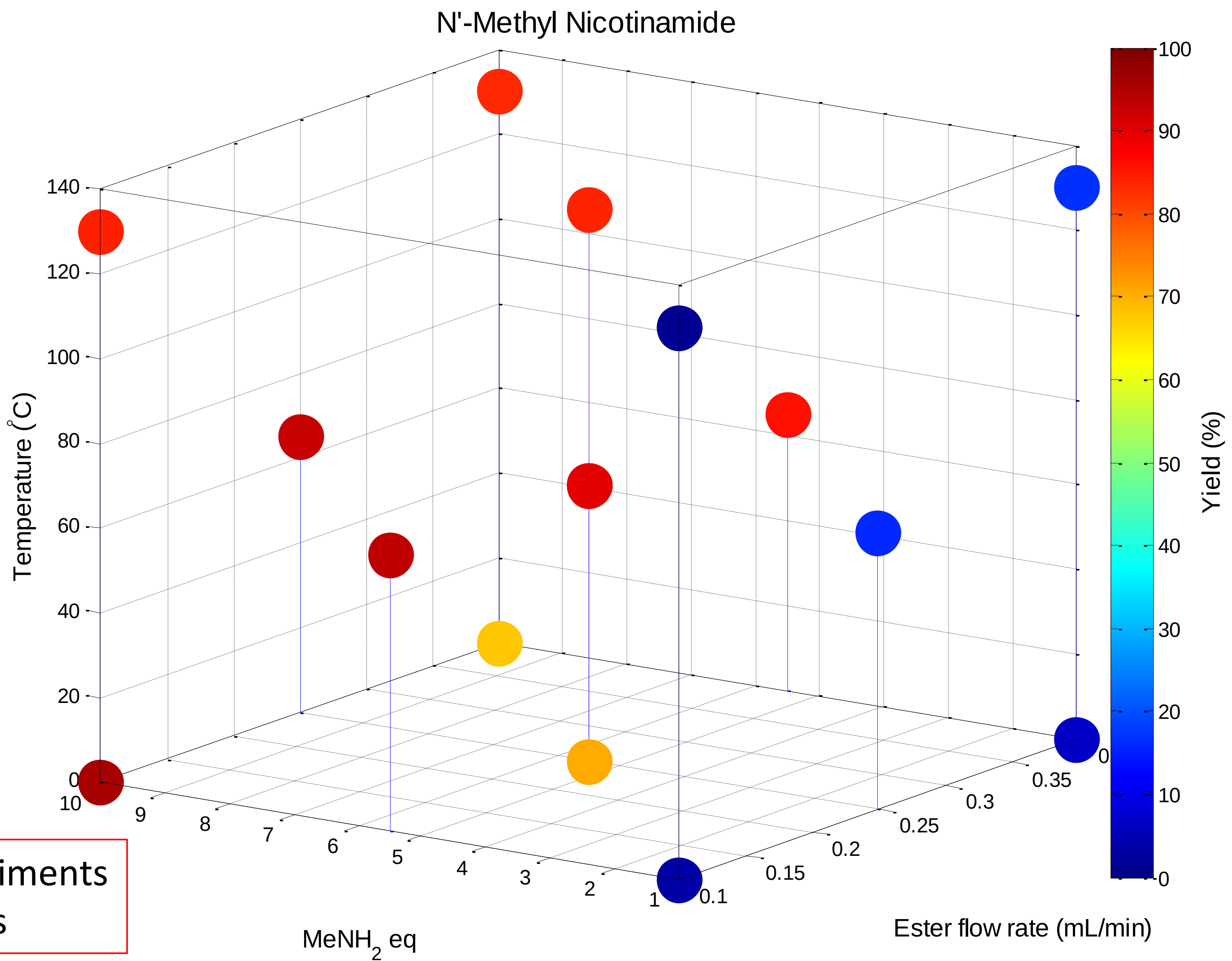
Optimum Conditions:
8.57 min, 10 ˚C,
10 eq $MeNH_2$, 94%



