

Run-to-run optimization of fed-batch processes with unfold-PLS

IFPAC 2009

Dr. José Camacho-Páez
Ass. Prof. Jesús Picó
Prof. Alberto Ferrer

Universidad Politécnica de Valencia
Spain



Batch Process Optimization

Outline

1. Batch Process Optimization
2. Optimization Method
3. Case Study: Simulation
4. Extensions
5. Conclusions

- Objectives: maximize production, improve quality, improve safety conditions, reduce costs, etc.
- Extremely hard task
 - Uncertainties
 - Lack of critical measurements
 - Non-linear nature
 - Slow response
 - ...
- Fundamental knowledge → quality of the model or the assumptions assumed.
- Repetitive nature → Useful for optimization



Optimization Method

Outline

1. Batch Process Optimization
2. **Optimization Method**
3. Case Study: Simulation
4. Extensions
5. Conclusions

- Run-to-run (R2R) optimization
 - Learn from the past batches to improve the performance of the current one
- Three ideas: 
- a) The batch-wise unfolding : $X(I, J, K) \rightarrow X(I, JK)$
- b) A PLS model \rightarrow gradient of the optimization function
- c) Non-linearities and Non-convexity \rightarrow adaptive PLS model + heuristic rules (CV).

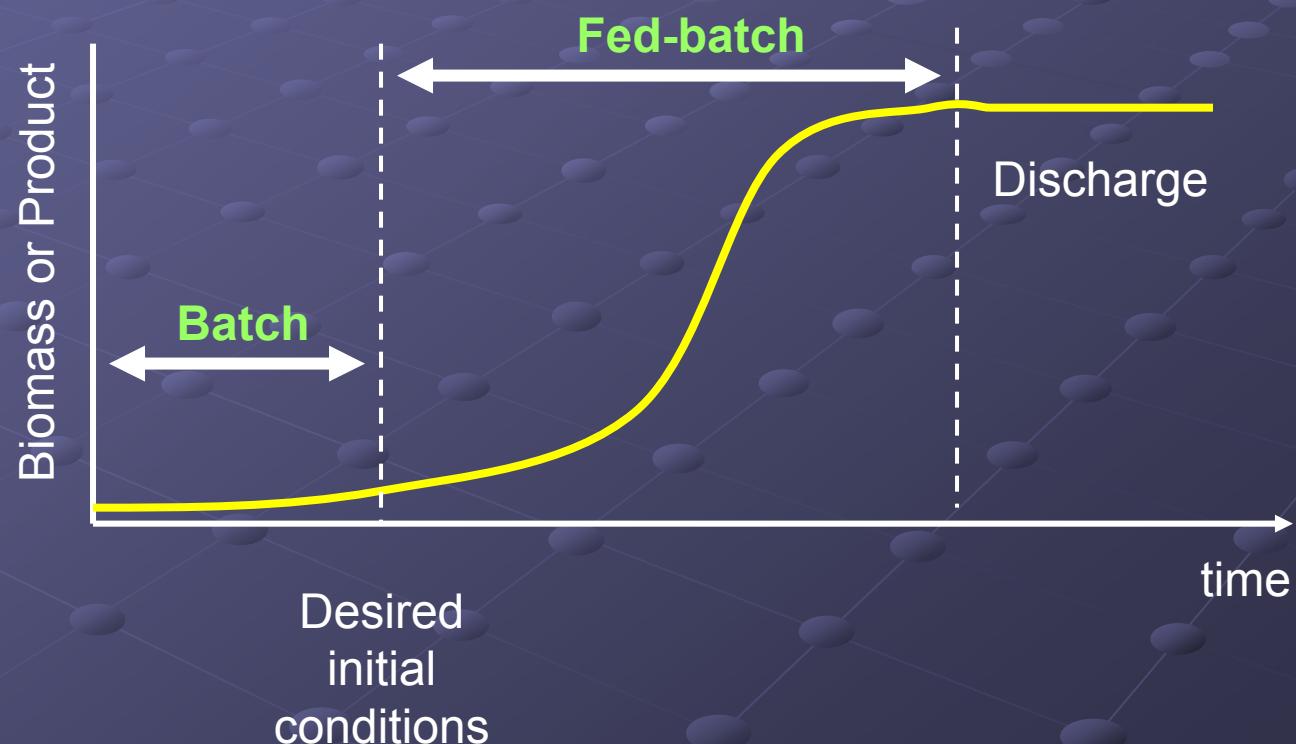


Optimization Method

Outline

1. Batch Process Optimization
2. **Optimization Method**
3. Case Study: Simulation
4. Extensions
5. Conclusions

Illustrative example: Fermentation process.

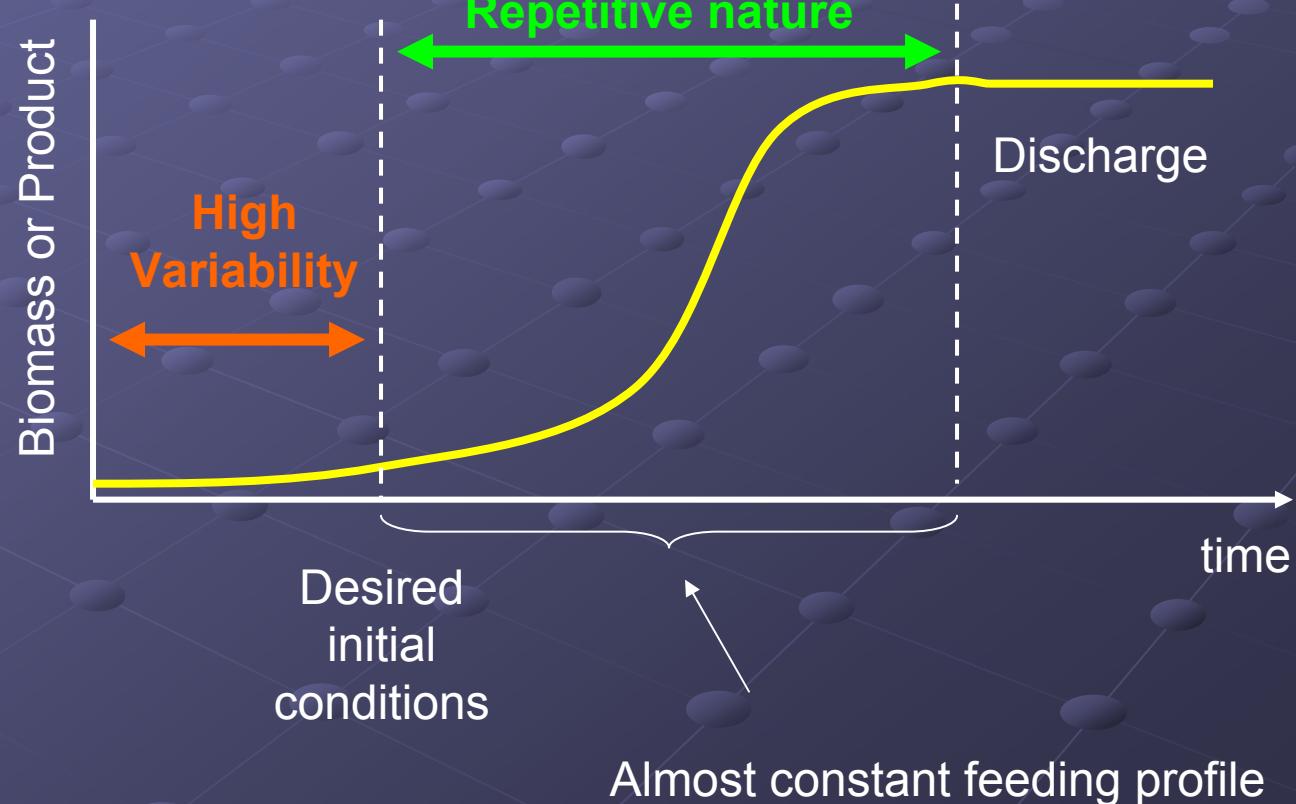


Optimization Method

Outline

1. Batch Process Optimization
2. **Optimization Method**
3. Case Study: Simulation
4. Extensions
5. Conclusions

Illustrative example: Fermentation process.

