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Inferential Control of Distillation Compositions

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Control of Distillation Compositions

Control with On-line Analyzer (GC, NIR)
- high investment and maintenance costs
- large measurement delay

Tray Temperature Control
- limited control performance

Inferential Control

Product quality (composition) is estimated from measured process variables, and the estimate is used for control.

Objectives & Conclusion

To answer a question:
"How can we design an inferential control system for enhancing the performance of composition control?"

1. **Selection of an inferential model**
   - operation data for modeling
   - input variables
   - static or dynamic
2. **Selection of a control configuration**
   - cascade control
   - predictive inferential control

Answer:
We can use predictive inferential control with a dynamic Inferential model within a cascade control configuration.

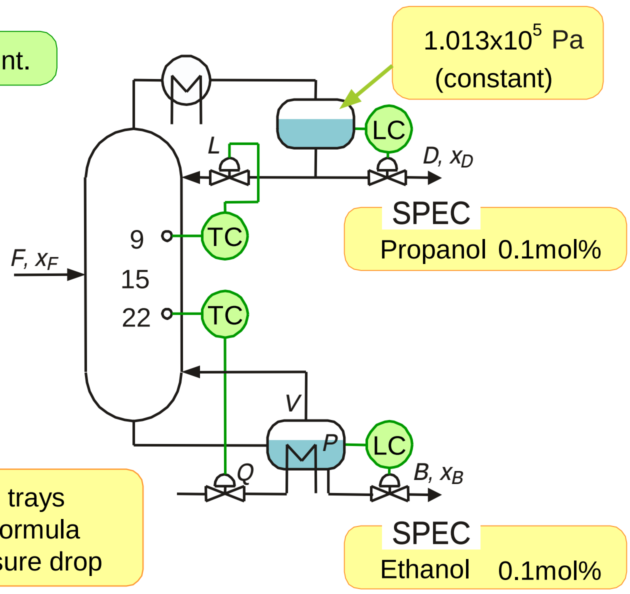
Multicomponent Distillation Column

TC, LC : PI cont.

Feed

	kmol/h
Methanol	32
Ethanol	32
Propanol	32
Butanol	32
358.15	K
1.150×10^5	Pa

30 theoretical trays
Francis weir formula
Varying pressure drop



Simulated Data for Modeling (1)

Input Variables
- Tray Temperatures
- Reflux Flow Rate (MV)
- Reboiler Heat Duty (MV)
- Pressure at the Reboiler

Output Variables
- Mole Fractions of Key Components
  - XD3 (Propanol)
  - XB2 (Ethanol)

< Time-series data >

Total 20 hours

Sampling Intervals : Compositions 10 min

Other variables 1 min

Usual operation data are good for modeling ?

Simulated Data for Modeling (2)

Under **Tray Temperature Control**

The controlled tray temperatures do not change significantly.

Under **Inferential Control**

The accuracy of the estimation may deteriorate due to large changes in the tray temperatures.

Deterioration of control performance

Operating condition under inferential control should be the same as that for generating identification data.

How ?

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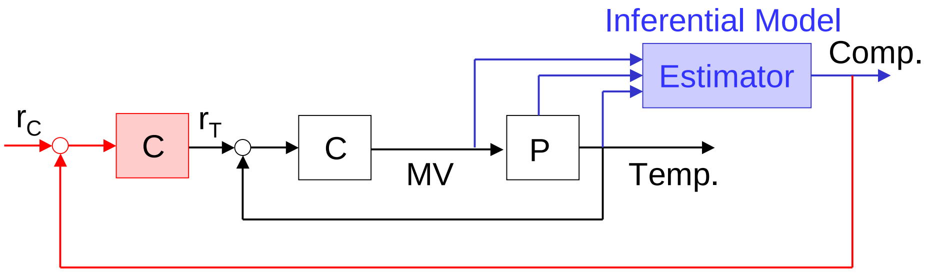
Simulated Data for Modeling (3)

Approaches (for closed-loop identification)

1. Add signals (set-point changes, dither signals).
2. Change parameters of temperature controllers.



Set-point changes are the same as what cascade control does.

