Abstract

Objectives: Closed-loop identification is reported to provide better results for identification of systems for control applications. This study conducted closed-loop identification on an Aspen Plus® dynamic simulation based on a pilot-plant distillation column to develop discrete-time linear time-invariant models.

Methods/Statistical Analysis: Identification data was generated using set-point perturbations in control variables under proportional-integral control. Identified models were compared with a model identified using open-loop data using 20-step ahead predictions.

Findings: Results indicate that closed-loop identification provides more precise prediction models than open-loop identification in this case study. 20-step predictions for closed loop models exceeded 90% fit, whereas the open loop model predictions provided a 70% fit and missed the steady-state values.

Application/Improvements: Thus closed-loop identification is more appropriate for applications in model-based controllers.

Keywords: Aspen Plus, Closed-Loop Identification, Distillation Column, Identification for Control, System Identification

1. Introduction

Any modern process industry is striving to be more and more energy efficient, productive, economic and environment-friendly, and achieving these conflicting objectives requires improvements in design and control of its major equipment. Model-based controllers have found applications in many process industries due to their inherent advantages of better conduct of constraints, disturbances and interactions. However, their efficacy depends profoundly on the identified model. A poor model will result in a suboptimal selection of input sequences and will result in poor control performance.

Open-Loop Identification (OLI) is straightforward but uneconomic. It is liable to provide poor Input-Output (I/O) predictions for closed-loop data due to the correlation between input and noise in closed-loop systems. Closed-Loop Identification (CLI) is reported to be more accurate for control purposes because it captures the closed loop behaviour and provides basis for accurate retuning of controllers. CLI can be performed using direct, indirect or joint I/O approach. Recent advances include identification with minimum excitation and moving horizon approach.

Figure 1 shows the general closed-loop structure. System is subjected to inputs (manipulating variables) and measured/unmeasured disturbances. The controller compares the system response (output) to the reference or desired set-point. This helps it to select the required input to achieve or maintain the desired values of outputs.

The discrete linear, time-invariant I/O models have the general form as follows:

\[
y_{(z)} = \frac{B}{F(z)} u_{(z)} + \frac{C}{D(z)} e_{(z)}
\]

The Auto Regressive Exogenous Input model (ARX) and Auto Regressive Moving Average with Exogenous Input (ARMAX) are the reduced forms of Equation 1. For ARX model, \(F(z)\), \(D(z)\), and \(C(z)\) = 1 where as for ARMAX model, \(F(z)\), \(D(z)\), and \(C(z)\) = 1. ARX is among the most used

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models for system identification\textsuperscript{14-15}. Although ARX and ARMAX models have many similarities, they can have similar or different efficacies in different aspects of signal processing depending on certain conditions\textsuperscript{16-17}.

The aim of this study was to develop linear time-invariant and discrete models using CLI with System Identification Toolbox in MATLAB\textsuperscript{®}, which is easy to use and is less time-consuming. The developed models predict the responses of compositions when the reflux flow and reboiler duty are changed. These models can be used with model-based controllers in order to maintain product quality and hence maximise economic and occupational benefits.

2. Closed-Loop Identification

2.1 Aspen Plus\textsuperscript{®} Model Development

This identification was carried out on the simulation based on a fully instrumented pilot distillation column in Universiti Teknologi PETRONAS, Malaysia. The specifications of this column are shown in Table 1.

The process can be summarised as follows:

A 3600 kmol/hr binary feed stream with 30% acetone and 70% Isopropyl Alcohol (IPA) was fed to the ninth tray of the column through valve V-101. A 1028 kmol/hr distillate was specified to be removed from the column as the product through valve V-102. A reflux ratio of 2.01 (molar) was maintained throughout the process. Under these specifications, the column yielded a distillate with a molar composition of 95% acetone.

A steady-state simulation of the distillation column was developed using CHAO-SEA property package. Aspen RadFrac Distillation model was used to simulate the distillation column as a continuous process. The system was operated at atmospheric pressure and other required inputs such as tray pressure drop, weir height and holdups were defined as explained in literature\textsuperscript{18-19}. Then the system was exported to Aspen Plus dynamics. Six controllers were installed to control reflux drum and sump levels, column pressure, feed flow rate, top and bottom compositions. The level controllers are Proportional (P) controllers whereas the other controllers are Proportional-Integral (PI). The controller tuning is summarised in Table 2. The details of the simulation development and controller tuning procedure have been reported in literature\textsuperscript{18-19}.