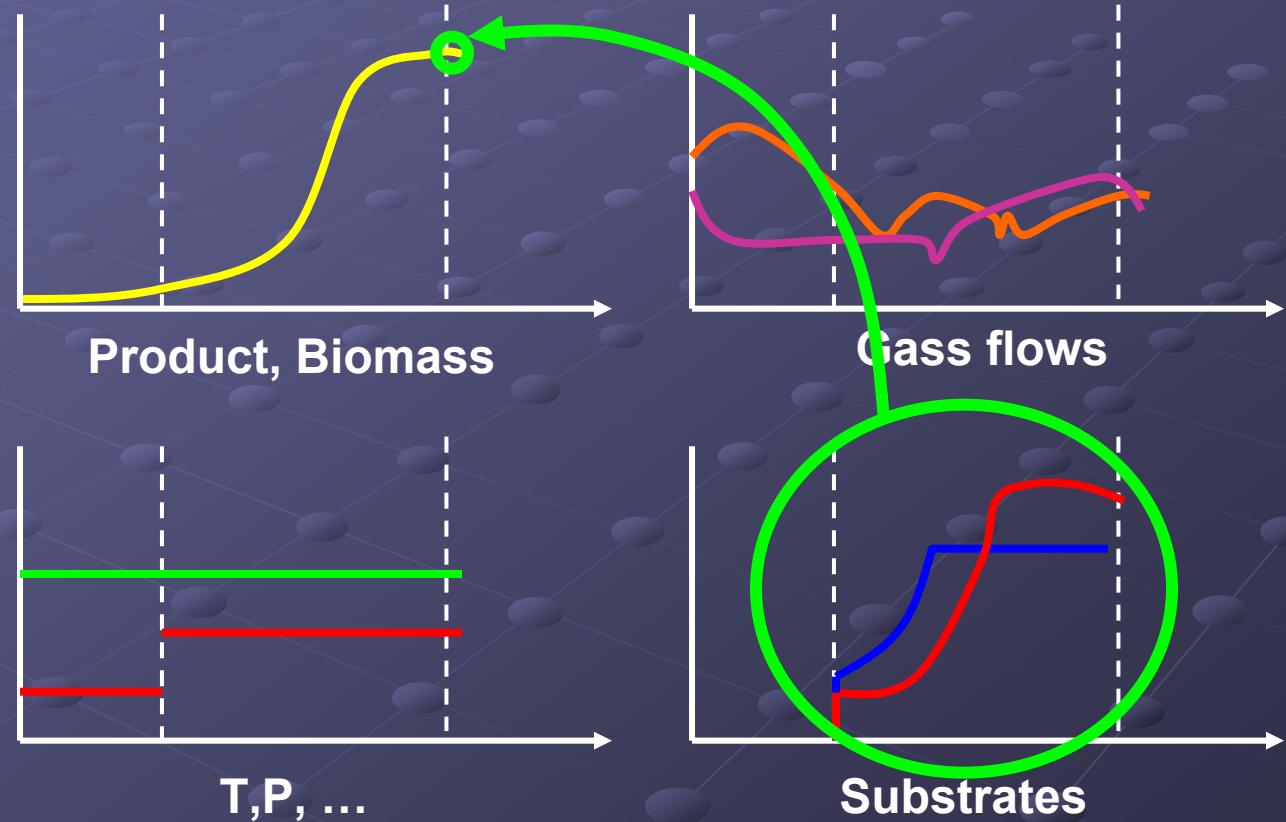


Optimization Method

Outline

1. Batch Process Optimization
2. **Optimization Method**
3. Case Study: Simulation
4. Extensions
5. Conclusions

Illustrative example: Fermentation process.



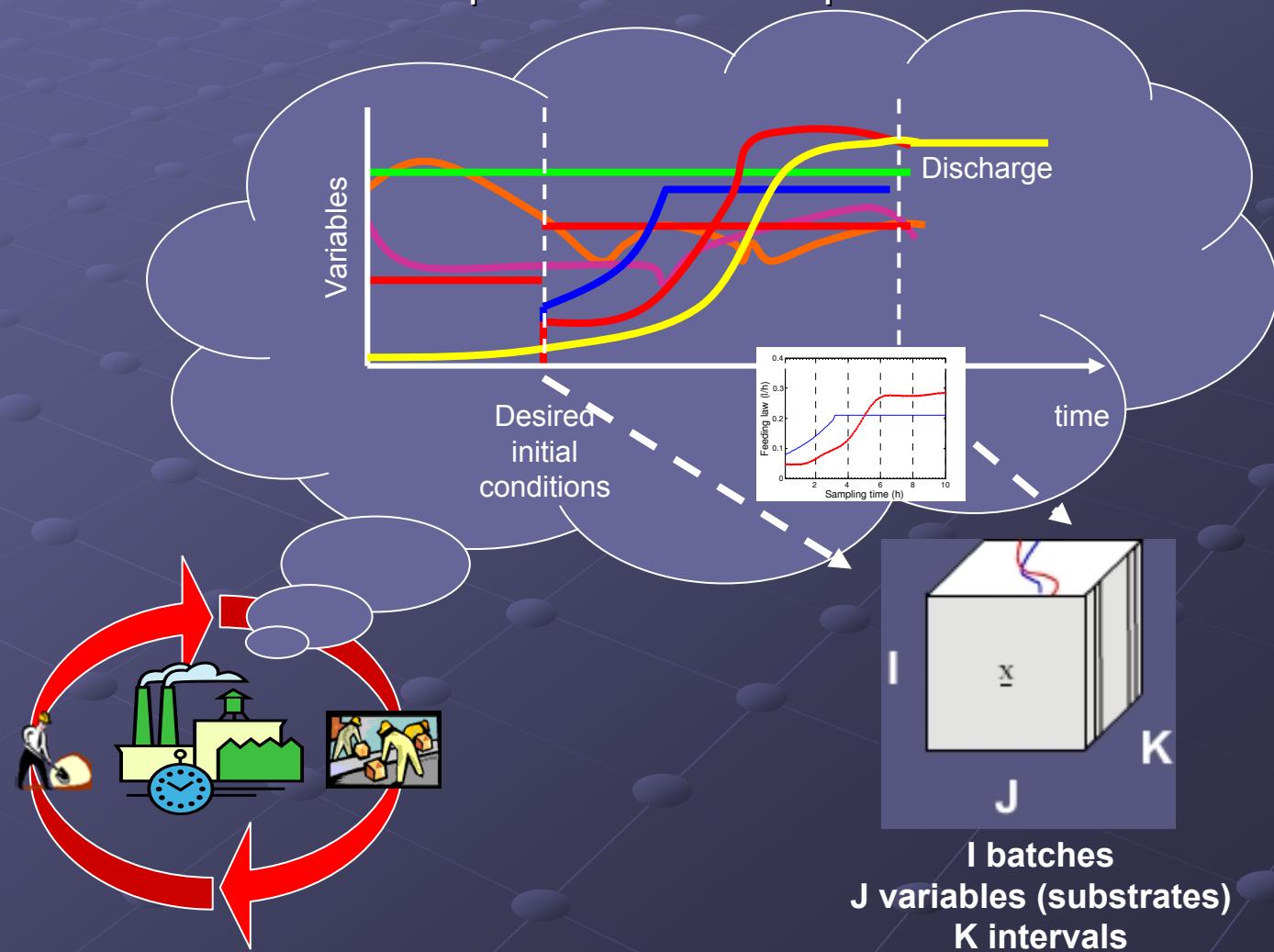
Objective: Select the feeding profile of substrate to maximize final product or biomass .