21 experiments
< 11 hours

Design of Experiment

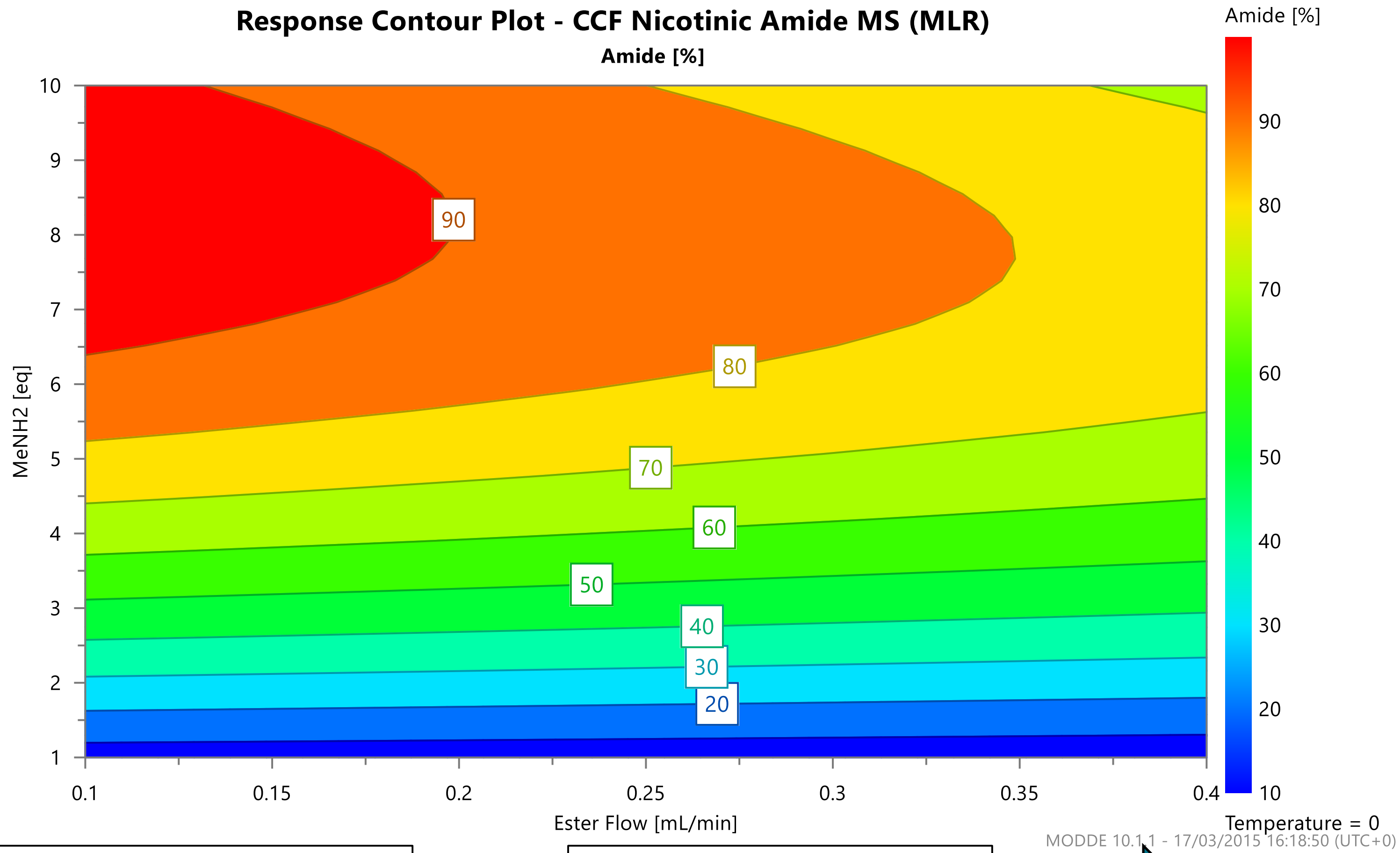
Central Composite Faced Design (CCF)



18 experiments
5.5 hours

Design of Experiments

Contour Plot (0 °C)



