Batch-to-batch strategies for cooling crystallization

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51th IEEE Conference on Decision and Control

Grand Wailea, Maui, Hawaii

Motivation

Many operations are performed in batch mode.
Batch processes bring both challenges and opportunities for control.

Challenges

- Wide dynamical range
- Limited measurements*

Opportunities

- Slow dynamics
- Repetitive nature*

In this presentation: batch-to-batch learning control for cooling crytallization which exploit the repetitive nature.

- Iterative Learning Control (ILC)
- Iterative Identification Control (IIC).

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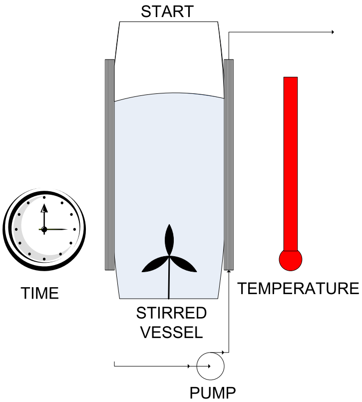
Outline

Batch Crystallization

Process Description

Separation and purification process of industrial interest.
A solution is cooled down, solid crystals are produced.



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2. Start cooling.
3. Introduce "seeds".
4. Cool to final temperature. Seeds grow, new crystal are generated.
5. Remove final product.

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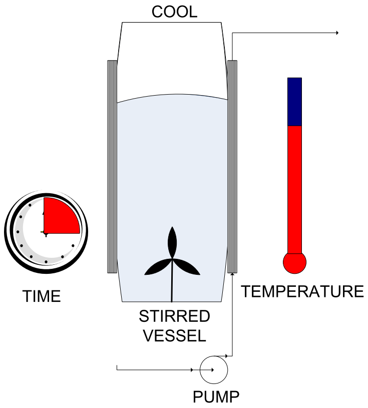

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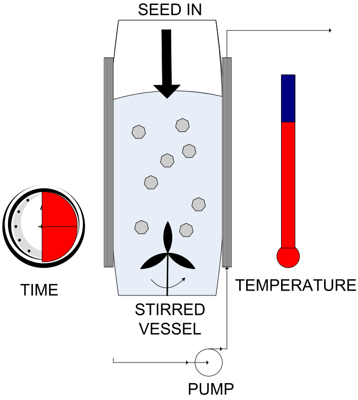

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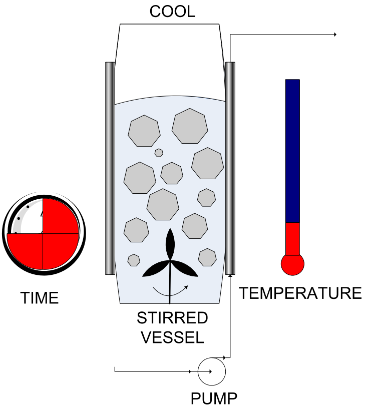

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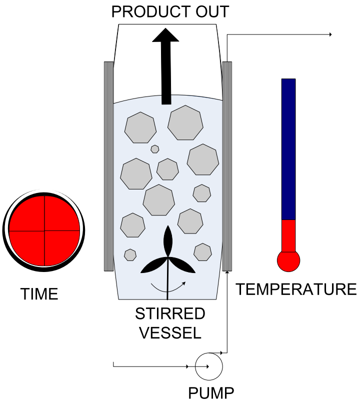

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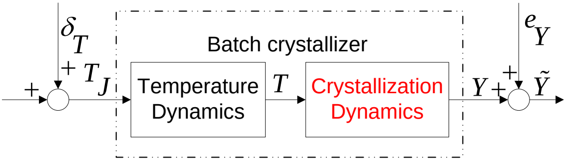
Batch Crystallization
Modeling

Process described by:

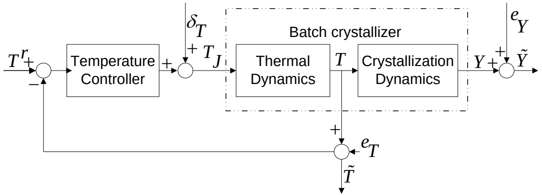
- Thermal Dynamics from the actuator to the vessel temperature.
  Linear, known or easy to derive/estimate.
- Crystallization Dynamics from the reactor temperature to the crystallization properties.
  Nonlinear PDE, parametric + structural uncertainties possible.