Optimization Method

Outline

1. Batch Process Optimization
2. **Optimization Method**
3. Case Study: Simulation
4. Extensions
5. Conclusions

Illustrative example: Fermentation process.



Optimization Method

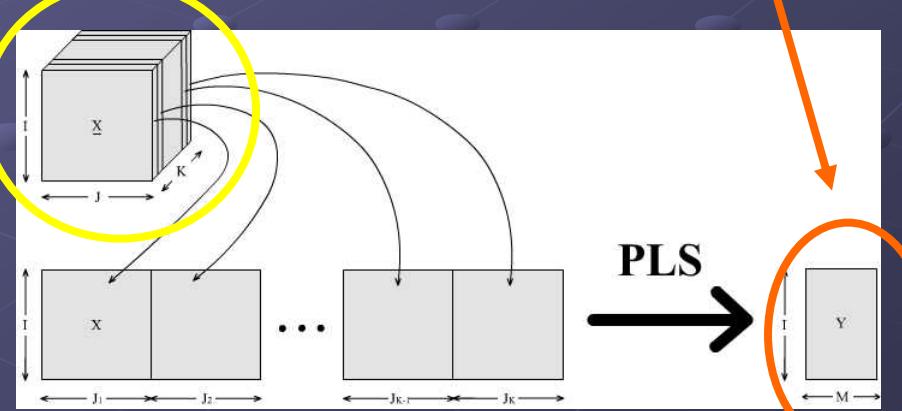
Outline

1. Batch Process Optimization
2. Optimization Method
3. Case Study: Simulation
4. Extensions
5. Conclusions

Three ideas: 

Fed-batch
data

Optimization index
(quality variables, energy
consumption, etc..)



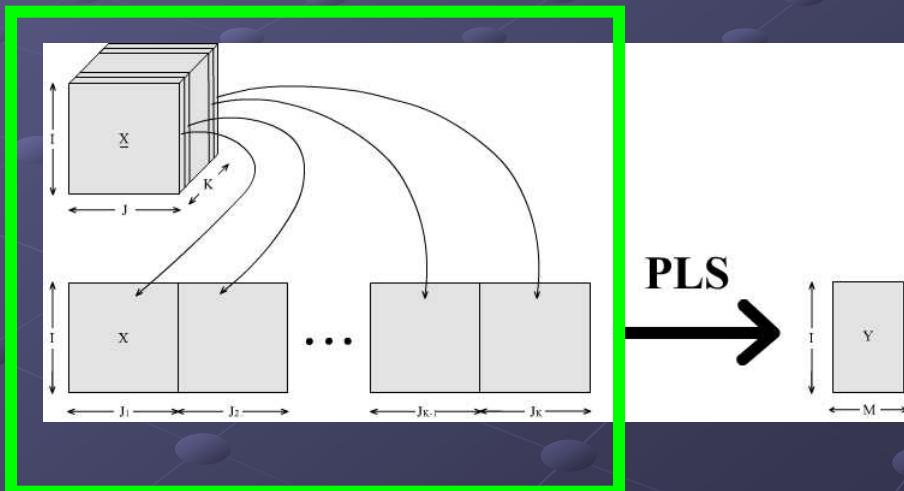
Optimization Method

Outline

1. Batch Process Optimization
2. Optimization Method
3. Case Study: Simulation
4. Extensions
5. Conclusions

Three ideas: 

a) The batch-wise unfolding : $X(I, J, K) \rightarrow X(I, JK)$



Optimization Method

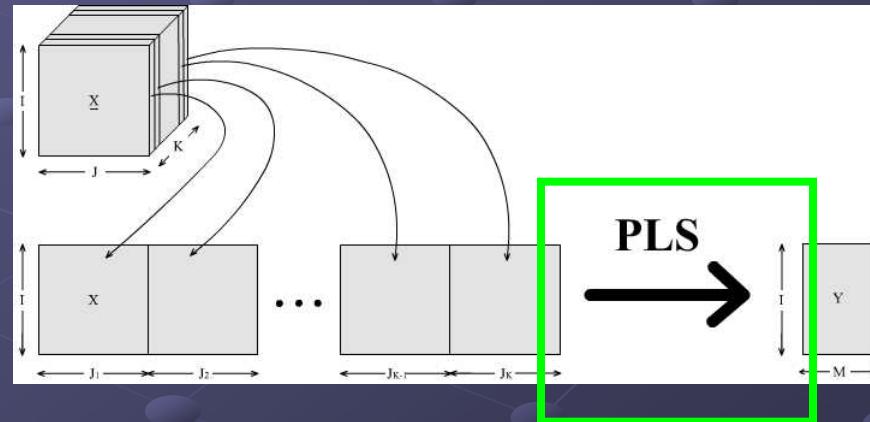
Outline

1. Batch Process Optimization
2. **Optimization Method**
3. Case Study: Simulation
4. Extensions
5. Conclusions

Three ideas: 

a) The batch-wise unfolding : $X(I, J, K) \rightarrow X(I, JK)$

b) A PLS model \rightarrow gradient of a function



Optimization Method

Outline

1. Batch Process Optimization
2. Optimization Method
3. Case Study: Simulation
4. Extensions
5. Conclusions

Three ideas: 

a) The batch-wise unfolding : $X(I, J, K) \rightarrow X(I, JK)$

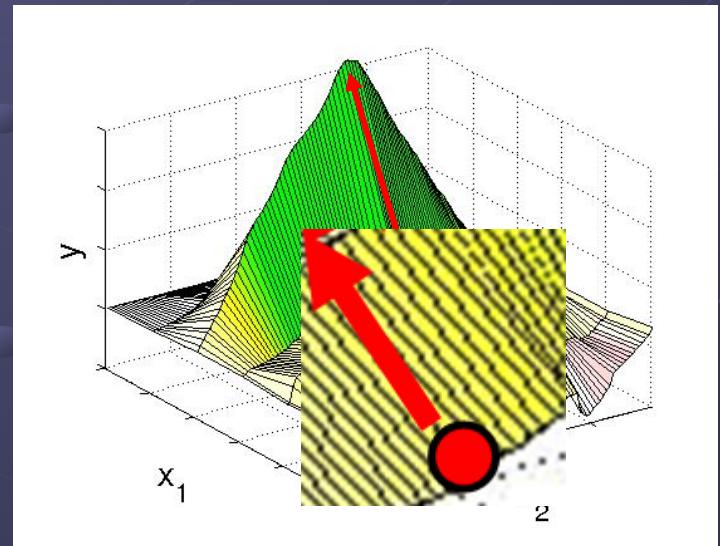
b) A PLS model \rightarrow gradient of a function

Gradient-based optimization:

$$X = [x_1, x_2] \rightarrow Y$$

$$X_{k+1} = X_k + c \cdot \frac{dy}{dX}$$

We need to estimate the gradient!!!