Model Optimum:
9.85 min, 7.6 °C, 9.79 eq $MeNH_2$, 96 %

Self-Optimisation:
8.57 min, 10 ˚C,
10 eq $MeNH_2$, 94%

Predictor

96%

iPRD: On the Chemistry – Engineering interface

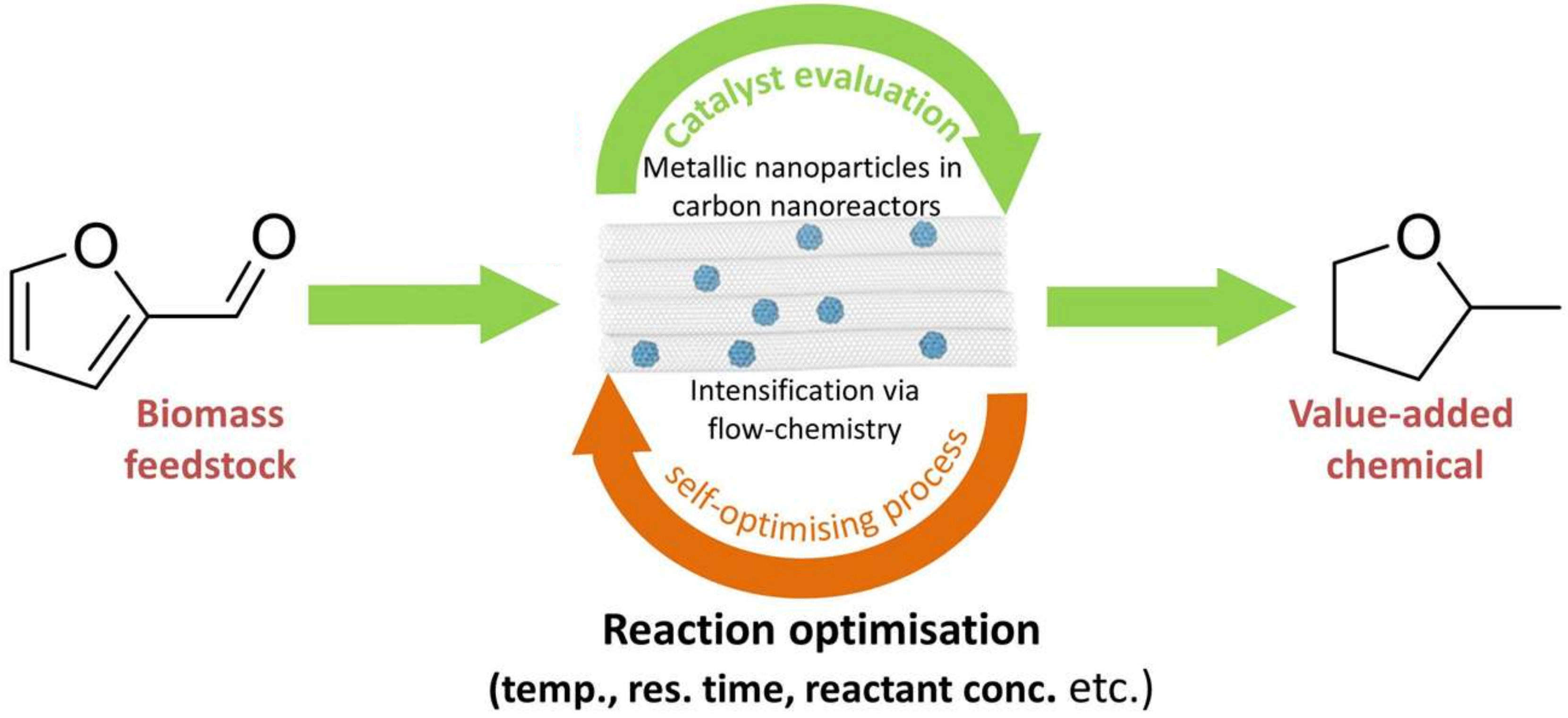
iPRD focus**:**

"Supporting chemical companies of all sizes
by providing ***understanding*** *and* ***solutions***
for product and process development"

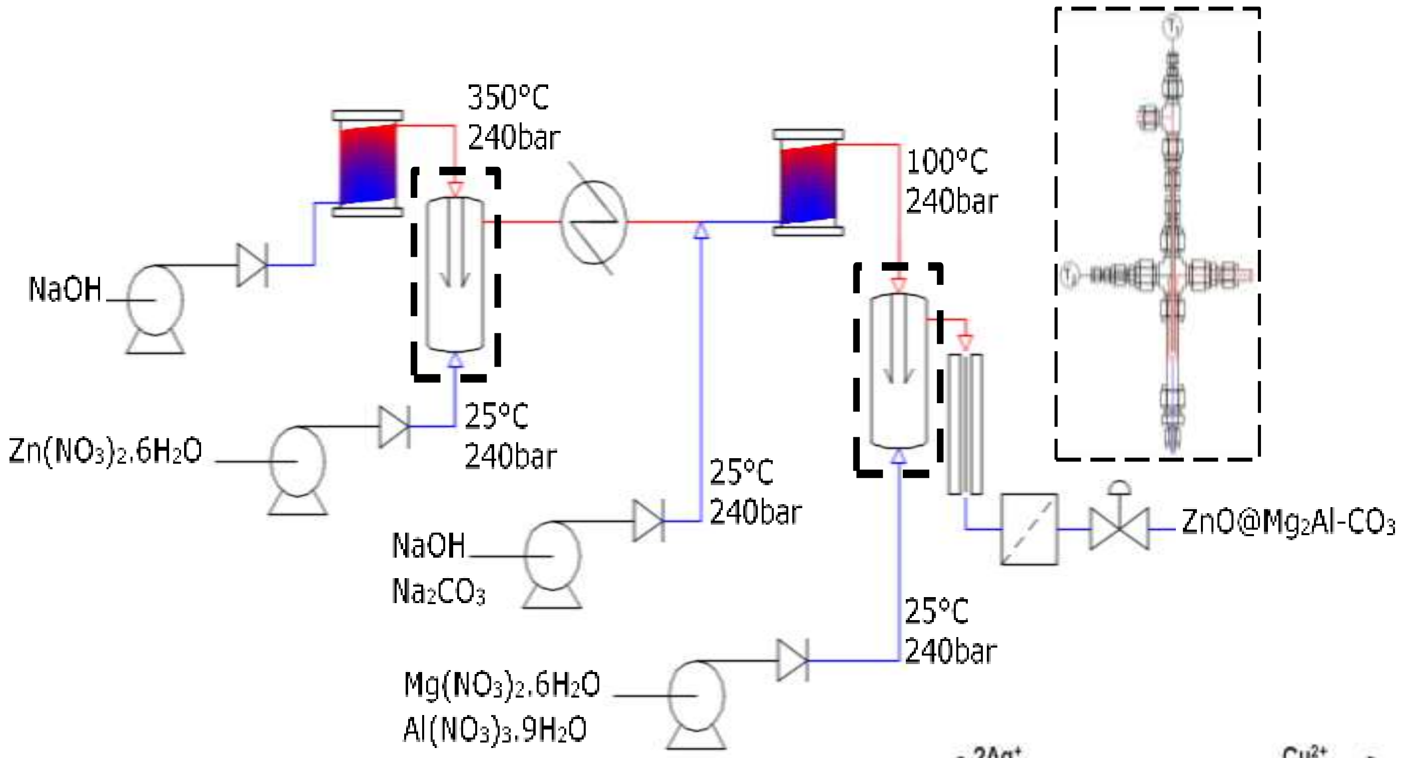
- Pre competitive fine chemical manufacture related R&D delivering process understanding & new technology
- Research focus driven by challenges in manufacturing
- Generate students with an aptitude for process R&D
- Facilities
    - Industrial standard development lab with Pilot Scale capabilities
    - 20 L scale kg laboratory
      funded by Yorkshire Forward/EU (ERDF)
    - 5 m FC for flow processing