Batch Crystallization

Control Strategies: industrial practice

Only the crystallizer temperature is measured and controlled on-line.



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Alternative approach based on Batch-to-batch Control.

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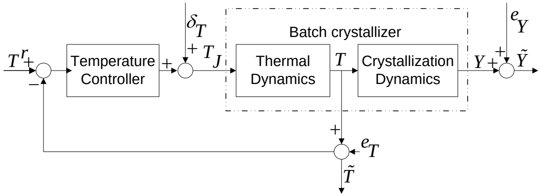

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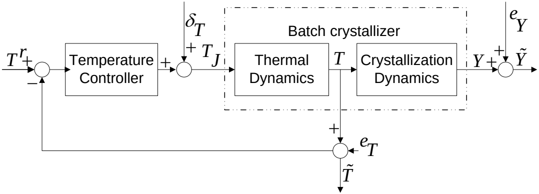

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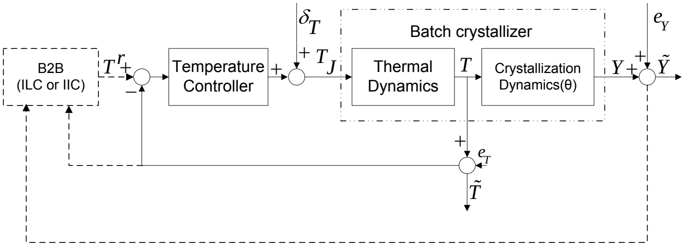
Batch-to-batch Control

Architecture

A framework for batch-to-batch control. $\mathbf{T}_k^r$ updated from batch to batch.

- Built on top of the standard industrial T control.
- Can use measurements available at the end of the batch.



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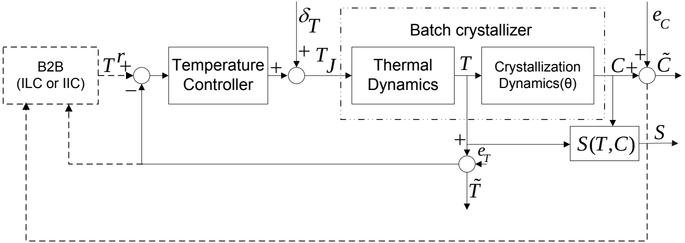

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Batch-to-batch Strategies

Iterative Learning Control

ILC based on an additive correction of a nominal model from $\mathbf{T}^r$ to $\mathbf{S}$.

$$\hat{S}(\mathbf{T}^r) \qquad \textit{nominal model}$$

$$\hat{S}_k(\mathbf{T}^r) \triangleq \hat{S}(\mathbf{T}^r) + \boldsymbol{\alpha}_k \qquad \textit{corrected model}$$

Note: $\mathbf{T}^r, \boldsymbol{\alpha}_k$ vectors of samples $\in \mathbb{R}^N$ ($N =$ batch length).
We describe the system in discrete, finite time (static mapping).

A nonparametric model correction. α_k can compensate for

- model mismatch (along a particular trajectory)
- effect of repetitive disturbances

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Iterative Learning Control

Correction vector

How to obtain the correction vector α?

- In principle, "match" the measurement from the previous batch.

$$\alpha_{k+1} = \tilde{\mathbf{S}}_k - \hat{S}(\mathbf{T}^r_k) \qquad = \qquad \text{model error}_k$$

Due to nonrepetitive disturbances on $\tilde{\mathbf{S}}_k$, this is not a good solution.

- Take into account the deviation from α_k.

$$\alpha_{k+1} = \arg \min_{\alpha \in \mathbb{R}^N} \|\tilde{\mathbf{S}}_k - (\hat{S}(\mathbf{T}^r) + \alpha)\|^2_{Q_\alpha} + \|\alpha - \alpha_k\|^2_{S_\alpha}$$

Careful tuning of Q_α, S_α is delicate.