Optimization Method

Outline

1. Batch Process Optimization
2. Optimization Method
3. Case Study: Simulation
4. Extensions
5. Conclusions

Three ideas: 

a) The batch-wise unfolding : $X(I, J, K) \rightarrow X(I, JK)$

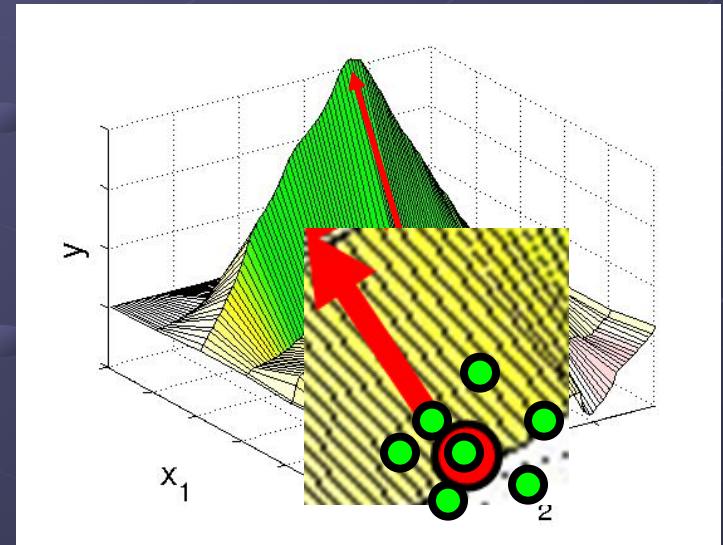
b) A PLS model \rightarrow gradient of a function

Gradient-based optimization:

$$X = [x_1, x_2] \rightarrow Y$$

$$X_{k+1} = X_k + c \cdot \frac{dy}{dX}$$

We need to estimate the gradient!!!



At least as many samples as process variables



Optimization Method

Outline

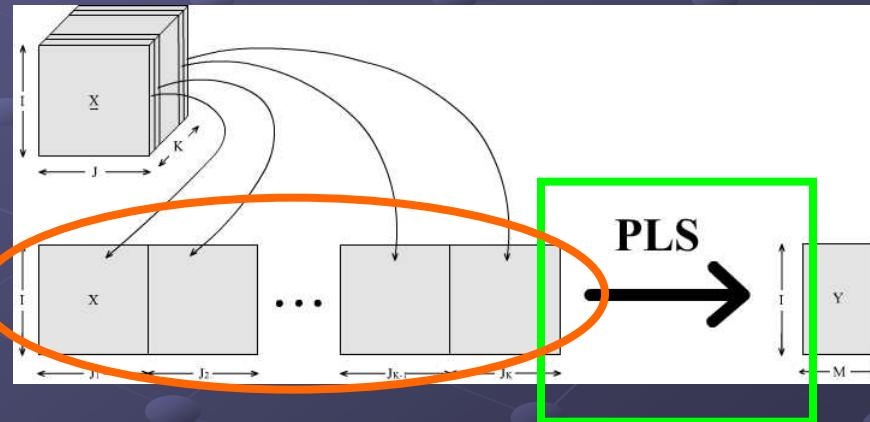
1. Batch Process Optimization
2. Optimization Method
3. Case Study: Simulation
4. Extensions
5. Conclusions

High number of process variables
 $\#Var(X) = J \cdot K$

Three ideas: 

a) The batch-wise unfolding : $X(I, J, K) \rightarrow X(I, JK)$

b) A PLS model \rightarrow gradient of a function



PLS \rightarrow Fast Gradient-based Optimization !!!



Optimization Method

Outline

1. Batch Process Optimization
2. Optimization Method
3. Case Study: Simulation
4. Extensions
5. Conclusions

Three ideas: 

- a) The batch-wise unfolding : $X(I, J, K) \rightarrow X(I, JK)$
- b) A PLS model \rightarrow gradient of a function
- c) Non-linearities and Non-convexity \rightarrow adaptive PLS model + heuristic rules (CV).
 - Construct the PLS model with the last N batches
 - Only trust the model with a certain degree:
Confidence degree [0,1] by cross-validation.



Optimization Method

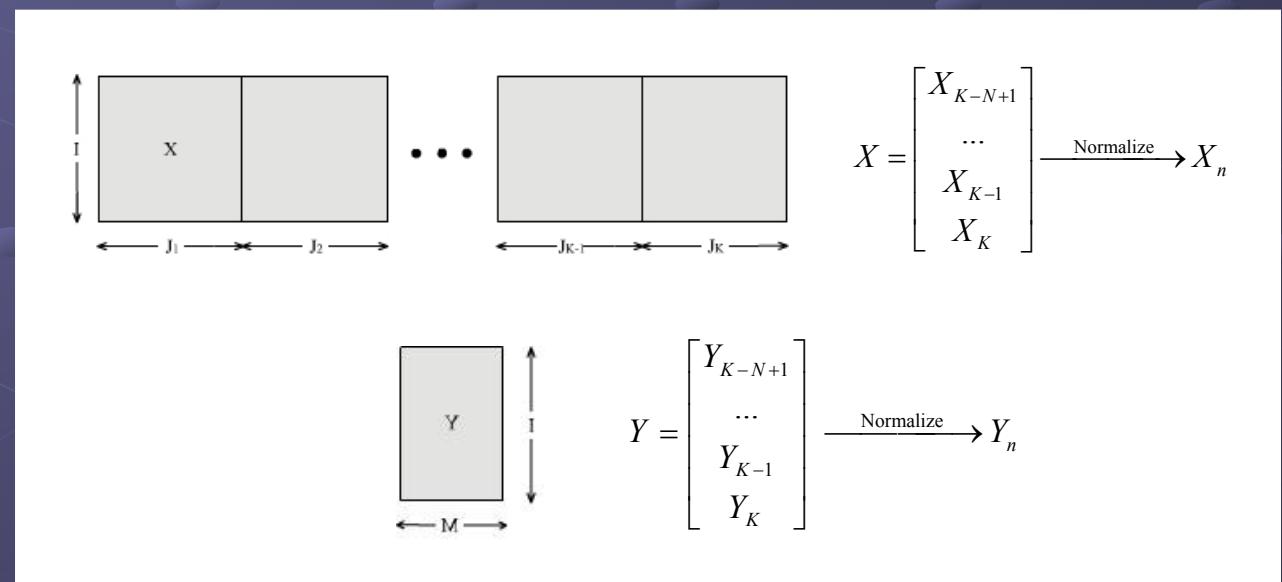
Outline

1. Batch Process Optimization
2. **Optimization Method**
3. Case Study: Simulation
4. Extensions
5. Conclusions

• Self-tuning algorithm:

- Step 1: Process a new batch k with feeding law X_k and obtain the output Y_k .