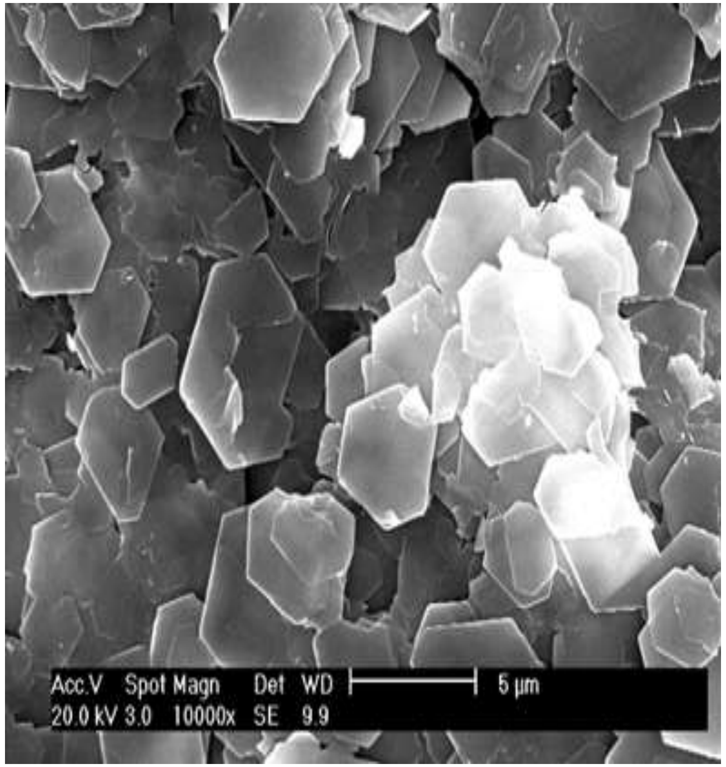
Project Part-Financed by the European Union
European Regional Development Fund

NP synthesis - in flow using a new Lab-Bot

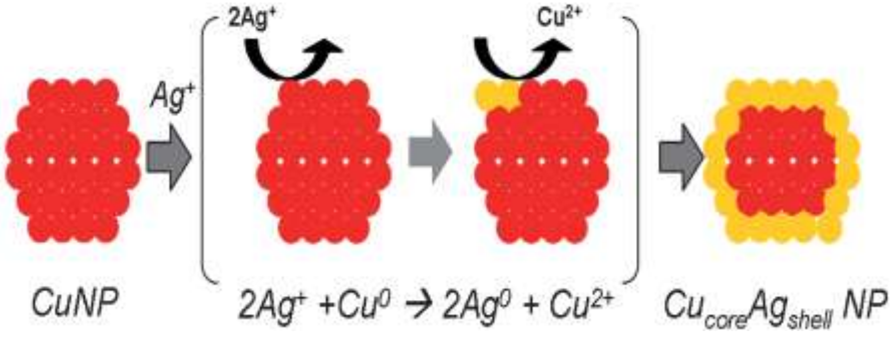


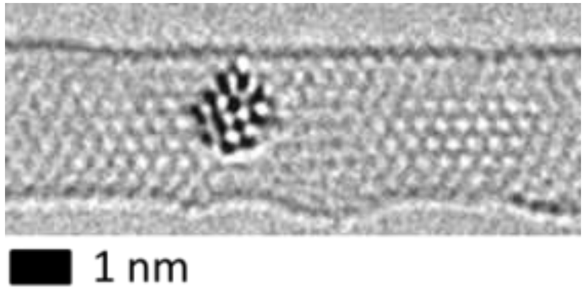
NP synthesis - in flow using a new Lab-Bot





