Multivariable and Closed-Loop Identification for Model Predictive Control

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Abstract: In this work we will study multivariable and closed-loop identification of large scale industrial processes for use in model predictive control (MPC). The advantages of closed-loop identification will be discussed and related problems of identification are outlined. Then, *asymptotic method* (ASYM) of identification is introduced. The four problems, test signal design for control, model order/structure selection, parameter estimation and model validation, are solved in a systematic manner. The method provides accurate input/output model and unmeasured disturbance model, model errors are quantified by an upper error bound matrix that can be used for model validation and test redesign. To demonstrate the use of the method, the identification of a deethanizer for use in MPC will be presented.

1 Introduction

Model predictive control (MPC) technology has been widely applied in refinery and petrochemical industries and is beginning to attract interest from other process industries. Dynamic models play a central role in MPC technology. Generally identified black-box models are used for MPC controllers. Industrial project experience has shown that the most difficult and time-consuming work in an MPC project is modelling and identification. Typical identification test will take several weeks. These long tests make production planning difficult. The tests are done manually, which dictates extremely high commitment of the engineers and operators and the quality of collected data depends heavily on the technical competence and experience of the control engineer and the operator. The data collected from these long tests may not be good enough for model identification due to not enough excitation and process nonlinearity. After the test, due to the lack of systematic identification approach, it can take another few weeks to analyse the data and to identify the models. Some people even believe that the long time needed for tests and data analysis is the price one must pay for a good model.

The high cost of identification of current industrial approach is caused by several factors. First single variable tests make the test time unnecessarily long. Secondly, open-loop tests are used in industrial MPC projects. When the process is sensitive and/or non-linear, such as a high purity distillation column, it is very difficult to carry out open-loop tests on the process. Upsets often occur and it is difficult to fit a linear model when controlled variable variations are too large. Finally, most industrial identification packages are based on FIR model that is a nonparametric model with a large number of parameters.

In control community, system (process) identification has been one of the most active branches in the last three decades. An astonishing fact is that most of the identification results developed in the last 30 years are not used by industrial control engineers, although there is an urgent need for efficient and effective identification methods in process control industry.

In the last decade, there is a renewed interest in closed-loop identification and control-relevant identification; see van den Hof (1997) for a recent summary of the work. Many identification schemes have been proposed. Unfortunately, most researchers involved in closed-loop identification assume that the existing controller is linear and the process is single variable. This makes their result not relevant for use in the framework of MPC, because a MPC controller is nonlinear and the process under control is multivariable. Although called "conventional" by many researchers, the prediction error method of Ljung (1987) is still a more powerful methodology than many newly proposed schemes for use in closed-loop identification for MPC.

Recently, Zhu (1998) has developed a so-called ASYM method that uses automated multivariable tests and parametric models. Better models can be obtained with much shorter test and over 60% time saving is reported.

In this work we will continue the development of Zhu (1998) and study closed-loop identification. In Section 2 the characteristics of refinery/petrochemical processes are discussed and closed-loop identification is motivated. In Section 3 the ASYM method is introduced where closed-loop test design and model validation will be emphasised. In Section 4, the ASYM is used to identify a deethanizer for MPC control. Section 5 contains the conclusions and perspectives.

2 Closed-Loop Identification, Why and How?

Closed-loop identification means that process model is identified using data collected from a closed-loop test where the underlying process is fully or partly under feedback control. In this section we will motivate the use of closed-loop identification from both process operation point of view and control theoretical point of view and discuss various issues around closed-loop identification. We will focus our discussion on hydrocarbon process industry (HPI) processes where MPC application is most challenging and also most beneficial. This class of processes can be characterised as follows:

1) **Large scale and complex.** A large size MPC will have 10 to 20 MVs and 20 to 40 CVs. Some CVs, such as product qualities, are very slow (with dominant time constant range from 30 minutes to several hours), and other CVs are very fast, such as valve positions (with time constant in few minutes). There exist inverse responses, oscillations and time delays.

2) **Dominant slow dynamics.** The time to steady state of a typical product quality model ranges from one hour to several hours. This dictates long identification test.

3) **High level and slow disturbances.** Typical sources of unmeasured disturbances are feed composition variations, weather changes and disturbances from other part of the unit.

These are slow and irregular variations. During an identification test, the level of disturbances is in average above 10% of that of CV variation (in power), but it can be much higher. Too large test signal amplitudes are not permitted because they will cause off-specification of product and/or will excite nonlinearity.

4) **Local nonlinearity.** Although in general linear models are relevant for MPC for this class of processes for a given range of operation, some nonlinear behaviour may still show up. Examples are CVs that are very pure product qualities and valve positions close to their limits.

Based on these observations we will outline the special needs in HPI process identification for MPC and give comments on the existing methods. The discussion will be around the four problems of identification: test design, model structure and parameter estimation, order selection and model validation.

1) Identification Test

A good identification test plays a key role in a successful identification. Current practice of MPC industry is to use a series of open loop and single-variable step tests. The tests are carried out manually. The advantage of this test method is that control engineer can watch many step responses during the tests and can learn about the process behaviour in an intuitive manner. The biggest problem of single variable step test is its high cost in time and in manpower. The second problem is that the data from single variable test may not contain good information about the multivariable character of the process (ratios between different models) and that step signals do not excite enough dynamic information of the process.

Using automatic multivariable test can solve these problems; see Zhu (1998). In an open-loop multivariable test, many, or, all MVs are perturbed using some test signals such as PRBS signals. If the process behaves linearly in the operating range, levels of disturbance are low and the operation constraints are not very tight, one can use open-loop test without problems.

However, as mentioned before, HPI processes often suffer from high level disturbances and will be nonlinear in a wide range. In such cases, identification tests can be done in closed-loop operation with part or all the CVs under feedback control. There are many advantages of closed-loop test:

- **Reduce the disturbance to process operation and eliminate product off-specification**. When a multivariable open-loop test is used, some of the CVs may drift away and operator needs to intervene in order to prevent product qualities from off-specification. In a closed-loop test, however, one can specify the amplitude of the setpoint movement and the controller will help to keep the CVs within their operation limits.
- **Easy to carry out**. During an identification test, to obtain sufficiently high signal-to-noise ratio and to maintain all the CVs in their operation constraints are often in conflict. It is most difficult to perform manual single-variable step tests. It demands very high commitment of the control engineer and of the operator if the process is sensitive and has tight constraints. An automatic multivariable open-loop test will be much easier, but operator intervention may still be necessary to keep the CVs within their limits. The work will become easiest if the process is under feedback control.
- **Better model for control**. This can be explained in several aspects. Under the same CV variance constraints, the control performance degradation caused by model errors will be less if closed-loop test is carried out; see Gevers and Ljung (1986) and Hjalmarsson *et. al.* (1996). In fact, CV variances in a closed-loop test can be actually larger than those in an

open loop test, because the process operation constraints are in CV amplitude limits, not in variance limits and the controller can remove the slow drifts of the CVs. This means that the signal-to-noise ratio can be higher in a data set from a closed-loop test. The effect of feedback will have additional advantage if the process is ill conditioned meaning that several CVs are strongly correlated. High purity distillation columns are often ill conditioned where top and bottom compositions have strong correlation. For the control of ill-conditioned processes, it is important to identify the model that has good estimate of low-gain direction. In an open loop test where MVs are moved independently, the information of low gain direction will have very low power and cannot be estimated accurately from noisy data. In order to amplify the power of low-gain direction, certain correlation between MV movement is needed. This correlation can be created naturally by (partial) feedback control; see Koung and MacGregor (1993) and Jacobsen (1994).