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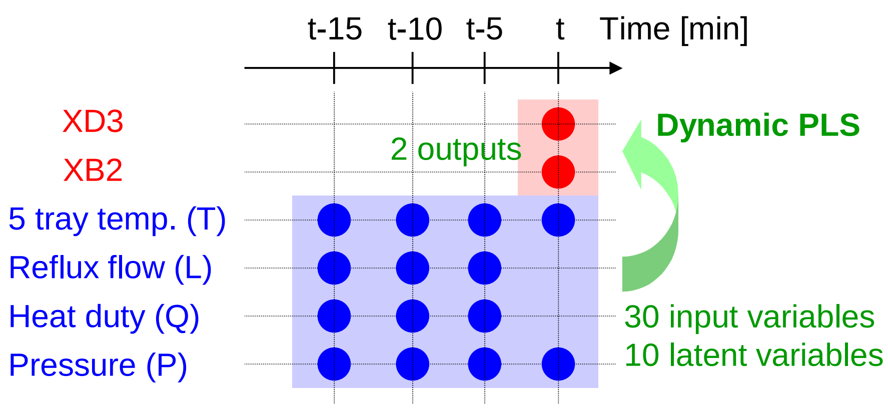
Structure of Inferential Model



L(t) and Q(t) are not used as input variables.

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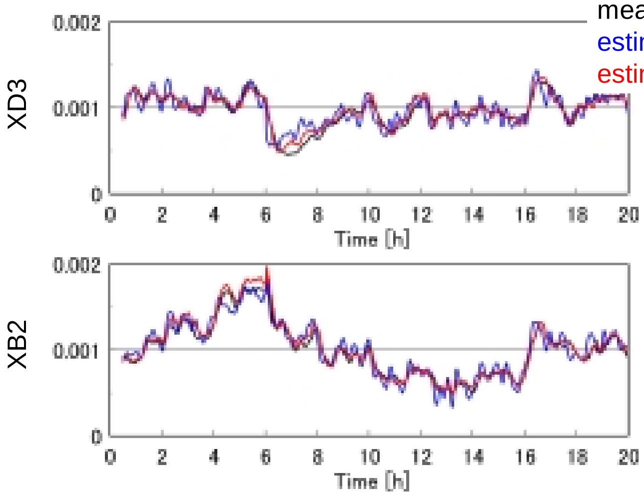
Estimation Results (under TC)



measurements
estimates (Static Model)
estimates (Dynamic Model)

The inferential models work well. However, the estimates using the static model show undesirable oscillation.

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Performance Index

For estimation accuracy

Explained Prediction Variance

$$\mathrm{EPV} = \left(1 - \frac{\sum_{n=1}^{N} \left(x(n) - \hat{x}(n) \right)^2}{\sum_{n=1}^{N} \left(x(n) - \bar{x}(n) \right)^2} \right) \times 100$$

For control performance

Mean Squared Error

$$\mathrm{MSE} = \frac{1}{N} \sum_{n=1}^{N} \left(r(n) - x(n) \right)^2$$

Comparison of Control Performance

Control Strategy	EPV [%] XD3	EPV [%] XB2	MSE x 10^7 XD3	MSE x 10^7 XB2	MSE x 10^7 Total
TC			**6.35**	**9.41**	**15.76**
Ideal CC			**5.15**	**7.77**	**12.92**
InfC-STA	**70.4**	**75.3**	**9.14**	**9.15**	**18.29**
InfC-DYN	**96.2**	**98.5**	**8.67**	**8.75**	**17.42**

Although DYN can outperform STA significantly from the viewpoint of estimation accuracy, the advantage of InfC-DYN over InfC-STA is not significant.

InfC cannot outperform TC.