3. Identification

In order to extract data from the dynamic simulation for identification, the step perturbations of set-points were introduced to the system as shown in Figure 2. Due to proper tuning, the controller readily responded to the step changes and the PV values were quickly converged to the new set-points. A total of 1500 data points were collected with the sampling time of 0.01 hour. The data obtained from the set-point perturbation was used to develop discrete ARX and ARMAX models. For control purposes, it is convenient to use deviation variables instead of the actual values. Thus each variable was converted into its deviation form by using:

$$x_d = x - x_{ss}$$ \hspace{1cm} (2)

System identification toolbox of MATLAB\textsuperscript{®} was utilised for the development of models. The models were simulated to compare the model prediction with the data.

![Figure 1. Closed-loop structure\textsuperscript{11}.](image)

Table 1. Distillation column specifications

| Specification               | Details          |
|-----------------------------|------------------|
| Diameter                    | 5.5m             |
| Column internal             | 15 stages (0.35m apart) |
| Reflux ratio                | 2.01 molar       |
| Distillate rate             | 1028 kmol/hr     |
| Condenser pressure          | 101.3kPa         |

**Feed condition**

| Temperature | 52° C |
| Pressure    | 1.47 MPa |
| Composition (Molar) | 0.3 Acetone, 0.7 IPA |
| Flow rate   | 3600 kmol/hr |

![Table 2. Controller tuning parameters](image)

| Controller  | Tuning Parameters |
|-------------|-------------------|
|             | Kc   | T_i (min) |
| CC-101, CC-102 | 5    | 20       |
| FC-101      | 1    | 20       |
| LC-101, LC-102 | 2    | –        |
| PC-101      | 20   | 12       |
used for identification. The different parameters of the models were selected on the rule of minimisation of Final Prediction Error (FPE) and Mean Squared Error (MSE).

4. Results and Discussion

Aspen Plus steady-state simulation was developed to serve as the source of data for model identification. Table 3 summarises the results of the simulation. It is observed that the system is able to achieve the desired level of purity. Distillate is observed to contain 95% acetone and is collected at 1028.57 kmol/hr. It is observed that low pressure in condenser results in low reflux ratios, as pressure has an adverse effect on relative volatilities. Also, the bottoms product is observed to contain 4% acetone. A high value of the high-volatile product in bottoms would lead to poor economic feasibility.

4.1 Perturbation Results

After ensuring that all the controllers are adequately tuned and performing satisfactorily, the system was perturbed for the generation of closed-loop data. Set-points of top and bottom compositions were perturbed with the magnitudes of ±0.01 and ±0.005 respectively as shown in Figure 3.

| Specification           | Details         |
|-------------------------|----------------|
| Reboiler duty           | 30.89 MW       |
| Condenser duty          | -26.13 MW      |
| Reflux ratio            | 2.01(molar)    |
| Reflux rate             | 101309 kg/hr   |
| Top tray temperature    | 58°C           |
| Bottom tray temperature | 83°C           |
| Distillate condition    |                |
| Temperature             | 58.44°C        |
| Pressure                | 101.3 kPa      |
| Composition             | 0.95 Acetone   |
| Flow rate               | 1028.57 kmol/hr|
| Bottoms condition       |                |
| Temperature             | 83.88°C        |
| Pressure                | 108.8 kPa      |
| Composition             | 0.04 Acetone   |

Figure 2. Schematic for distillation column.

Table 3. Simulation results

Figure 3. (a) PV and (b) OP values for Set-point perturbation.
The input changes by the controller to achieve the set-point were recorded. It is observed that the controllers were able to achieve the set-points within 0.5 hours.

4.2 Identified Models

Data consisting of 1500 samples, as reported in section 3.1, was entered in System identification toolbox. ARX and ARMAX models (Equations 3 and 4) were identified, summary of which is presented in Table 4.

\[ A_{(z^{-1})} y(k) = B_{(z^{-1})} u(k) + e(k) \]  
\[ A_{(z^{-1})} y(k) = B_{(z^{-1})} u(k) + C_{(z^{-1})} e(k) \]

