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#### **Motivation**

 Loss of productivity: Fluctuations in reaction processes are partly due to variations in the concentration of initial reactants (suboptimal operating conditions).

Another source of fluctuations comes from impurities present in the initial reactants causing unexpected side reactions.

 Loss of time: Initial concentrations are often determined by offline analysis (e.g. HPLC, spectroscopy) and can result in delaying the batch start.

#### Trends in favour of online Kinetic Hard-Modelling (KHM)

- Improving knowledge: Fine chemical industries try to improve manufacturing by elucidating the underlying kinetic model (rate law) of processes whose patents have expired.
- Multivariate on-line sensors: Recent progress in Process
   Analytical Technology (PAT) allows now the monitoring of
   processes in real time using multivariate probes.

## **KHM in Research phase**

 Kinetic hard-modelling compares a measured signal with a modelled one obtained from a 1<sup>st</sup> principle hard model (rate law). The residuals are used as driving force for the least-square optimisation of the kinetic parameters.

Hard model = <i>function</i> (kinetic parameters, IC, CV, NCV)			
<ul><li>IC</li><li>CV</li><li>NCV</li></ul>	Initial Conditions Control Variables Non-Controlled Variables	e.g. initial concentrations e.g. dosing rate, temperature e.g. concentration of the dosing agent	

 Our kinetic hard-modelling approach is a calibration free method in the sense that the calibration (the absorptivity spectra) is nested into the non-linear optimisation and linearly fitted at each iteration.

# **Online KHM in Production phase**

- In production phase, differences between batches result from different IC and/or NCV that can be optimised in a nonlinear way, setting the kinetic parameters to the values found during the research phase.
- Subsequently, Control Variables (e.g. dosing flow rate) can be optimised and/or the process can be monitored for detection of possible faults.

## **Concept of online KHM**



#### Phase 1: OPTIMISATION OF THE IC/NCV AND PROCESS UPSET DETECTION

Optimisation of **IC/NCV** (e.g.  $c_{0, react 1}$  and  $c_{dos, react 2}$ ) with kinetic parameters fixed. Possible Process Fault is detected.

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#### Phase 2: OPTIMISATION OF THE CV

Extrapolation to a future time and optimisation of future **CV** under constraints to maximise  $\Psi$  (= Yield, Selectivity or Conversion).

$$\begin{array}{l} \max_{f(t)} \Psi(t_{\textit{end}}) \\ \textit{s.c.} \ \textit{V}(t_{\textit{end}}) \!\leq \! \textit{V}_{\textit{max}} \\ f_{\textit{min}} \leq \! f(t) \!\leq \! f_{\textit{max}} \end{array}$$

#### Phase 3: OBSERVATION PHASE

Process running under optimal CV.

# **Kinetic model**

#### Absorptivity spectra





modelled:

 $\Delta H_{r1} = -10.0 \text{ kJmol}^{-1}$  $\Delta H_{r2} = -5.0 \text{ kJmol}^{-1}$ unmodelled:

$$\Delta H_{r_3} = -10.0 \text{ kJmol}^{-1}$$

modelled:  $A + B \xrightarrow{k_1 = 0.0656} C$   $A + C \xrightarrow{k_2 = 0.0383} D$ unmodelled:  $B + I \xrightarrow{k_3 = 0.0468} S$  A : dosed C : wanted product D : side product I : contaminant in A

# Base Case simulation Mean IC / NCV No process fault

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 $f_{opt}(\overline{c}_0,\overline{c}_{dos}) = 0.025$ 

A B C D I S $IC: \overline{c}_0 = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \end{bmatrix}$ 

A B C D I S  $NCV: \overline{c}_{dos} = \begin{bmatrix} 2 & 0 & 0 & 0 & 0 \end{bmatrix}$ 

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#### **Base case**

$$A B C D I S$$
$$IC: \overline{c}_0 = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$
$$A B C D I S$$
$$A B C D I S$$
$$NCV: \overline{c}_{dos} = \begin{bmatrix} 2 & 0 & 0 & 0 & 0 \end{bmatrix}$$