Iterative Modeling

Procedure

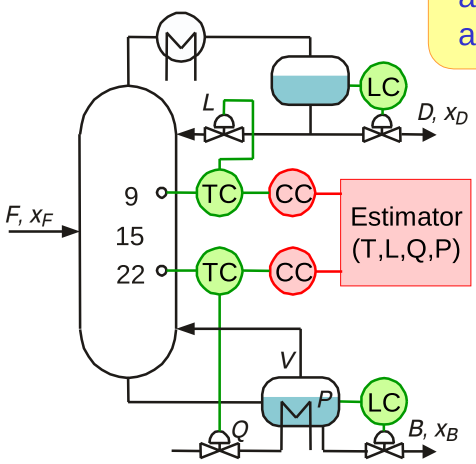
Temp. Control →
0) Modeling → Inferential Control →
1) Modeling → Inferential Control →
2) Modeling → Inferential Control ……

Iteration	MSE x 10^7 0	1	2	3	TC
InfC-STA	**18.29**	**17.99**	**17.61**	**17.47**	**15.76**
InfC-DYN	**17.42**	**15.99**	**15.27**	**15.30**	

Control performance can be improved through iterative modeling especially when dynamic model is used.

Cascade Control

Disturbances can be detected and compensated before they affect product compositions.

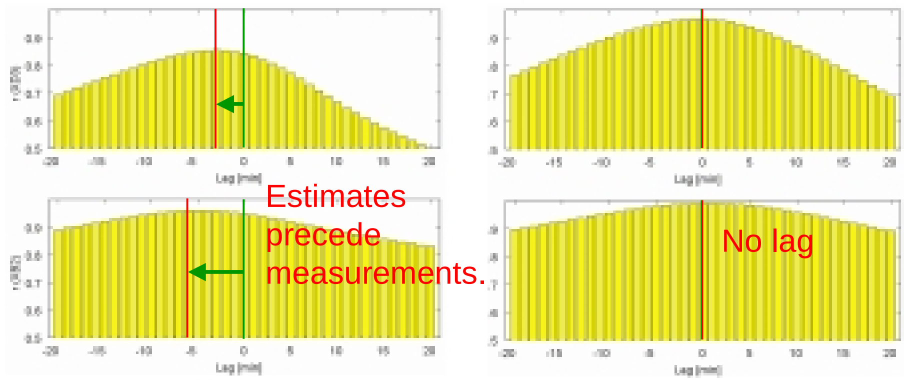


	MSE x 10^7
TC	**15.76**
InfC-DYN	**17.42**
CasInfC-DYN	**14.09**

Cascade control system works very well.

Characteristic of Static Model

Cross-correlation between measurements and estimates.



Static Model　　Dynamic Model

Static model has an inherent function to predict future compositions.

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Predictive Inferential Control

To achieve the high control performance, we can use:

1. **Iterative modeling**
2. **Cascade control**
3. **Inherent feedforward control effect**

↓

To further improve the control performance

Predictive Inferential Control
taking advantage of the characteristics
of a distillation column

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Predictive Inferential Control

Conventional Inferential Model

$$\hat{y}(t) = f_C(\boldsymbol{u}(t), \boldsymbol{u}(t-s_1), \boldsymbol{u}(t-s_2), \ldots)$$

Predictive Inferential Model

$$\hat{y}(t+\alpha) = f_P(\boldsymbol{u}(t), \boldsymbol{u}(t-s_1), \boldsymbol{u}(t-s_2), \ldots)$$

Predictive Inferential Control
Predicted future composition is
used as a controlled variable.

Predictive inferential control is essentially different from model-based predictive control, because predictive inferential control does not require a dynamic model.

Comparison of Control Performance

Iteration	MSE x 10^7 0	1	2
InfC-STA	**18.29**	**17.99**	**17.61**
InfC-DYN	**17.42**	**15.99**	**15.27**
PredInfC-STA	**16.99**	**16.56**	**16.28**
PredInfC-DYN	**15.99**	**15.42**	**14.40**
CasInfC-DYN	**14.09**	**13.99**	**13.91**
CasPredInfC-DYN	**13.16**	**13.03**	**12.98**
TC	**15.76**		
Ideal CC	**12.92**		

Good performance can be achieved without iterative modeling.

Conclusion

1. Dynamic models are better than static models even though the inherent feedforward control effect of static models is taken into account.
2. Iterative modeling and cascade control are useful to improve the control performance.
3. Predictive inferential control can outperform conventional inferential control.
4. Cascade control can achieve good control performance without iterative modeling.

Use predictive inferential control with a dynamic model within the cascade control configuration to achieve the good control performance without iterative modeling.