- Metal oxides
- Core shell NPs
- Hybrid materials





NP synthesis - Scale up

PrometheanParticles
Formulating solutions with nanomaterials

- Printed electronics >
- Metal Organic Frameworks (MOF) >
- Green energy and catalysts >
- Healthcare/medical >
- Nanocomposites (incl. plastics & coatings) >

Kinetic models and parametrisation

Simbot

- UCL

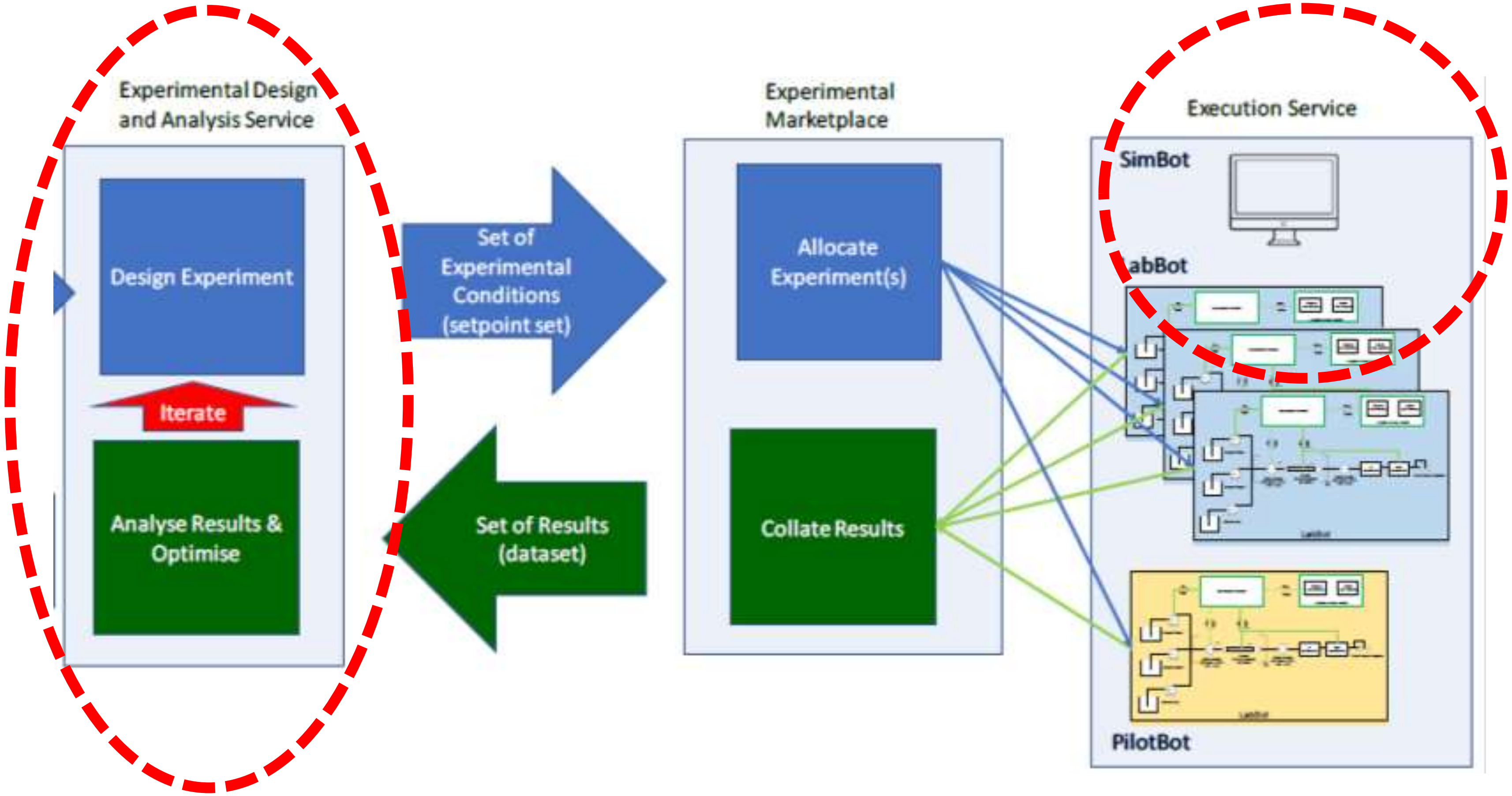
Control/monitoring

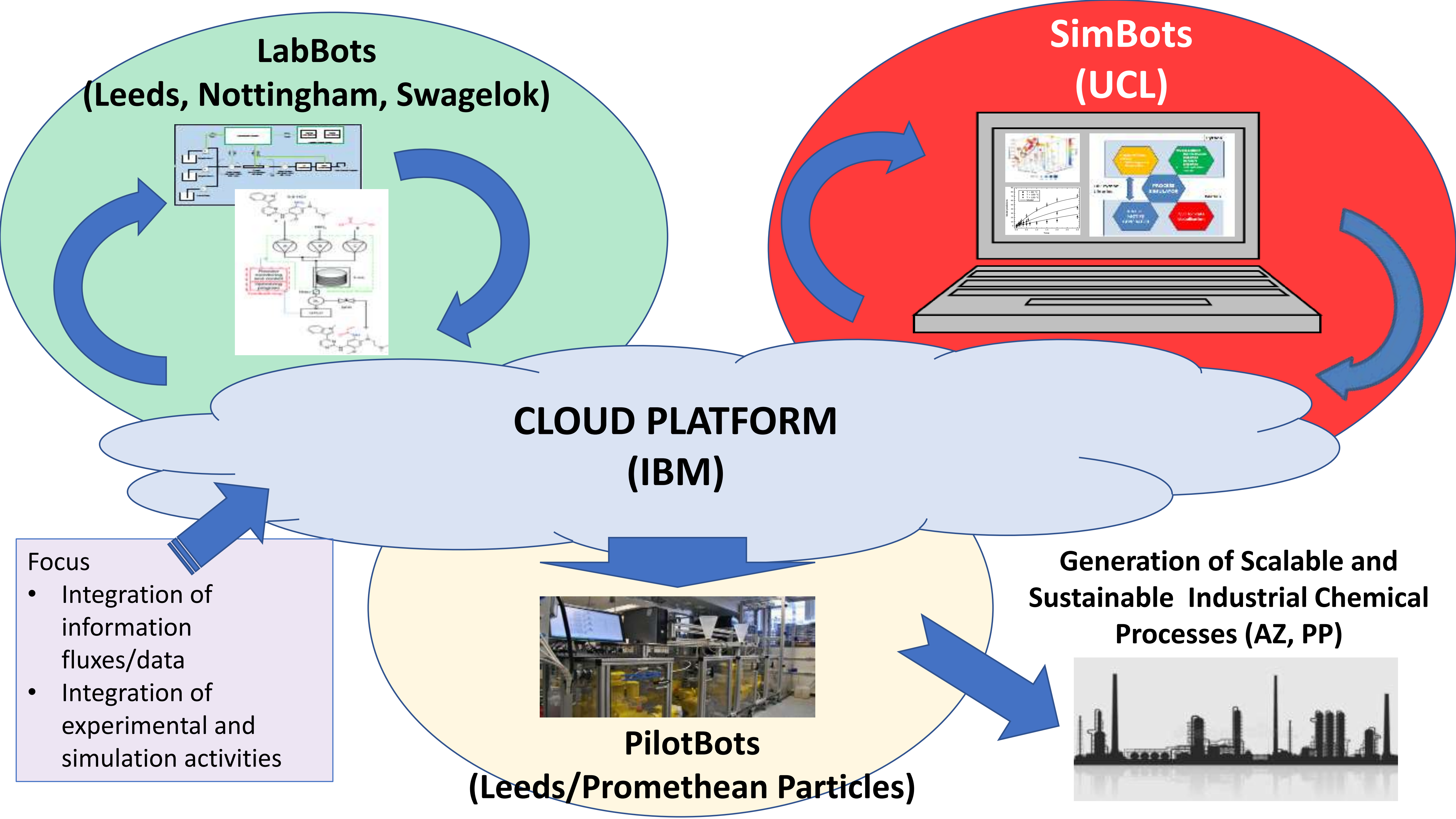
Lab and plant scale

- University of Leeds

Kinetic modelling

- UCL




LabBots
(Leeds, Nottingham, Swagelok)
SimBots
(UCL)
CLOUD PLATFORM
(IBM)
Focus
• Integration of information fluxes/data
• Integration of experimental and simulation activities
PilotBots
(Leeds/Promethean Particles)
Generation of Scalable and Sustainable Industrial Chemical Processes (AZ, PP)

The UCL Team

Dr. Federico Galvanin (UCL Lead)

Imperial College London

Centre for Process Systems Engineering

Research Interests

- Design of Experiments (DoE) and statistical planning
- Model-based Design of Experiments (MBDoE)
- Kinetic modelling in catalytic systems
- Machine learning applications to model identification
- Modelling of stochastic systems

Dr. Michail Stamatakis

Research Interests

- Computational catalysis
- Chemical reaction engineering
- Multiscale modelling
- Microkinetic modelling
- Kinetic Monte Carlo