Take last N batches



Optimization Method

Outline

1. Batch Process Optimization
2. **Optimization Method**
3. Case Study: Simulation
4. Extensions
5. Conclusions

● Self-tuning algorithm:

- Step 1: Process a new batch k with feeding law X_k and obtain the output Y_k .
- Step 2: Rebuild the BW-PLS model with the data of batch i .

$$Y_n = \hat{B}_{PLS} \cdot X_n + E$$

$$\hat{B}_{PLS} = W \cdot (P^T \cdot W)^{-1} \cdot Q^T$$



Optimization Method

Outline

1. Batch Process Optimization
2. **Optimization Method**
3. Case Study: Simulation
4. Extensions
5. Conclusions

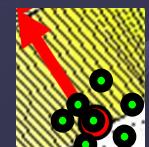
• Self-tuning algorithm:

- Step 1: Process a new batch k with feeding law X_k and obtain the output Y_k .
- Step 2: Rebuild the BW-PLS model with the data of batch i.
- Step 3: Compute the gradient and the next feeding law.

$$\hat{\frac{dY}{dX}} = \frac{\sigma_y}{\sigma_x} \cdot W \cdot (P^T \cdot W)^{-1} \cdot Q^T$$

Heuristics
(CV)

$$X_{k+1} = X_k + c_k \cdot \hat{\frac{dY}{dX}} + o_k$$



Excitation



Optimization Method

Outline

1. Batch Process Optimization
2. **Optimization Method**
3. Case Study: Simulation
4. Extensions
5. Conclusions

● Self-tuning algorithm:

- Step 1: Process a new batch k with feeding law X_k and obtain the output Y_k .
- Step 2: Rebuild the BW-PLS model with the data of batch i.
- Step 3: Compute the gradient and the next feeding law.
- Step 4: Increment the counter $k = k+1$ and loop back to Step 1.

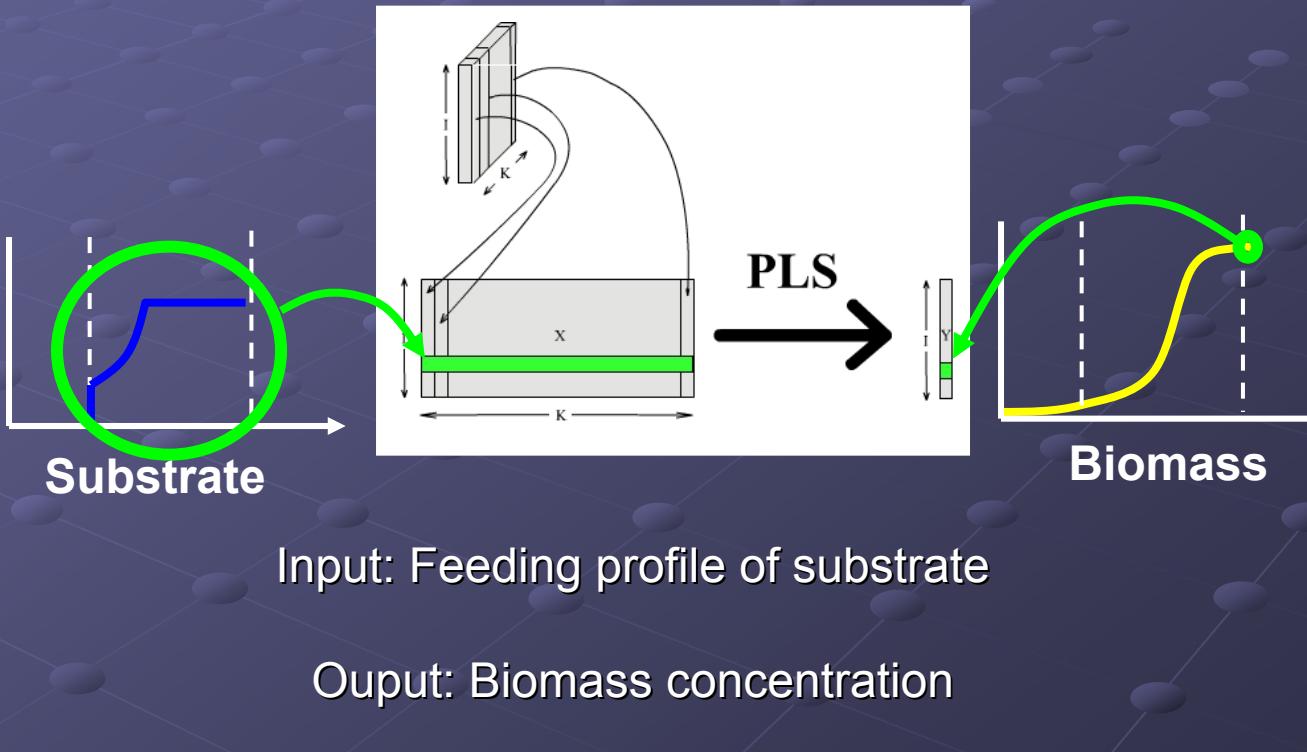


Case Study: Simulation

Outline

1. Batch Process Optimization
2. Optimization Method
3. **Case Study: Simulation**
4. Extensions
5. Conclusions

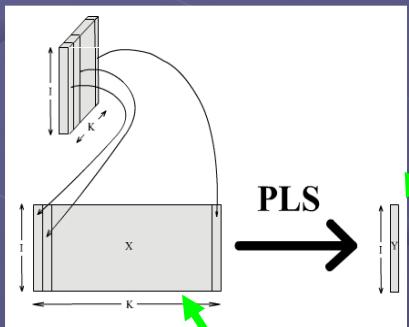
● Saccharomyces cerevisiae fed-batch cultivation



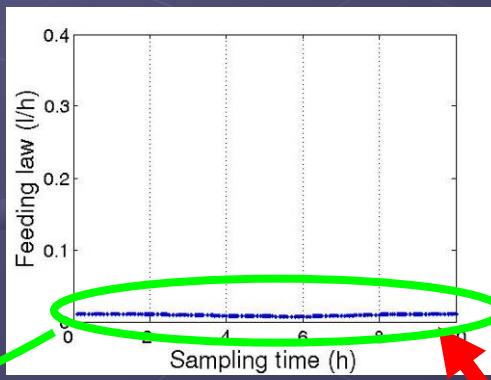
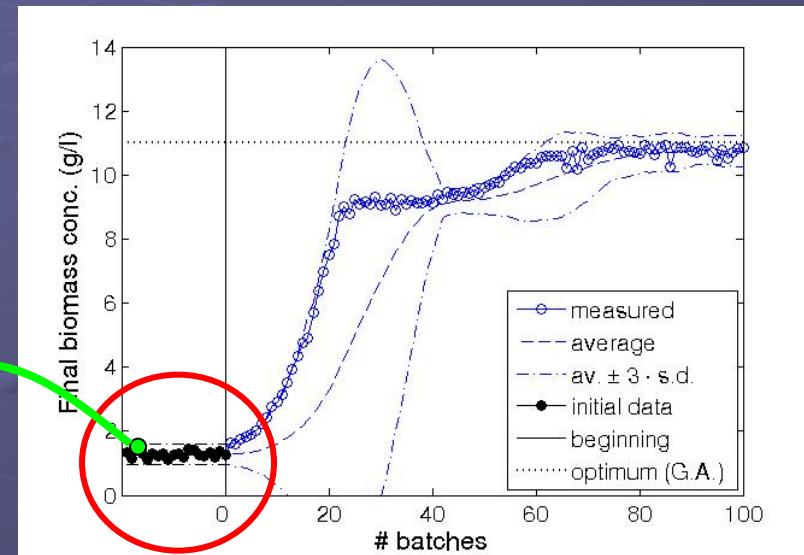
Case Study: Simulation