Remark on the feedback controller

The controller is used to keep important CVs within their operation constraints during the identification test. It can be one or several PID loops or it is an existing MPC controller. For example, when testing a distillation column, it is often sufficient to control the top and bottom compositions or (pressure compensated) temperatures using two PID controllers. If only one quality is sensitive and has tight constraints, one PID controller will be sufficient. These controllers often exist for HPI processes due to the evolution of advanced process control in HP industry.

Remark on process identifiability in closed-loop test

Some researchers and engineers have mistakenly believed that the process is only identifiable when open-loop test is performed and when MVs are moved independently. This may explain why so little closed-loop identification applications have been reported. It has been shown long time ago that, if persistent excitation signals are added on the MVs and/or on the CV setpoints, the process will be identifiable in a closed-loop test, provided a right model structure is used; see Gustavsson et. al. (1977). It is true that some model structures and some estimation methods will be biased and not consistent if used for closed-loop identification; see the next paragraph.

Test signal design is another important issue that will be discussed in the next section.

2) Model Structure and Parameter Estimation

Before further discussion, let us introduce some notations. Given a multivariable process with *m* manipulated variables (MVs or inputs) and *p* controlled variables (CVs or outputs). Denote the data sequence collected from an identification test as

$$Z^N := \{u(1), y(1), u(2), y(2), ..., u(N), y(N)\} \tag{2.1}$$

where $u(t)$ is m-dimensional input vector (MVs), $y(t)$ is p-dimensional output vector (CVs) and N is the number of samples.

We assume that a linear discrete-time process generates the data

$$y(t) = G^o(z^{-1})u(t) + H^o(z^{-1})e(t) \tag{2.2}$$

where z^{-1} is the unit time delay operator, $G^o(z^{-1})$ is the process transfer function matrix, $H^o(z^{-1})$ is the noise filter and $e(t)$ is a p-dimensional white noise vector. Here the term $H^o(z^{-1})e(t)$ represent the unmeasured disturbances acting at the process outputs.

The model to be identified is in the same structure as in (2.1):

$$y(t) = G(z^{-1})u(t) + H(z^{-1})e(t) \quad (2.3)$$

Depending on how to parameterise the model in (2.3), different parameter estimation methods studied in literature can be derived.

FIR (finite impulse response) model

$$y(t) = B(z^{-1})u(t) + e(t) = (\sum_{k=0}^{n_b} B_k z^{-k})u(t) + e(t) \quad (2.4)$$

where B_k is a constant matrix.

Several industrial identification software packages are based on finite impulse response (FIR) model. This model class has inherent problems for use in identifying processes with slow dynamics. Model variance error is high due to its high order; yet bias error is often not negligible due to truncation. Therefore, model errors of FIR models are considerably larger than that of parametric or compact models; see Zhu *et. al.* (1998) for comparative studies.

ARX (AutoRgressive with eXternal input) model, or, least-squares model

$$y(t) = A^{-1}(z^{-1})B(z^{-1})u(t) + A^{-1}(z^{-1})e(t) \quad (2.5a)$$

or

$$A(z^{-1})y(t) = B(z^{-1})u(t) + e(t) \quad (2.5b)$$

where $A(z^{-1}) = I + \sum_{k=1}^{n} A_k z^{-k}$ and $B(z^{-1}) = \sum_{k=0}^{n} B_k z^{-k}$ are called polynomial matrices.

Output error (OE) model

$$y(t) = A^{-1}(z^{-1})B(z^{-1})u(t) + e(t) \quad (2.6)$$

where $A(z^{-1})$ and $B(z^{-1})$ are polynomial matrices.

ARMAX (AutoRgressive Moving Average with eXternal input) model

$$y(t) = A^{-1}(z^{-1})B(z^{-1})u(t) + A^{-1}(z^{-1})C(z^{-1})e(t) \quad (2.7a)$$

or

$$A(z^{-1})y(t) = B(z^{-1})u(t) + C(z^{-1})e(t) \quad (2.7b)$$

where $A(z^{-1})$, $B(z^{-1})$ and $C(z^{-1})$ are polynomial matrices.

Box-Jenkins model

$$y(t) = A^{-1}(z^{-1})B(z^{-1})u(t) + D^{-1}(z^{-1})C(z^{-1})e(t) \quad (2.8)$$

where $A(z^{-1})$, $B(z^{-1})$, $C(z^{-1})$ and $D(z^{-1})$ are polynomial matrices.

The model parameters are determined by minimising the sum of squares of the error $e(t)$. In literature, ARX, OE, ARMAX and Box-Jenkins models are called parametric models and FIR model is called nonparametric model. The difference between the two types of models is that parametric models are much more compact than FIR models and need much less parameters to describe the same dynamic behaviour. Let us use the degree of polynomial matrix as a measure of model compactness. Then a model is said to be more compact if the polynomial degree is lower.

Subspace method

In recent years, the so called subspace method of parameter estimation has been proposed and studied in the literature; see van Overschee and de Moor (1994), Verhaegen (1994) and Larimore (1990). Subspace methods estimate state space model of a multivariable process directly from input/output data. A state space model of a linear process with disturbance can be given as

$$\begin{aligned} x(t+1) &= Ax(t) + Bu(t) + Ke(t) \\ y(t) &= Cx(t) + Du(t) + e(t) \end{aligned} \tag{2.9}$$

where $x(t)$ is the state vector of dimension n_A, the constant matrices A, B, C *and* D form the state space description of the process and constant matrix K is the Kalman gain that characterise the state noise, $e(t)$ is a p dimensional white noise vector.

For closed-loop identification, the choice of model structure depends on three and often conflict issues:

1) the compactness of the model
2) the numerical complexity in parameter estimation
3) the consistency of the model in closed-loop identification.

When noisy data is used in identification, a more compact model will be more accurate provided that the parameter estimation algorithm converges to global minimum and the model order is selected properly; see Section 3.