Note that \( y_1 \) represents the mole fraction of IPA in the distillate, whereas \( y_2 \) represents the mole fraction of

| Table 4. Closed-loop ARX and ARMAX models |
|-------------------------------------------|
| **ARX (FPE: 3.3 x 10^{-18}, MSE: 9.46 x 10^{-4})** |
| A | \[
A_1 \ A_{12} \\
A_{21} \ A_2
\] |
| B | \[
B_{11} \ B_{12} \\
B_{21} \ B_{22}
\] |
| A_1 | 1 - 1.087z^{-1} + 0.221z^{-2} - 0.174z^{-3} + 0.028z^{-4} + 0.024z^{-5} |
| A_{12} | -3.772z^{-1} + 5.988z^{-2} - 1.763z^{-3} - 1.808z^{-4} + 1.331z^{-5} |
| A_{21} | -0.0016z^{-1} + 0.0074z^{-2} - 0.0055z^{-3} - 0.004z^{-4} + 0.0039z^{-5} |
| A_2 | 1 - 3.064z^{-1} + 3.837z^{-2} - 2.599z^{-3} + 0.007z^{-4} + 0.184z^{-5} |
| B_{11} | 10^{-5} (-53.31 + 22.3z^{-1} - 3.5z^{-2} + 3.8z^{-3} + 0.06z^{-4} + 0.9z^{-5}) |
| B_{12} | 10^{-5} (142.9 + 86.72z^{-1} + 37.51z^{-2} - 20.3z^{-3} - 26.8z^{-4} + 0.84z^{-5}) |
| B_{21} | 10^{-5} (217.6 - 99.23z^{-1} + 64.9z^{-2} - 32.8z^{-3} - 10.8z^{-4} + 74.49z^{-5}) |
| B_{22} | 10^{-5} (-20.23 + 3.3z^{-1} + 11.8z^{-2} - 1.16z^{-3} + 2.16z^{-4} - 1.402z^{-5}) |
| **ARMAX (FPE: 2.9 x 10^{-18}, MSE: 9.34 x 10^{-8})** |
| A | \[
A_1 \ A_{12} \\
A_{21} \ A_2
\] |
| B | \[
B_{11} \ B_{12} \\
B_{21} \ B_{22}
\] |
| C | \[
C_1 \ C_2
\] |
| A_1 | 1 - 1.388z^{-1} + 0.204z^{-2} - 0.237z^{-3} + 0.015z^{-4} + 0.045z^{-5} |
| A_{12} | -3.187z^{-1} + 6.782z^{-2} - 4.896z^{-3} + 2.335z^{-4} + 1.338z^{-5} + 0.304z^{-6} |
| A_{21} | -0.0026z^{-1} + 0.0077z^{-2} - 0.0057z^{-3} - 0.0018z^{-4} + 0.0009z^{-5} |
| A_2 | 1 - 2.45z^{-1} + 2.02z^{-2} - 0.627z^{-3} + 0.063z^{-4} - 0.038z^{-5} + 0.03z^{-6} |
| B_{11} | 10^{-5} (-53.89 + 38.6z^{-1} - 27.35z^{-2} + 15.48z^{-3} + 36.8z^{-4} + 7.55z^{-5}) |
| B_{12} | 10^{-5} (143.8 + 21.18z^{-1} + 97.62z^{-2} - 106.5z^{-3} - 52.3z^{-4} + 2.89z^{-5}) |
| B_{21} | 10^{-5} (-215.8 + 88.5z^{-1} - 11.47z^{-2} + 11.6z^{-3} - 17.43z^{-4} - 30.5z^{-5}) |
| B_{22} | 10^{-5} (-20.24 + 3.3z^{-1} + 11.8z^{-2} - 1.16z^{-3} + 2.16z^{-4} - 1.402z^{-5}) |
| C_1 | 1 + 0.318z^{-1} - 0.77z^{-2} - 0.618z^{-3} - 0.056z^{-4} + 0.124z^{-5} - 0.0969z^{-6} |
| C_2 | 1 + 0.92z^{-1} - 0.013z^{-2} - 0.387z^{-3} - 0.287z^{-4} - 0.171z^{-5} - 0.051z^{-6} |
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7. References

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Figure 4. Comparison of identified models with simulation data of (a) Top and (b) bottom composition.

Acetone in bottoms. The 20 step prediction plots of the models are presented in Figure 4.

It can be observed that the models produced by CLI can predict the behaviour of the plant with sufficient accuracy. Although higher accuracies are observed at 5 or 10 step prediction, but 20 step prediction is used for determining the effectiveness of the identified model because, for model-based controllers, the control horizon may exceed 10 samples. CLI model predictions were more than 90% fit whereas OLI model had only 70% fit on closed loop data.

5. Conclusion

The CLI was carried out on Aspen Plus® simulation based on a pilot plant distillation column. IPA-Acetone separation was utilized in this case study. Closed loop ARX and ARMAX models were identified and compared with the open-loop ARX model. It was observed that the CLI models exhibited better predictions for closed-loop dynamics of the system. Therefore, CLI is more promising for the applications in model-based controllers.
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