Outline

1. Batch Process Optimization
2. Optimization Method
3. **Case Study: Simulation**
4. Extensions
5. Conclusions



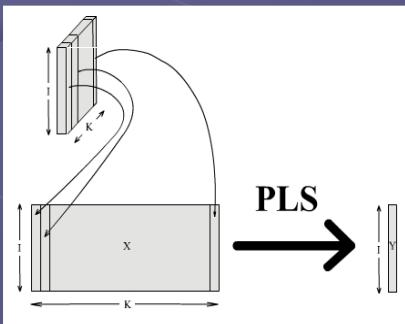
• Saccharomyces cerevisiae fed-batch cultivation



Case Study: Simulation

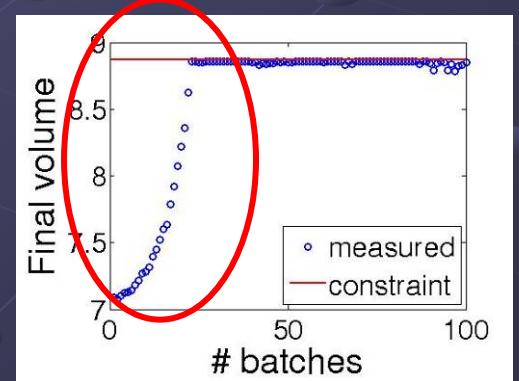
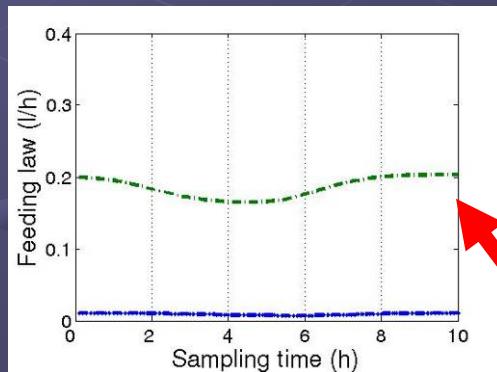
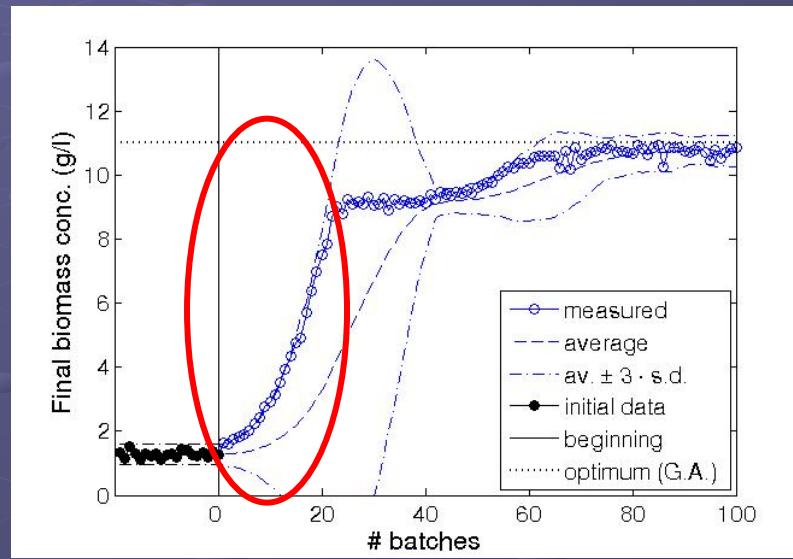
Outline

1. Batch Process Optimization
2. Optimization Method
3. **Case Study:
Simulation**
4. Extensions
5. Conclusions



PLS

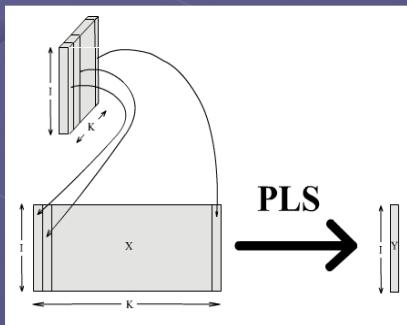
• Saccharomyces cerevisiae fed-batch cultivation



Case Study: Simulation

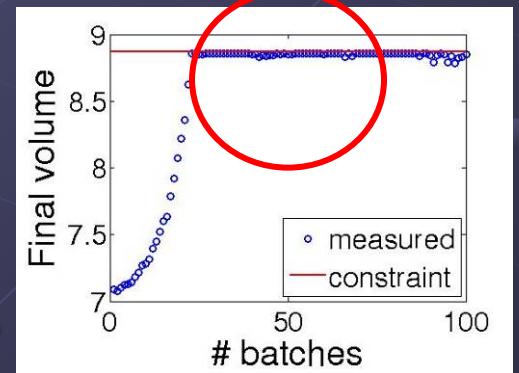
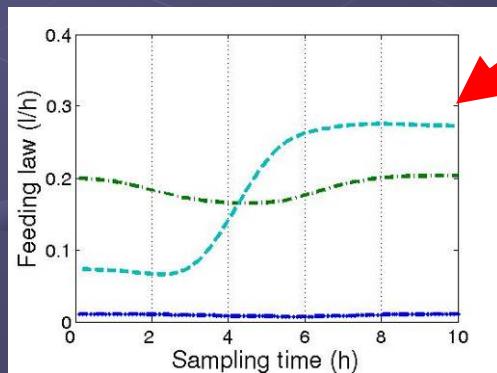
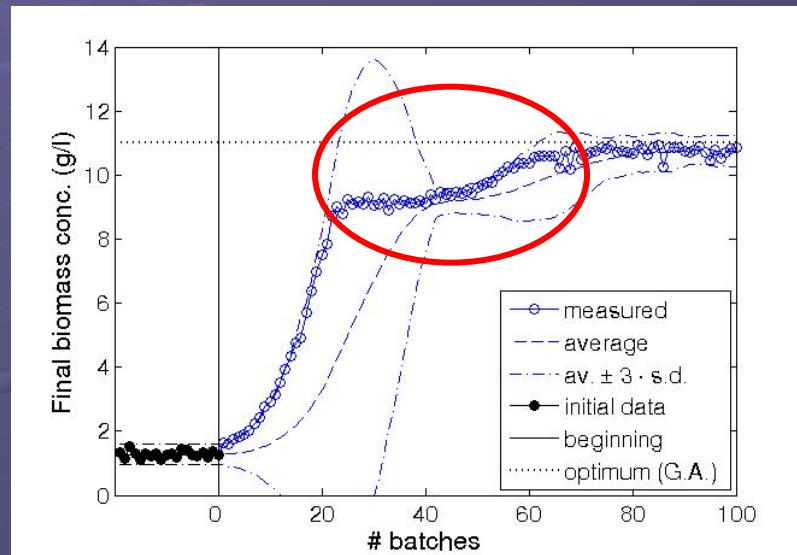
Outline