Among the parametric models, one would like to have the model that is most accurate or, in identification term, minimum variance. In general a model structure or an estimation method that includes a disturbance model will be better than a method without the disturbance model; see Ljung (1987) and Söderström and Stoica (1989). Prediction error criterion and maximum likelihood criterion belongs to the first class; while output error criterion belongs to the second class. At present it is not clear what criterion subspace methods use. Moreover, prediction error method and maximum likelihood method will give consistent estimate for closed-loop data meaning that the effect of the disturbance will decrease when test time increases; while output error criterion will deliver biased model when using closed-loop data. The consistency of subspace methods can only be proven in for open-loop test case; see Jansson and Wahlberg (1996).

However, a more compact model needs more complex parameter estimation algorithms. To estimate OE models, Box-Jenkins models and ARMAX models, nonlinear optimisation routines are needed which often suffer from local minima and convergence problems when identifying a multivariable process. In FIR and ARX models, the error term $e(t)$ is linear in the parameters; see (2.4) and (2.5b). Due to this property, linear least-squares method can be used in parameter estimation that is numerically simple and reliable, and no problem of local minimum and convergence will occur. This explains partly why FIR model is often used in industrial identification. The subspace methods are exceptional: they estimate a parametric model and they are numerically efficient. The main part of a subspace method consists of matrix singular value decomposition (SVD) and linear least-squares estimation which are numerically simple and reliable.

Recently, orthonormal basis functions are studied for use in identification; see, e.g., Wahlberg (1991) and van den Hof et. al. (1995). One of the motivations of using this class of models is to estimate an output error model using the numerically simple least-squares method.

To summarise the discussion, the following table compares the advantages and disadvantages of various model structures or parameter estimation methods. It is clear that Box-Jenkins model is the best candidate for closed-loop identification, provided that parameter estimation and order selection problems can be solved.

Table 2.1 Comparison of various model structures and estimation methods

Model structure or estimation method	Numerical difficulty	Compactness	Consistency in closed-loop test
FIR	Low	Low	No
ARX (high order)	Low	Medium	Yes
OE	High	Highest	No
ARMAX	High	High	Yes
Box-Jenkins	High	Highest	Yes
Subspace method	Low	High	No
Orthonormal basis function	Medium	Medium	No

3) Order Selection

In identification literature, when prediction error is used in parameter estimation, it is also used in order selection. We will argue that, although prediction error is a good choice for parameter estimation, it is not the best criterion for order selection for control. For the purpose of control, it is most important to select the model order so that the process model $G(z^{-1})$ is most accurate. In the time domain, this requires that the simulation error or, output error of the model be minimal; see Zhu (1988b) for more details and an example. In the frequency domain, this requires that the bias part and the variance part of the model are nearly equal so that the total error is minimal; see Section 3.

4) Model Validation

The goal of model validation is to test whether the model is good enough for its purpose and to provide advise for possible re-identification if the identified model is not valid for its intended use. Commonly used methods of model validation are simulation using estimation data or fresh data, whiteness test of model residuals and testing the independence between the residuals and past MVs. These methods only tell how well the model agrees with the test data. They can neither quantify the model quality with respect to the purpose of modelling, in our case, closed-loop control, nor can they give good advice for re-identification. In this way, the fundamental problem of model validation is basically unsolved in both literature and practice, especially for multivariable processes. Trial-and-error approach in this step makes industrial identification a very expensive practice. In linear model identification for control, a logical approach for model validation is to quantify model errors in the frequency domain and to find relationship between this kind of error description and model based control performance. Model error estimation has attracted much interest in the last decade, which is motivated by linear robust control theory.

The above mentioned four problems are fundamental in industrial process identification. Solving these problems in a systematic manner is a challenging task. In the next section the so called ASYM method of identification is introduced that provide industrial solutions to these problems.

3 Asymptotic Method of Identification

The asymptotic method (ASYM) of identification was developed for the purpose model based control; see Zhu (1998).

Denote frequency responses of the process (2.2) and of the model (2.3) are denoted as

$$T^o(e^{i\omega}) := col[G^o(e^{i\omega}), H^o(e^{i\omega})]$$

$$\hat{T}^n(e^{i\omega}) := col[\hat{G}^n(e^{i\omega}), \hat{H}^n(e^{i\omega})]$$

where n is the degree of the polynomials of the model, *col*(.) denotes the column operator.

The Asymptotic Properties of Prediction Error Method

Assume that

— $n \to \infty$ *and* $n^2 / N \to 0$ *as* $N \to \infty$

— Test signals have continuous none zero spectra until the Nyquist frequency.

Then (Ljung, 1986 and Zhu 1989)

— $\hat{T}^n(e^{i\omega}) \to T^o(e^{i\omega})$ *as* $N \to \infty$ (3.1)

— The errors of $\hat{T}^n(e^{i\omega})$ follows a Gaussian distribution, with covariance given as

$$\text{cov}[\hat{T}^n(e^{iw}) \approx \frac{n}{N}\Phi^{-T}(\omega) \otimes \Phi_v(\omega) \quad (3.2)$$

where $\Phi(\omega)$ is the spectrum matrix of inputs and prediction error residual $col[u^T(t), \xi^T(t)]$, $\Phi_v(\omega)$ is spectrum matrix of unmeasured disturbances, ⊗ denotes the Kronecker product and -*T* denotes inverse and then transpose.

Note that the theory holds for the general case of closed-loop test. For open-loop test, the following simplified results can be obtained for process model

$$\text{cov}[col[\hat{G}^n(e^{iw})] \approx \frac{n}{N}\Phi_u^{-T}(\omega) \otimes \Phi_v(\omega) \quad (3.3)$$

where $\Phi_u(\omega)$ is the spectrum matrix of inputs.

In the following, we will outline the ASYM method that makes extensive use of the asymptotic theory. In order to minimise the presentation complexity, we will outline the method for open-loop experiment and also assume that the test inputs are mutually independent.

The Procedure of the Asymptotic Method

1) Identification Test

One should realise that a theory for practical identification test design does not exist and, therefore, project experience and control engineering intuition are combined with the asymptotic theory in developing the ASYM test scheme. The following are the important features of the ASYM test:

a) **Duration of identification test.** The duration of ASYM is determined by several factors: the validation of the asymptotic expression, the process time to steady state (settling time), and the number of MVs. The experience has shown that when compared to traditional step test, 70% of test time can be saved using multivariable test. Note that this test is designed for parametric model identification. The test time may not be long enough for nonparametric FIR models, because the identification of nonparametric models needs much longer test time; see Zhu et. al. (1999).

b) **(Partial) Closed-loop test.** When the level of disturbance is not high and all the CVs have large operation ranges, it will be easy to test the process in open loop operation. But often some CVs are sensitive and have tight constraints; open loop test may be difficult to carry out. In this situation, closed-loop will be used with these sensitive CVs being controlled by some single loop PID controllers or by an existing MPC controller.