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Iterative Learning Control

Algorithm

Steps of the ILC algorithm. At each batch k:

1. $\mathbf{T}_k^r$ is set as the input to the T controller, the batch is executed. $\tilde{\mathbf{S}}_k$ is estimated from measurements.
2. An additive correction of the nominal model is performed: $\hat{S}_k(\mathbf{T}^r) \triangleq \hat{S}(\mathbf{T}^r) + \alpha_k$.
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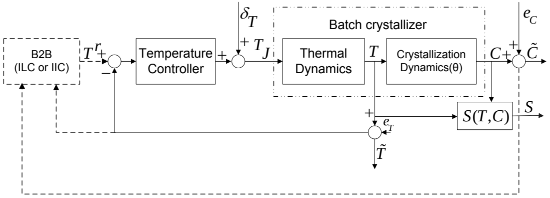

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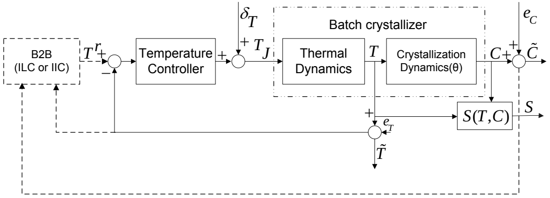

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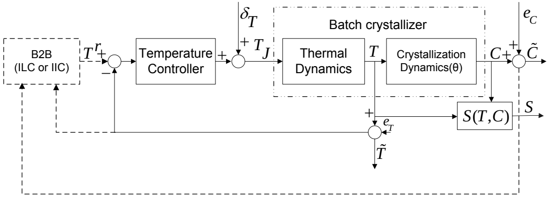

Iterative Identification Control

Implementation

IIC is based on a parametric correction assuming a certain model structure.

$\hat{S}(\mathbf{T}^r, \theta)$ *model structure*

$\hat{S}_k(\mathbf{T}^r, \hat{\theta}_k)$ *IIC corrected model*

Iterative estimation of $\hat{\theta}_k$ combining information from previous measurement.

Given a new measurement $\tilde{\mathbf{Y}}_k = (\tilde{\mathbf{T}}_k \; \tilde{\mathbf{C}}_k)$:

- The *a posteriori* probability of θ is computed (Bayes rules):
- $\hat{\theta}_{k+1}$ is taken as arg max over θ of the distribution (MAP estimate)

In our case (under simplifying assumptions)

$$\hat{\theta}_{k+1} = \arg\min_{\theta} \left(\|\tilde{\mathbf{C}}_k - \hat{C}(\tilde{\mathbf{T}}_k, \theta)\|^2_{\Sigma_e^{-1}} + \|\theta - \hat{\theta}_k\|^2_{\Sigma_{\theta_k}^{-1}} \right)$$

A Nonlinear Least Squares problem with a regularization term.

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Steps of the IIC algorithm. At each k:

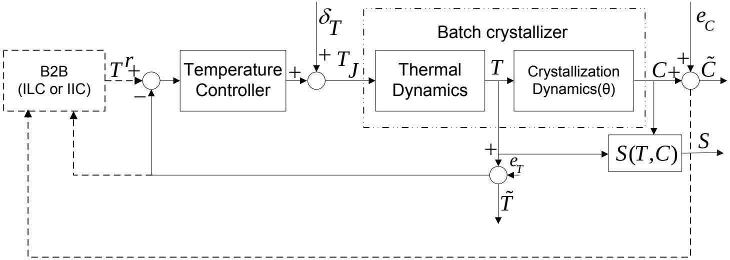
1. $\mathbf{T}^r_k$ is set as the input to the T controller, the batch is executed. $(\tilde{\mathbf{C}}_k, \tilde{\mathbf{T}}_k)^\top$ are measured.
2. The updated parameter $\hat{\theta}_k$ is computed and the corrected model is defined as $\hat{S}_k(\mathbf{T}^r) \triangleq \hat{S}(\mathbf{T}^r, \hat{\theta}_k)$.
3. The corrected model is used to design $\mathbf{T}^r_{k+1}$ for the next batch to track a set-point $\overline{\mathbf{S}}_{k+1}$

$$\mathbf{T}^r_{k+1} = \arg\min_{\mathbf{T}^r \in \mathbb{R}^N} \|\overline{\mathbf{S}}_{k+1} - \hat{S}_k(\mathbf{T}^r)\|^2$$

Simulation Results

Scenario

- $N_{it} = 30$ iterations (batches)
- Objective: tracking of a set-point $\overline{\mathbf{S}}_k$
- Set-point change in batch 11
- $\mathbf{T}^r$ updated from batch to batch using ILC and IIC