UCL Team Contribution to the Project

Co-supervision (with Michail) of a **4-year PDRA at UCL**

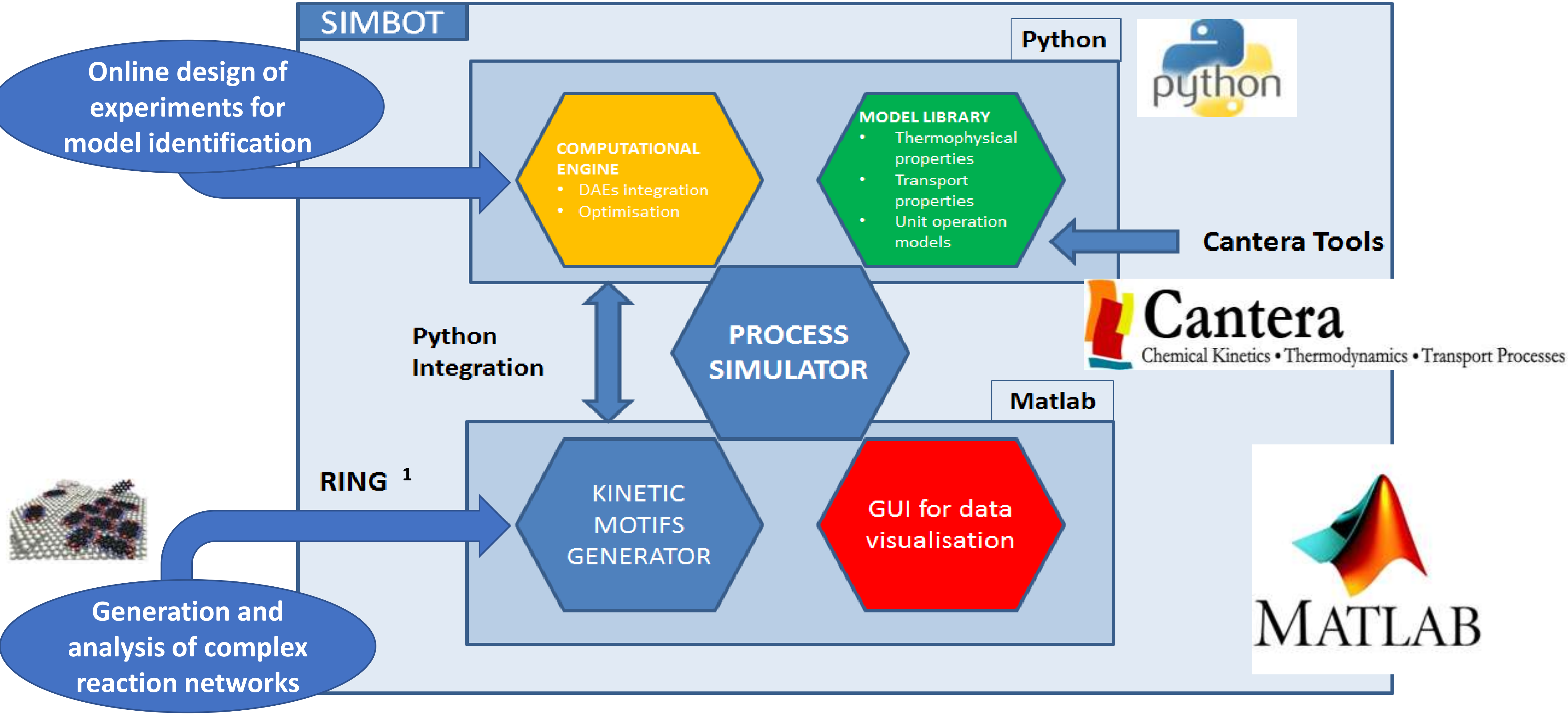
Main goal of the UCL team: to develop a **SimBot platform** for the automated generation and identification of kinetic models based on kinetic motifs.

The **Simbot** will be developed in a high level programming language, and it will integrate:

- Automated generation of kinetic motifs/model structure generation
- Online model-based design of automated experiments
- Data analysis
- Process simulation
- Machine learning techniques for model identification

The Simbot will be integrated in the cloud systems for the easy simulation, identification and optimisation of process models.

Development of the Simbot



[1]Rangarajan, S., Bhan, A., Daoutidis, P. (2012). Computers & Chemical Engineering, 45, 114.

Online design of experiments for fast identification of kinetic models

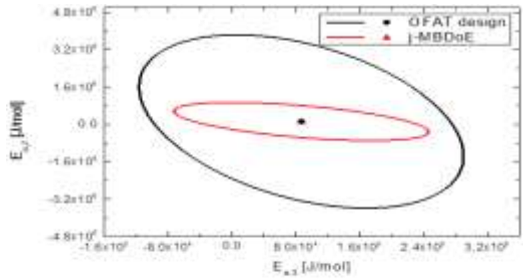
Online design of experiments for model identification[1]

Identification of a suitable kinetic **model structure**

MBDoE for kinetic model discrimination[2]

Identification of the **kinetic parameters**

MBDoE for improving parameter precision[3]



Set of an **optimal experiment**

Optimally informative

Feasible

Operability
Controllability
Safety
Process Economics

Minimisation of the experimental effort

[1]Galvanin, F., Barolo, M., & Bezzo, F. (2009). *Industrial & Engineering Chemistry Research*, **48**, 4415-4427.
[2]Hunter, W. G., A. M. Reiner (1965). *Technometrics*, **7**, 307-323.
[3]Box, G. E. P., H. L. Lucas (1959). *Biometrika*, **46**, 77-90.