When single loop controllers are used, the test signals are applied to the MVs which are not under feedback control and the setpoints of the CVs which are under control. If an MV under closed-loop test does not move sufficiently due to too slow control action, additional test signal can be added on that MV.

c) **Spectra of test signals.** The optimal test signal is designed to minimise the sum of the squares of the simulation error (often called prediction error in MPC term). In open-loop test, the spectra of the test signals are based on the following formula which can be derived from (3.6) assuming open-loop test (Ljung and Yuan, 1985):

$$\Phi_{u_j}^{opt}(\omega) = \mu_j \sqrt{\Phi_{u_j}^{sim}(\omega) \sum_{i=1}^{p} \Phi_{v_i}(\omega)} \qquad (3.4)$$

where $\Phi_{u_j}^{sim}(\omega)$ is the spectrum of the j-th input movement in a controlled system, μ_j is a constant which is adjusted to meet the amplitude constraint of the signal.

In closed-loop test, the following formula can derived for the single variable case (Zhu and van den Bosch, 1999)

$$\Phi_{r}^{opt}(\omega) \approx \mu \sqrt{\Phi_{r}(\omega)\Phi_{v}(\omega)} \qquad (3.5)$$

where $\Phi_r(\omega)$ is the reference signal at setpoint of the closed-loop system.

In practice, (3.4) or (3.5) is used in combination with upper error bound (3.9) to give general guidelines for the test design. The spectra of the test signals can be realised by PRBS (pseudo-random-binary-sequence) signals or filtered white noises.

Before model identification, some data pre-treatment is carried out. This includes removing the spikes, data slicing, hi-pass filtering (de-trending), known delay correction and signal scaling. This part of the work is well known; see Ljung (1987) and Zhu and Backx (1993).

2) Estimate a high order ARX (equation error) model

$$\hat{A}^n(z^{-1})y(t) = \hat{B}^n(z^{-1})u(t) + \hat{e}(t) \tag{3.6}$$

where $\hat{A}^n(z^{-1})$ is a diagonal polynomial matrix and $\hat{B}^n(z^{-1})$ is full polynomial matrix, both with degree n polynomials. Denote $\hat{G}^n(z^{-1})$ as the high order ARX model of the process, and $\hat{H}^n(z^{-1})$ as the high order model of the disturbance.

3) Perform frequency weighted model reduction (ML estimate)

The high order model in (3.6) is practically unbiased, provided that the process behaves linear around the working point. The variance of this model is high due to its high order. Here we intend to reduce the variance by perform a model reduction on the high order model. If we view the frequency response of the high order estimates as the noisy observations of the true transfer function, we can then apply the maximum likelihood principle. Using the asymptotic result of (3.1) and (3.3), we can show that the asymptotic negative log-likelihood function for the reduced process model is given by (Wahlberg, 1989, Zhu and Backx, 1993)

$$\mathrm{V} = \sum_{i=1}^{p}\sum_{j=1}^{m}\int_{\omega_1}^{\omega_2} |\{|\hat{G}_{ij}^n(\omega) - \hat{G}_{ij}(\omega)|^2 [\Phi^{-1}(\omega)]_{jj}^{-1} \Phi_{v_i}^{-1}(\omega)\}| \mathrm{d}\,\omega \tag{3.7}$$

The reduced model $\hat{G}(z^{-1})$ is thus calculated by minimizing (3.7) for a fixed order. The same can be done for the disturbance model $\hat{H}^n(z^{-1}) = 1/\hat{A}^n(z^{-1})$.

There are some theoretical evidence that the high order plus model reduction approach will produce more accurate models than that obtained using direct estimation of low order models; see Tjärnström and Ljung (1999).

4) Use *asymptotic criterion* (ASYC) for order selection

The best order of the reduced model is determined using a frequency domain criterion ASYC which is related naturally to the noise-to-signal ratios and to the test time; see Zhu (1994) for the motivation and evaluation. The basic idea of this criterion is to equalise the bias error and variance error of each transfer function in the frequency range that is important for control. Let $[\omega_1, \ \omega_2]$ defines the frequency band that is important for the MPC application, the asymptotic criterion (ASYC) is given by:

$$\mathrm{ASYC} := \sum_{i=1}^{p}\sum_{j=1}^{m}\int_{\omega_1}^{\omega_2} |[|\hat{G}_{ij}^n(\omega) - \hat{G}_{ij}(\omega)|^2 - \frac{n}{N}[\Phi^{-1}]_{jj}(\omega)\Phi_{v_i}(\omega)]| \mathrm{d}\,\omega \tag{3.8}$$

5) Model validation using error bound matrix

According to the result (3.1) and (3.3), a 3-δ bound can be derived for the high order model as follows:

$$\left|G_{ij}^o(e^{i\omega}) - \hat{G}_{ij}^n(e^{i\omega})\right| \le 3\sqrt{\frac{n}{N}[\Phi^{-1}(\omega)]_{jj}\,\Phi_{v_i}(\omega)} \quad \text{w.p. } 99.9\% \tag{3.9}$$

We will also use this bound for the reduced model because the model reduction will in general improve model quality.

For use in MPC, model validation is done by comparing the relative size of the bound with the model over the low and middle frequencies. More specifically, identified transfer functions are graded in:

A, very good, when bound $\leq$ 30%model

B, good, when 30%model < bound $\leq$ 60%model

C, marginal, when 60%model < bound $\leq$ 90%model

D, poor, or, no model exists, when bound >90%model).

1) Zero them when there are no transfer between the MV/CV pairs. This can be determined by using the process knowledge and cross checking.
2) If a transfer function is expected and needed in the control, redesign a test in order to improve the accuracy of these models.

Using upper bound formula (3.9) we can easily give some guidelines for improving the test design:

- doubling the amplitudes of test signals or quadruple the test time will half the error over all frequencies;
- doubling the average switch time of PRBS signals will half the model error at low frequencies and double the error at high frequencies.

Because ASYM provides systematic solutions to all the four identification problems, it can be made very user friendly for non-expert users. Recently, ASYM has been implemented in automated identification software Tai-Ji ID; see Zhu and Ge (1997). Using the software, the time needed for model identification of HPI processes ranges from few hours to few days.

4 Closed-Loop Identification of a Deethanizer for MPC

The process is a Deethanizer which separates C2 and lighter from C3 and heavier. The light product leaves the column overhead as vapor distillate and the heavy product exits the column as bottom liquid flow. The column operates in a high purity range.