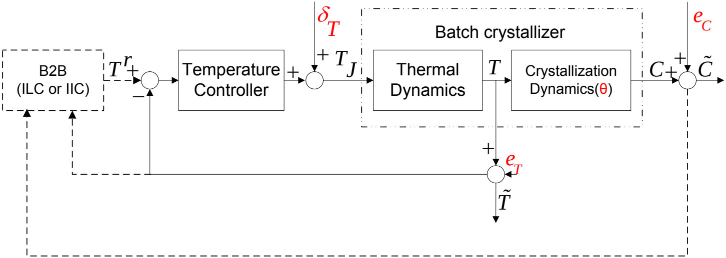


Simulation Results

Cases

Simulation study in two different scenarios

Case 1: Disturbances + parametric model mismatch

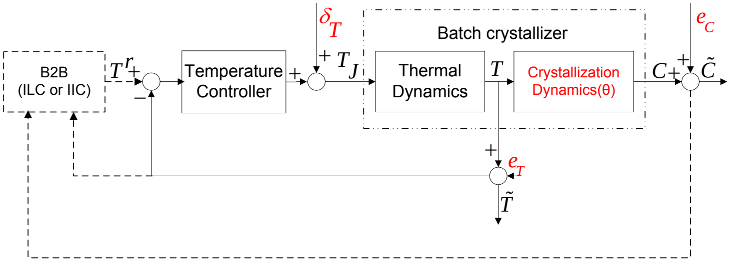


Simulation Results

Cases

Simulation study in two different scenarios

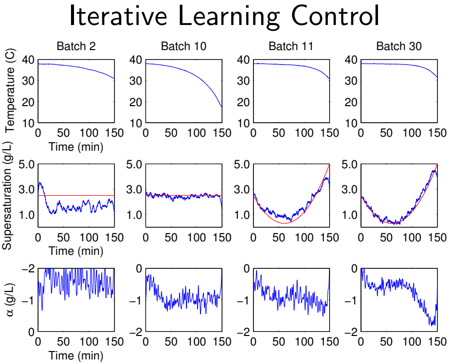
Case 2: Disturbances + structural model mismatch

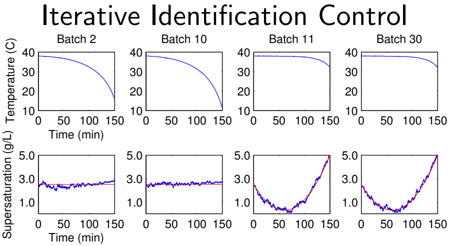


Simulation Results

Case 1

Results for Case 1





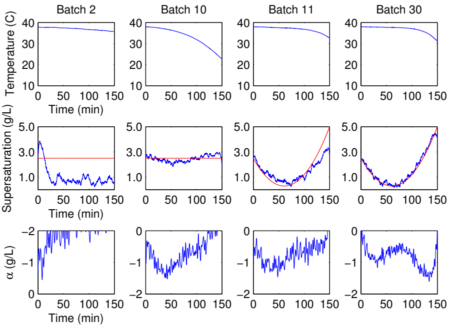
- IIC: faster convergence

Simulation Results

Case 2

Results for Case 2

Iterative Learning Control



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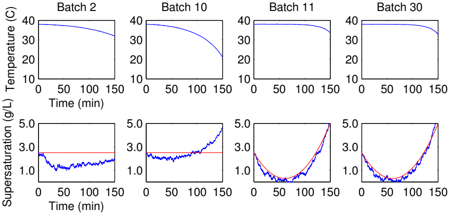


- ILC: convergence despite mismatch

Simulation Results

Summary

Iterative Learning

- Tracking in presence of structure mismatch
- Close-form algorithm
- Slower convergence of the algorithm
- Learning of a trajectory: degradation if we change the set-point

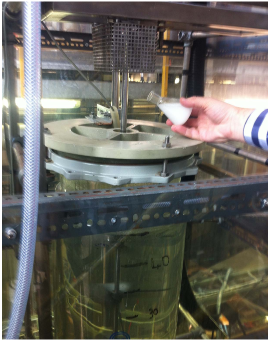
Iterative Identification

- Faster convergence with right model structure
- Learning of the full dynamics: easy to follow different setpoint
- Performance degradation with mismatches
- Numerical solution NLSQ required

Conclusions

A batch-to-batch architecture for cooling crystallization.

- Uses measurements available at the end of a batch.
- Built on top of standard T control.
- Can cope with model mismatches and disturbances.
- Experiments going on.



Future work

- Introduce excitation signals
- Combine ILC and IIC strategies.

Thank you.
Questions?