Framework for the online identification of parametric models[1]

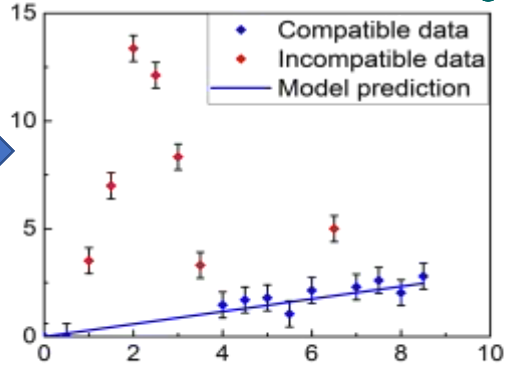
Identification requires

- a precise estimation of $\boldsymbol{\theta}$
- the conditions $\mathbf{u} \in U$ where the model is reliable, i.e. the domain of validity

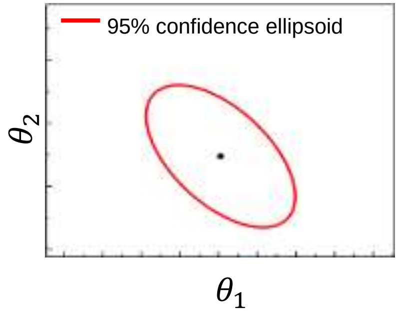
experimental data

approximated model structure
$\hat{\mathbf{y}} = \mathbf{g}(\boldsymbol{\theta}, \mathbf{u})$

Model-Based Data Mining

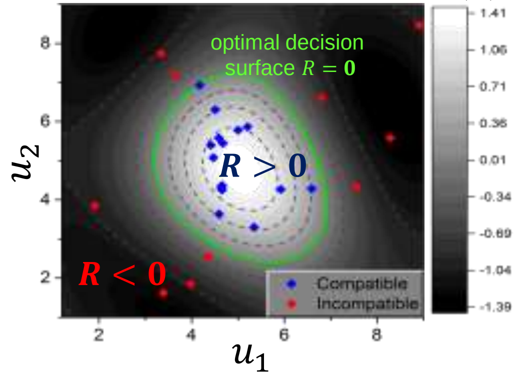


Parameter statistics

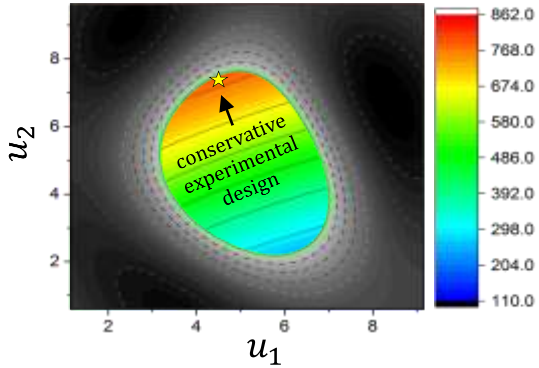


The procedure continues until a pre-defined statistical quality of parameters is achieved

Model Reliability Map $R(\mathbf{u})$



Constrained MBDoE $I(\mathbf{u})$



optimal conservative experimental conditions for improving parameter statistics

additional experimental data

[1]M. Quaglio, E.S. Fraga, E. Cao, A. Gavriilidis, F. Galvanin (2018), *Chemometrics and Intelligent Laboratory Systems* , 12, 134-149.

Overall vision

- Individual reactions are allocated from the cloud based on reactor capability and the efficiency of performing experiments
- Outputs
  - Optimal design of experimental conditions/kinetic modelling (speed/resource/cost)
  - Demonstration of optimisation using **pilot scale flow reactors** (IPRD/Promethean Particles)
  - Reactors will be cognitive, capable of detecting possible future failures and performing experiments in reaction to previous results
  - Model-based process design and optimisation

Cognitive Chemical Manufacturing

UNIVERSITY OF LEEDS

- Federico Galvanin (UCL)
- Michail Stamatakis (UCL)
- Frans Muller (Leeds)
- Richard Bourne (Leeds)
- Tom Chamberlain (Leeds)
- Edward Lester (Nottingham)
- Brian Taylor (AstraZeneca)
- Graeme Clemens (AstraZeneca)
- Selina Ambrose (Promethean Particles)
- Edward Pyzer (IBM/Hartree)

IBM

iPRD

AstraZeneca

UCL

Swagelok

University of Nottingham
UK | CHINA | MALAYSIA

PrometheanParticles
Formulating solutions with nanomaterials

EPSRC
Engineering and Physical Sciences Research Council