**Concentration profiles** 





#### Dosing rate (a CV) 0.04 0.035

ate [-]

Mol 0.025 0.02

8 0.015 Jormali

0.01

0.005

0.03





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Added noise: 10-4



# Optimisation of the Initial Conditions (IC) and Non-Controlled Variables (NCV)

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# and subsequent optimisation of the Control Variables (CV)

A B C D I S	A B C D I S	
$IC: \overline{c}_0 - 15\% = [0 \ 0.85 \ 0 \ 0 \ 0]$	NCV: $\overline{c}_{dos}$ + 15% = [2.30 0 0 0 0 0]	$f_{opt}\left(\overline{c}_{0}-15\%,\overline{c}_{dos}+15\% ight)=?$

#### **Optimisation of the Control Variables (CV)**



Calorimetry		
Normalised time [-]		
Normalised time [-]		

	UV-vis	Calorimetry
Time of calculation	0.516	0.616
σ <sub>p</sub> /p	≤0.20%	≤1.70%
Calculated dosing rate	0	0
Yield increase	+4.05%	+3.30%
Maximum Yield increase	+4.08%	+4.08%

Extrapolation time = 0.0167

#### CV optimisation and comparison with offline analysis

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IC	NCV	Signal	Yield increase	Error of prediction	Time criterion for online KHM to be more efficient than offline analysis
0% (base case)	0% (base case)	Spectroscopy	0.09%	+0.00%	always
		Calorimetry	0.09%	+0.00%	always
		Offline	0.09%	-	-
-15%	+15%	Spectroscopy	4.05%	+0.02%	0.02%
		Calorimetry	3.30%	+0.30%	0.75%
		Offline	4.08%	-	-
-30%	+30%	Spectroscopy	11.06%	+0.15%	3.30%
		Calorimetry	8.47%	+0.45%	5.76%
		Offline	14.72%	-	-

### **Optimisation of the CV**

- For this particular mechanism and these pure component spectra, spectroscopy can be used to optimise online the CV.
- Due to its univariate nature, calorimetry produces a low improvement in yield when used in online KHM.
- For extreme variations in the IC/NCV, online KHM is only better than offline analysis if the time required for the offline analysis largely delays the batch start.
- For this particular mechanism, the concentration of the dosing agent has the most impact on the yield.

## Process Fault Detection (PFD) or Process Upset Detection



 $NCV: \overline{c}_{dos} + I = \begin{bmatrix} 2 & 0 & 0 & 0 & c_{dos, I} & 0 \end{bmatrix}$ 

 $f_{opt}(\overline{c}_0,\overline{c}_{dos}) = 0.025$ 

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### SSQ and Standard deviation of the residuals as Process Fault indicators

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ssq

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 $\sigma_{residuals}$ 

## Known absorptivity spectra (in eigen-space) as Process Fault indicators



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Spectrum	<i>PVE<sub>A</sub></i> at t <sub>end</sub>		
selected for PFD	With fault	Without fault	
Spectrum of A	85.51%	98.68%	
Spectrum of B	98.50%	99.47%	
Spectrum of C	78.33%	97.57%	
Spectrum of D	69.82%	96.62%	

# Known reaction enthalpies as Process Fault indicator





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#### **Process Fault Detection**

- Spectroscopy and calorimetry can be used to detect Process Faults
- The best process fault indicators are generally the ones based on a priori information, i.e. the absorptivity spectra and the reaction enthalpies

### Conclusion

- The capabilities of online KHM have been demonstrated by:
  - Optimisation of the Initial Conditions (IC) and Non-Controlled Variables (NCV)
  - Subsequent optimisation of the Control Variables (CV)
  - And constant Detection of possible Process Faults (PFD)
- Next, online KHM will be applied on experimental data for a simple chemical system.

# Thank you for your attention

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