A DMC controller was designed and was going to be commissioned as part of an APC and optimization project. The purpose of the deethanizer DMC is to reduce the variations of product qualities while respecting process operation constraints.

The MVs of the controller:

Reflux:	Reflux flow setpoint
Steam:	Reboiler steam flow setpoint
Preheater:	Feed preheater flow setpoint

DV:

Feed:	Column feed flow

Main CVs of the controller:

OverheadC3:	Overhead C3 composition
DeltaPress:	Column pressure difference

BotTemp: Bottom temperature
TopTemp: Top temperature
TrayTemp: A tray temperature

The experience of column operation has shown that the tray temperature TrayTemp is an important variable. It should be controlled in a range of 6 degrees for normal operation. When the try temperature is outside this range, it will be difficult to control the column.

Initially, an open loop multivariable test has been carried out; see Figures 4.1 and 4.2. PRBS signals are used as test signals. The following have happened during the open loop test:

- The tray temperature varied in a range of about 20 degrees, which is far beyond the normal operation range. The accepted moves to apply on MV's and determined during the pretest session turned out to be too big.
- The tray temperature became too high at about sample 600. The operator closed the PI control loop in order to bring it back. The control action reduced the steam flow to a very low level, which may cause nonlinearity in the data.
- The preheater flow could not be moved during the most part of the test period due to high level of disturbance introduced by reflux and steam.
- The column pressure difference became too high after sample 2200, which indicates the column was in flooding. The overhead C3 composition increased during this period.
- The second half of the test has disturbed normal unit operation.

The data have been used for identification using several software packages. Data slicing is used to remove the portion during column flooding. When the identified models are used in the DMC controller, the closed-loop performance was not satisfactory. During the control commissioning it was quickly decided that the best solution would to retest the plant to get better data set.

Remark: The difficulty of the test is caused more by the high purity characteristics of the column than by the multivariable test approach. A single variable open test will face the same problem for high purity distillation columns. In general a well designed multivariable test will not cause more disturbance than a conventional single variable step test; see Zhu (1998).

Finally, it was decided to carry out a partial closed-loop test with the tray temperature controlled by the steam flow using an existing PI controller; see Figures 4.1 and 4.2 for the test data. The test can be summarised as follows:

- CV variations are much smaller than the CV variations of the open loop test. The tray temperature is within a range of 7 ^{o}C during the test.
- All the three MVs could be tested according to the plan. The test did not disturb normal operation.
- Much less operator intervention has taken place, which implies easy test.
- During the second half of the test, the feed flow had to be reduced by about 20% due to production planning. The operator could handle this easily, thanks to the tray temperature controller.

The ASYM method is used to identify the models using the closed-loop data. The DMC commissioning using the closed-loop model went smoothly and the controller has been online for over half year without major problems.

For comparison, the identification results of the open loop data and the closed-loop data are shown in Figures 4.3, 4.4 and 4.5. Note that the tray temperature TrayTemp is identified as an integral process and the models of its derivative are shown. One can see that the quality of closed-loop model is higher than that of open loop model according to upper error bounds. The difference can also be seen using the process knowledge. For example, the gains between the reflux and both top and bottom temperatures should be negative. The closed-loop model correctly determines these. However, the gain of the open loop model is positive for the bottom temperature and is nearly zero for the top temperature. The model fit of the closed-loop model is slightly better that that of the open-loop data. The difference is partly due to the different operation range and partly due to uncertainty caused by disturbance and/or nonlinearity.

Due to the change of feed flow during the closed-loop test, the usable data for identification is less than desired. Fortunately, the model from this very short test period is good enough for control. This shows the accuracy of parametric models.

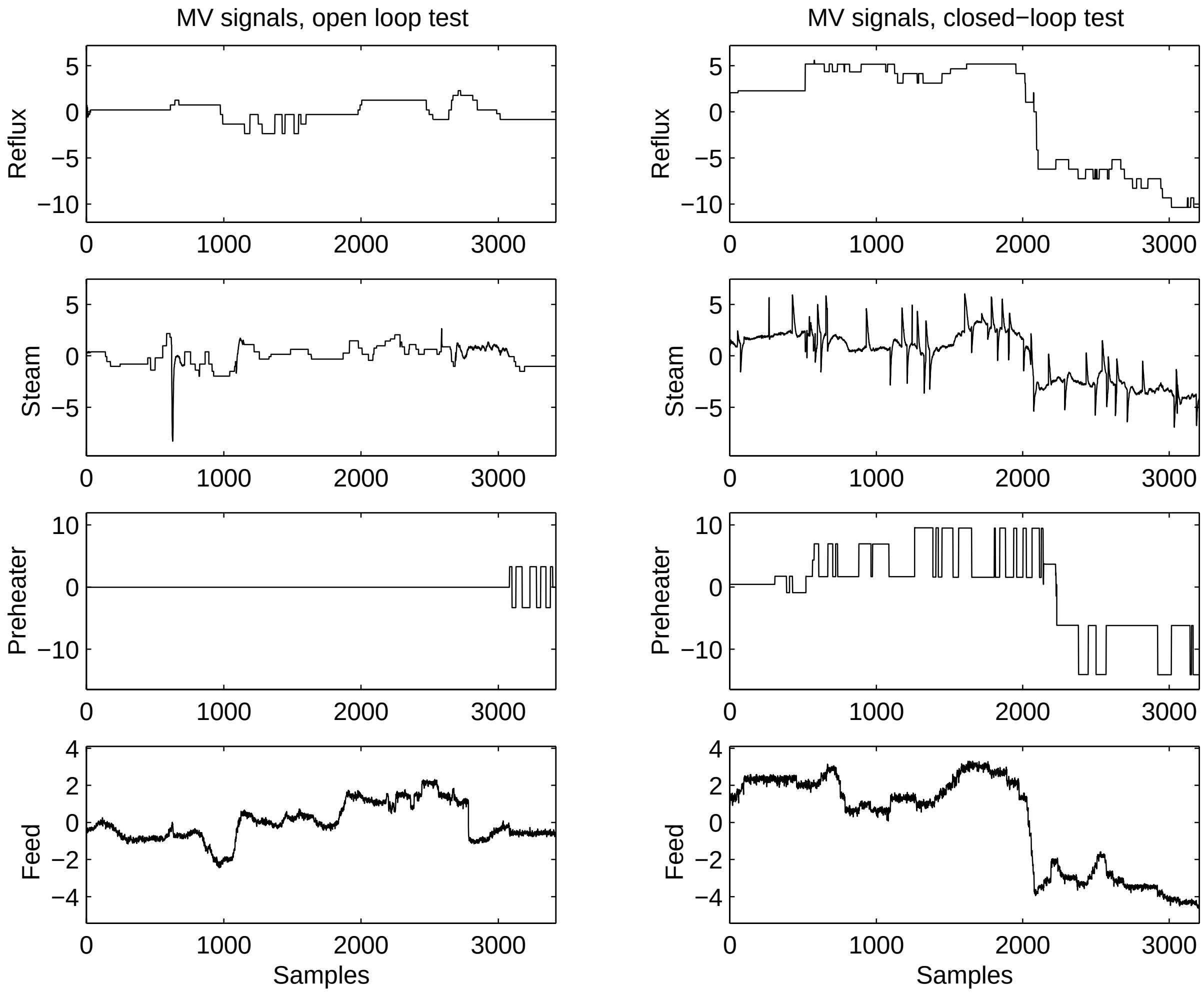


Figure 4.1 MV plots of the open loop test and closed-loop test. The data are normalised by subtracting their mean values and by dividing by some factors. For each MV, the same scaling factor is used for both open loop test and closed-loop test.