1. Batch Process Optimization
2. Optimization Method
3. **Case Study: Simulation**
4. Extensions
5. Conclusions



PLS

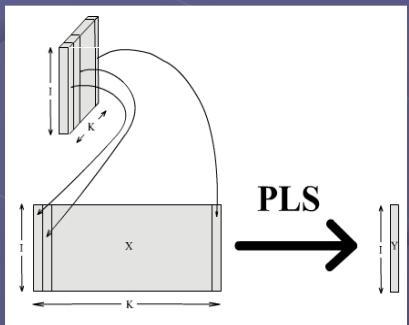
• Saccharomyces cerevisiae fed-batch cultivation



Case Study: Simulation

Outline

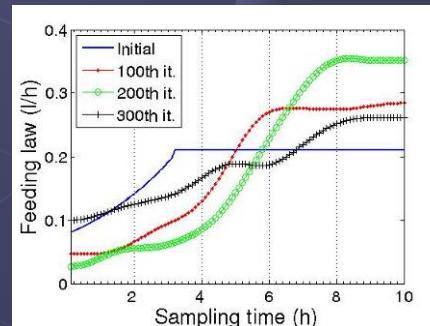
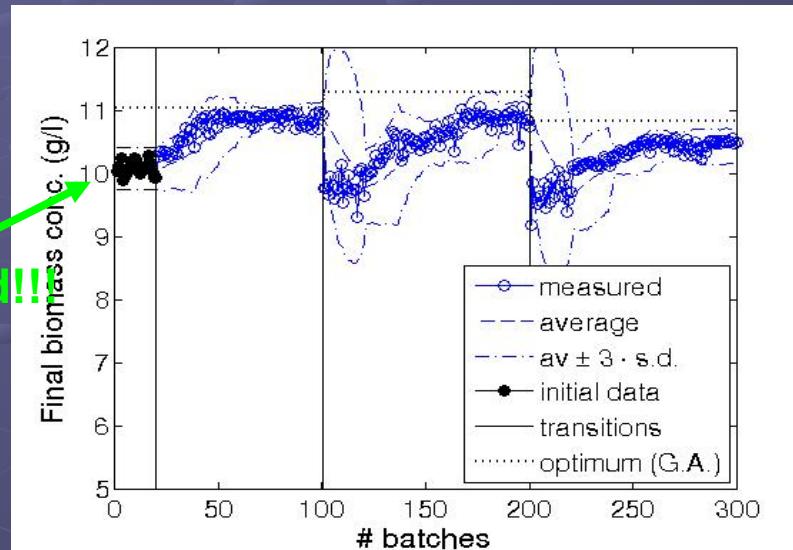
1. Batch Process Optimization
2. Optimization Method
3. **Case Study: Simulation**
4. Extensions
5. Conclusions



Universidad Politécnica
de Valencia, Spain

• Saccharomyces cerevisiae cultivation

The one
suggested!!!



J. Camacho, J. Picó and A. Ferrer. *Self-tuning run to run optimization of fed-batch processes using unfold-PLS*, AIChE Journal, 53(7):1789-1804 (2007).

Optimization Method

Outline

1. Batch Process Optimization
2. Optimization Method
3. Case Study:
Simulation
4. Extensions
5. Conclusions

Three ideas: 

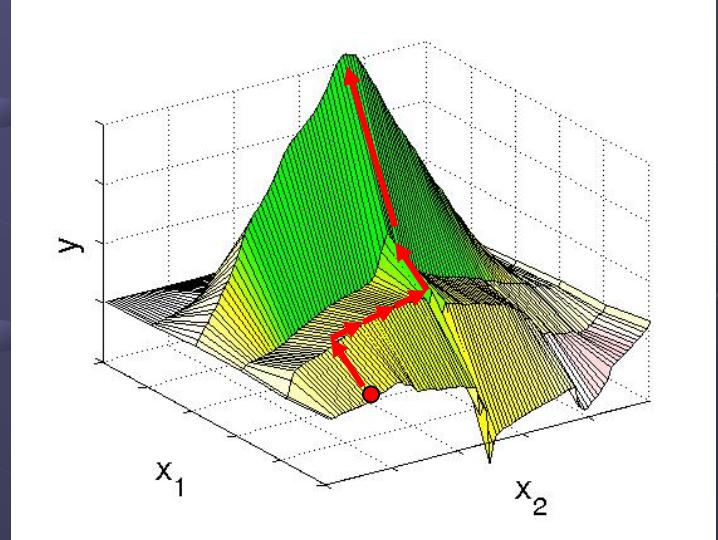
a) The batch-wise unfolding : $X(I, J, K) \rightarrow X(I, JK)$

b) A PLS model \rightarrow gradient of a function

Gradient-based
optimization:

$$X = [x_1, x_2] \rightarrow Y$$

$$X_{k+1} = X_k + c \cdot \frac{dy}{dX}$$



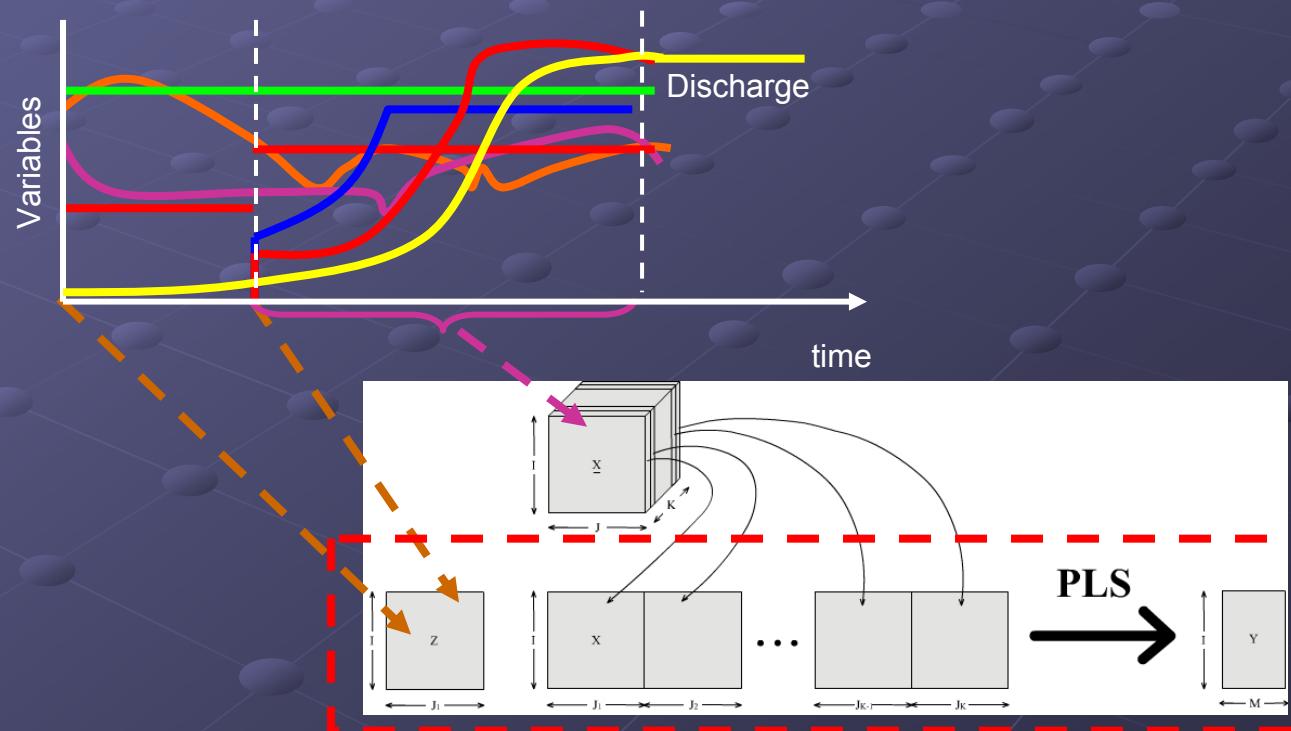
Extensions

Outline

1. Batch Process Optimization
2. Optimization Method
3. Case Study: Simulation
4. **Extensions**
5. Conclusions

• Straightforward use of additional information:

e.g. initial conditions + process variables

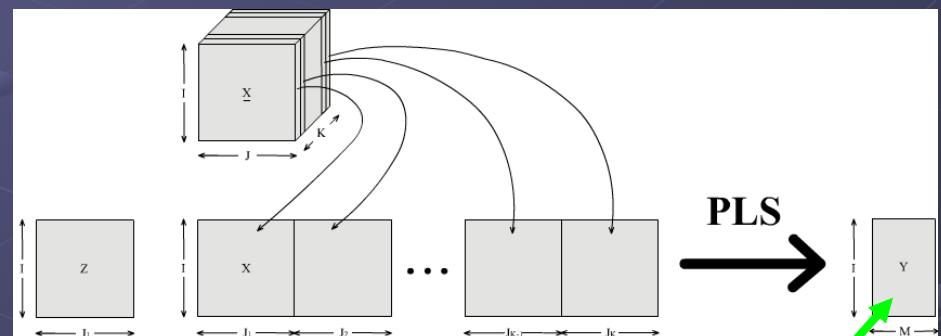


Extensions

Outline

1. Batch Process Optimization
2. Optimization Method
3. Case Study: Simulation
4. Extensions
5. Conclusions

- Straightforward use of additional information:
- Straightforward extension to multi-criteria:
e.g. maximize biomass while reducing final volume



Multiple Y variables



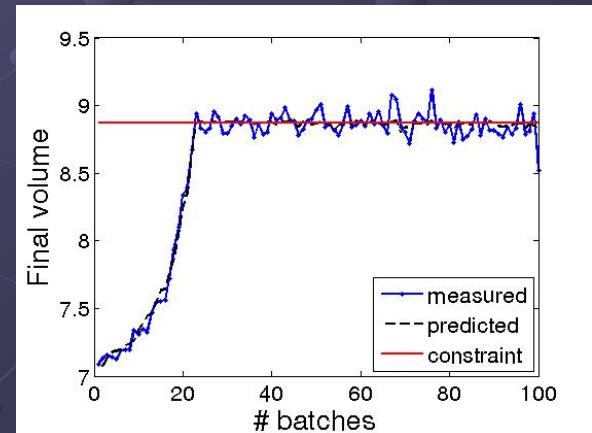
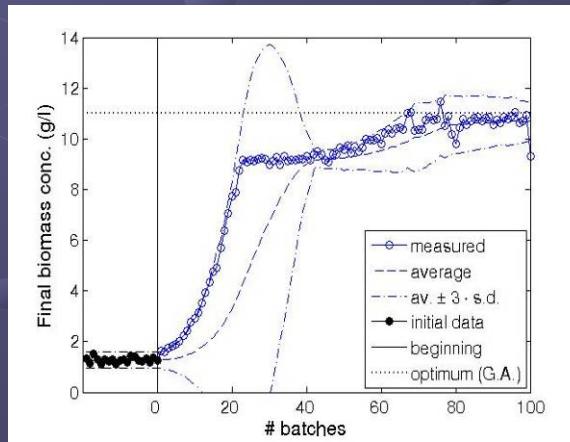
Extensions

Outline

1. Batch Process Optimization
2. Optimization Method
3. Case Study: Simulation
4. **Extensions**
5. Conclusions

- Straightforward use of additional information:
- Straightforward extension to multi-criteria:
- Soft constraints on Y can be handled by using PLS estimations.

e.g. constraint final volume

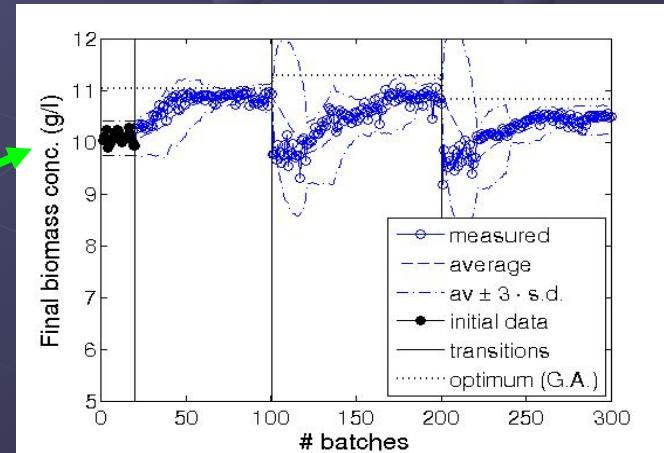
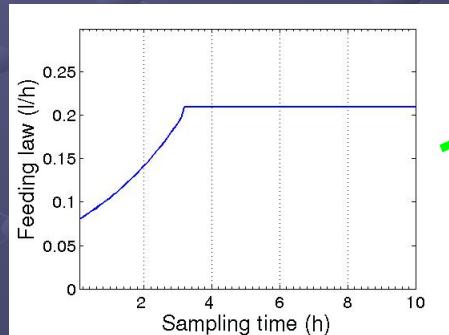


Extensions

Outline

1. Batch Process Optimization
2. Optimization Method
3. Case Study: Simulation
4. **Extensions**
5. Conclusions

- Straightforward use of additional information:
- Straightforward extension to multi-criteria:
- Soft constraints on Y can be handled by using PLS estimations.
- Possible combination with fundamental knowledge.

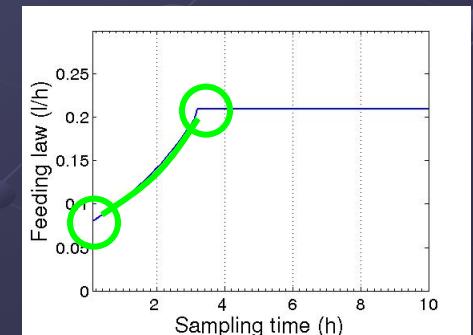


Extensions

Outline

1. Batch Process Optimization
2. Optimization Method
3. Case Study: Simulation
4. **Extensions**
5. Conclusions

- Straightforward use of additional information:
- Straightforward extension to multi-criteria:
- Soft constraints on Y can be handled by using PLS estimations.
- Possible combination with fundamental knowledge.
e.g. parameterization of the feeding profile.
 - a) Data-based → divide in 100 intervals and optimize (100 parameters)
 - b) Grey approach → 3 parameters



Conclusions

Outline

1. Batch Process Optimization
2. Optimization Method
3. Case Study: Simulation
4. Extensions
5. **Conclusions**

● Advantages:

- No fundamental knowledge is required but can be used.
- The only requirement is to measure the performance index.
- Applicable to any batch process.
- High degree of discretization of the input.
- Any other measurement can be integrated straightforwardly.
- Extension to several performance indices.
- Extension to constraints handling.



Run-to-run optimization of fed-batch processes with unfold-PLS

IFPAC 2009

Dr. José Camacho-Páez
Ass. Prof. Jesús Picó
Prof. Alberto Ferrer

Universidad Politécnica de Valencia
Spain