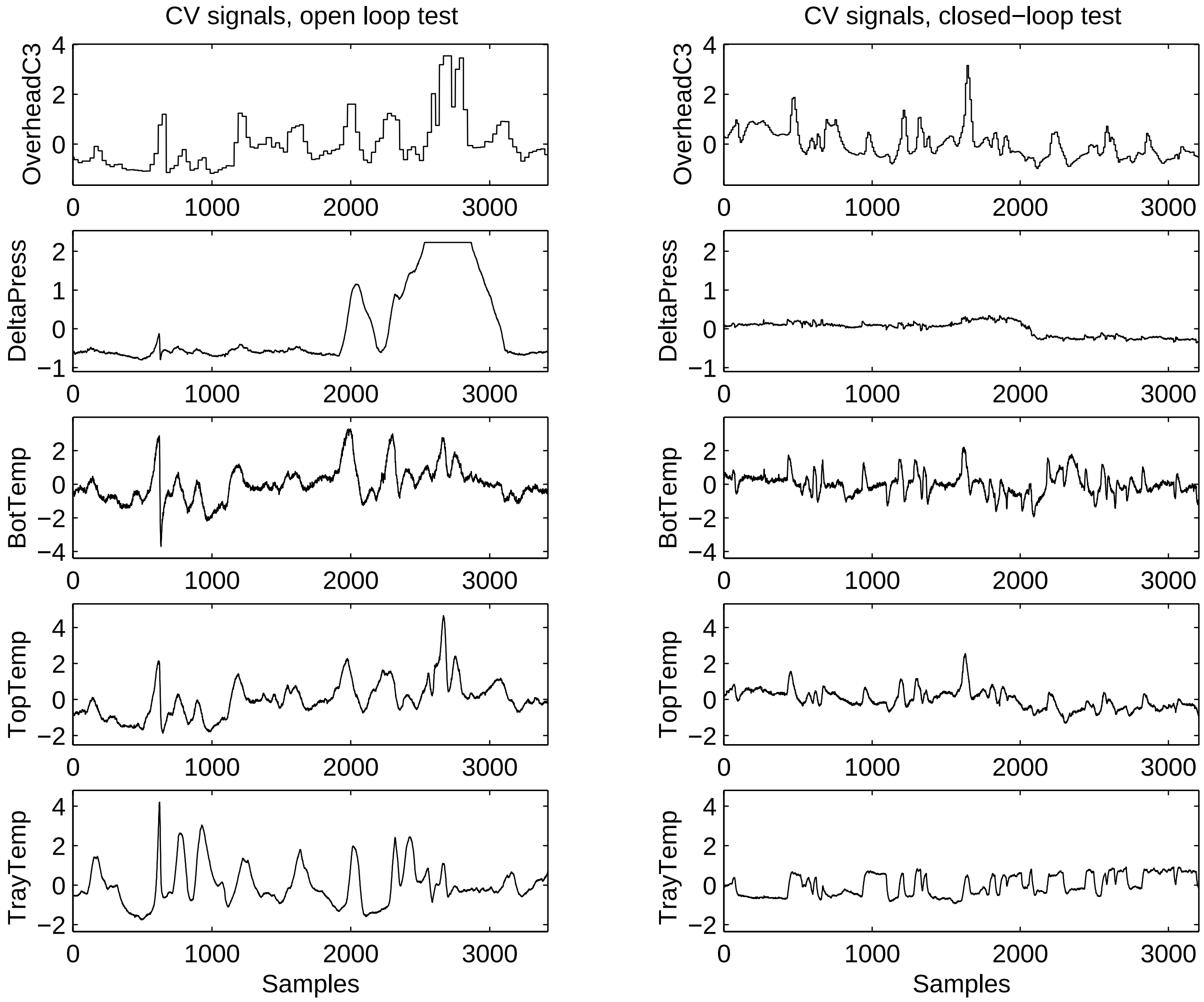
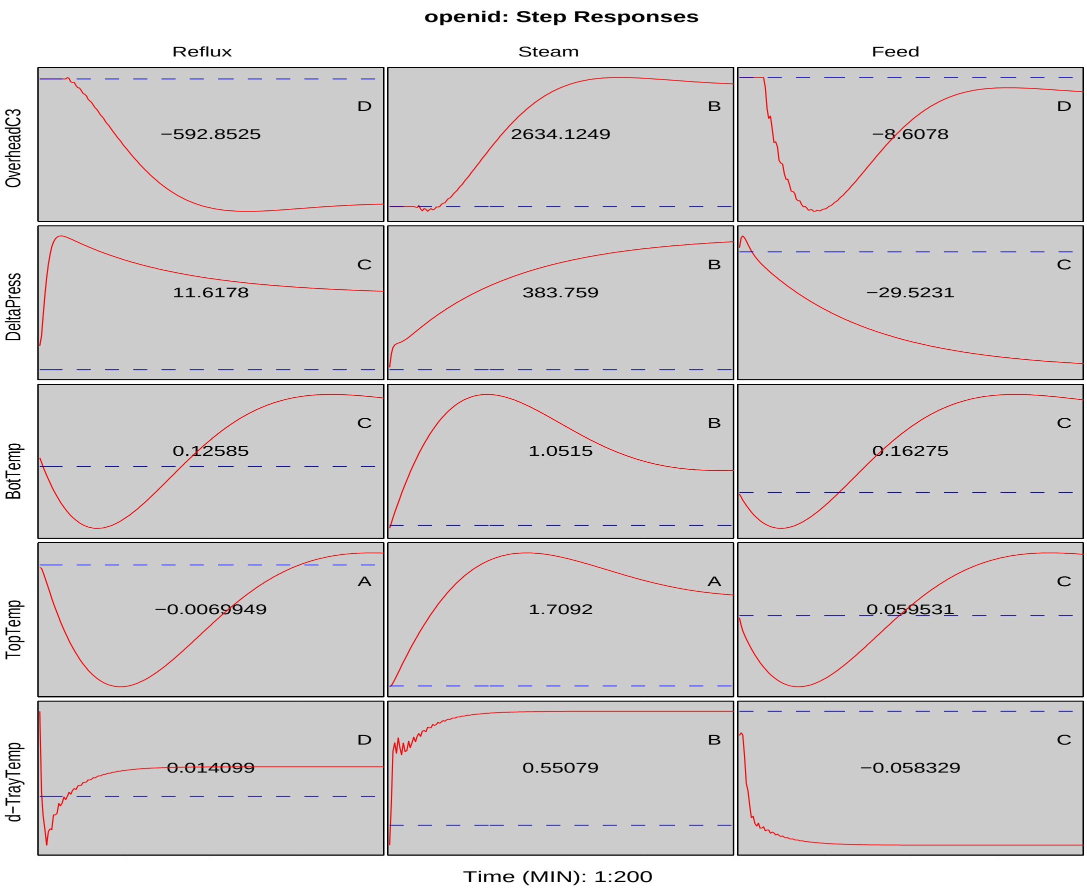


Figure 4.2 CV plots of the open loop test and closed-loop test. The data are normalised by subtracting their mean values and by dividing by some factors. For each CV, the same scaling factor is used for both open loop test and closed-loop test.



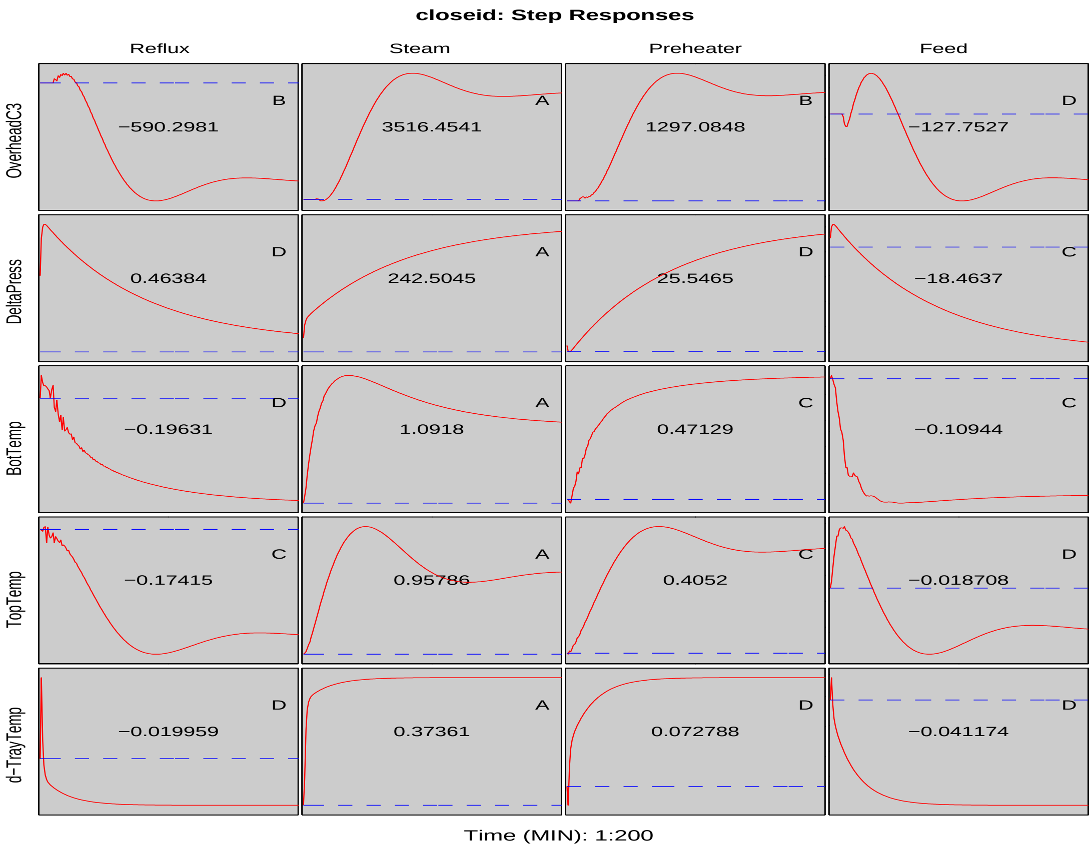


Figure 4.3 Step responses of open loop model (up) and closed-loop model

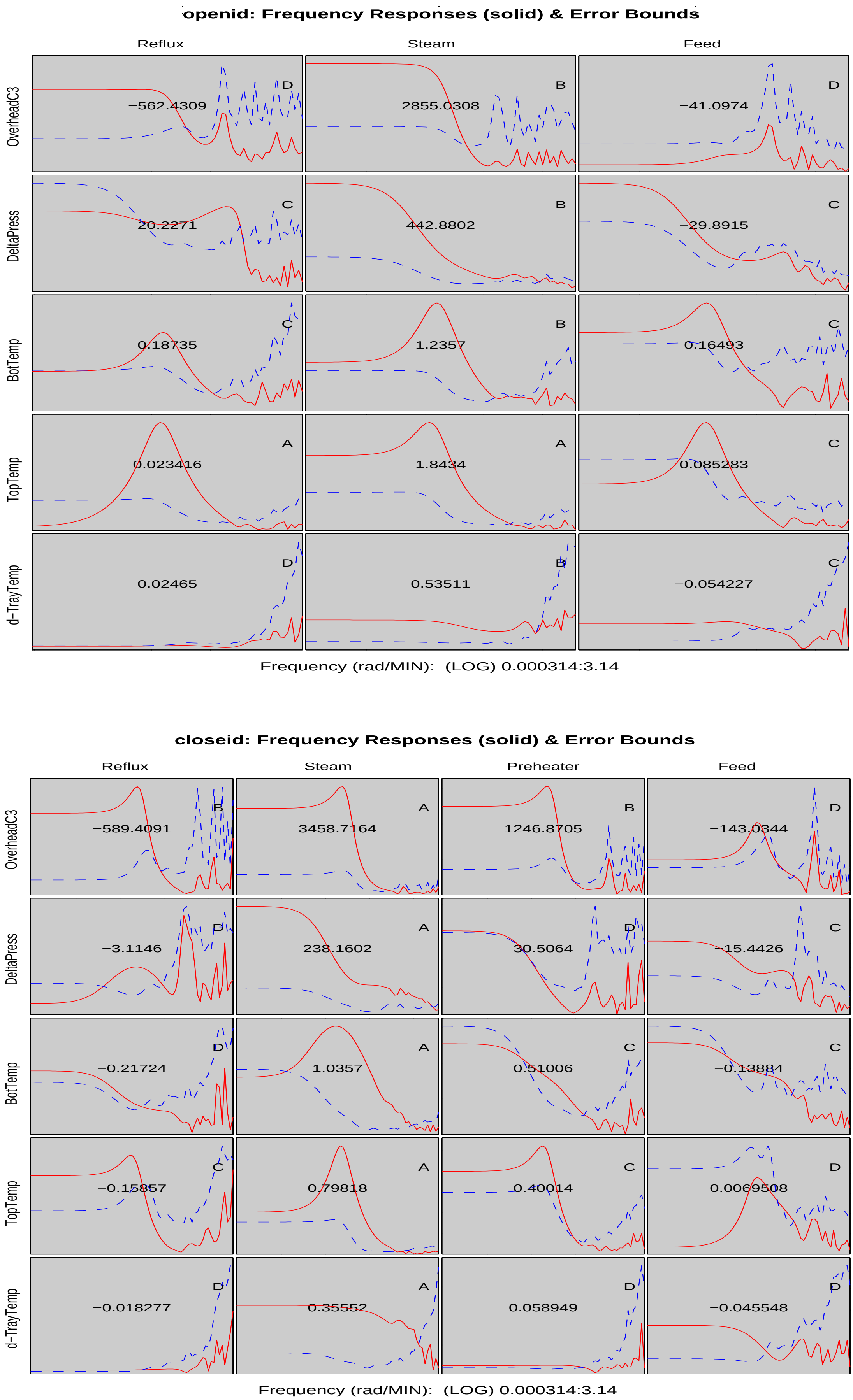


Figure 4.4 Frequency responses and error bounds of open loop and closed-loop models

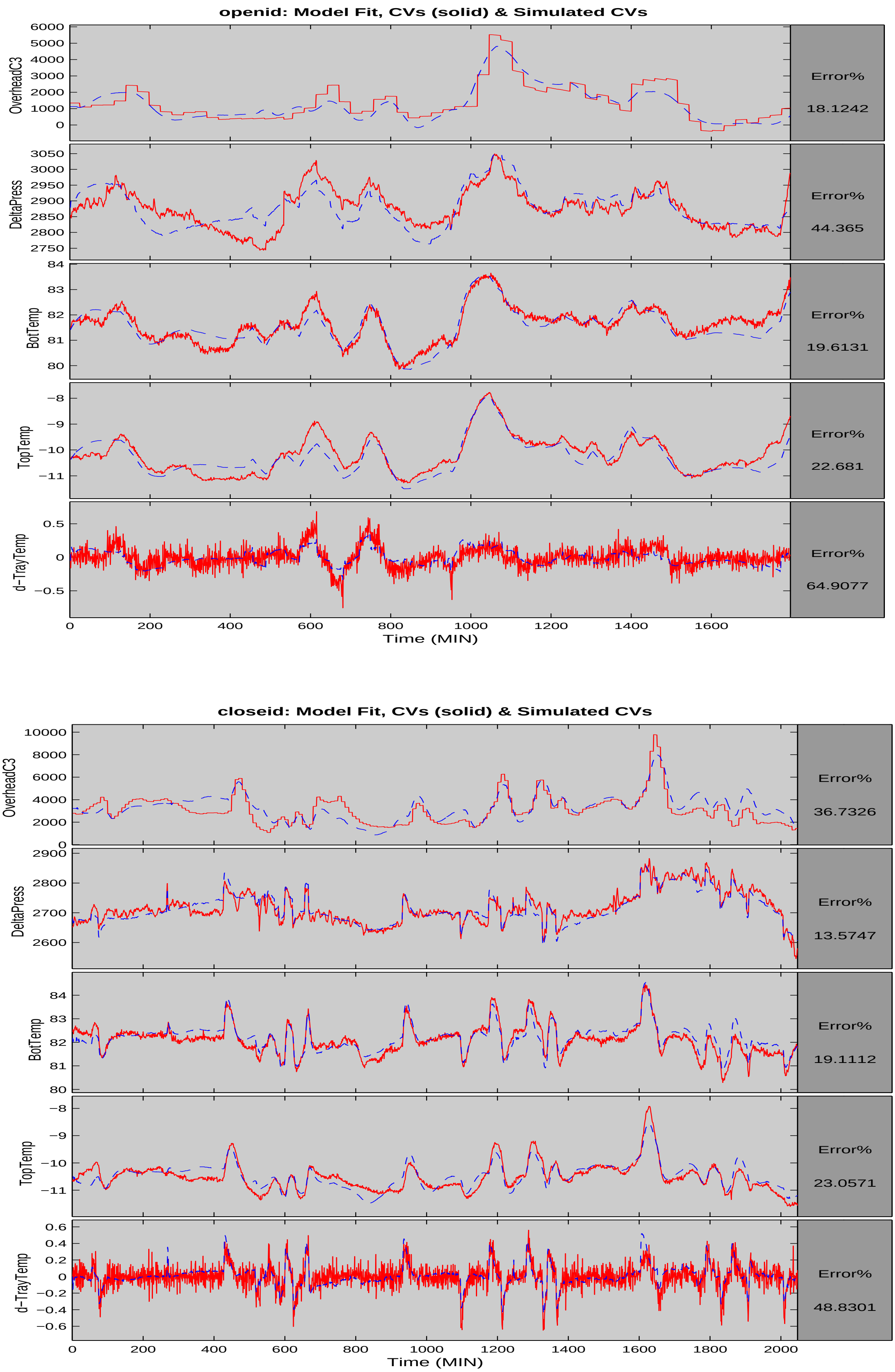


Figure 4.5 Model fit of open loop model (up) and closed-loop model

5 Conclusions and Perspectives

In this work we have studied multivariable and closed-loop identification for use in MPC. The ASYM method is introduced to solve the problem. An industrial application is reported. We have shown that closed-loop tests have many advantages over open-loop tests. When comparing to the conventional open-loop step test approach, the following improvements have been made by the ASYM method:

- The model quality is higher due to well-designed test, the use of parametric models and ability to keep the process in a linear range.
- The disturbance to uint operation is much smaller, due to closed-loop control and encouraged operator intervention when necessary.
- The cost of identification is significantly reduced. Reduction of both test time and data analysis time by 70% can be realised. The method requires less user knowledge and experience on identification.

A powerful and efficient identification method can make MPC economically feasible for more process units.

From application point of view, the next logical step is to use full closed-loop test with an MPC controller online. The identified models can be used for MPC controller diagnosis and maintenance. When sufficient industrial experience of closed-loop identification is obtained, it would be natural to try adaptive MPC. Closed-loop identification of nonlinear models can be very useful for difficult processes such as high purity distillation columns and more research is needed for this challenging topic.

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