Increase MPC Project Efficiency by using a Modern Identification Method

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Abstract: In industrial model predictive control (MPC), there is a demand for efficient model identification technology. In this work we will study the identification of industrial processes for use in MPC. The advantages of closed-loop identification will be discussed and related issues are outlined. Then, the *asymptotic method* (ASYM) of identification is introduced. Two case studies are carried out to demonstrate the feasibility of the technology. The first one is a partial closed-loop identification of two distillation columns within a chemical plant. The second case is a total closed-loop identification of a simulated distillation column.

1 Introduction

Dynamic models play a central role in MPC technology. Generally identified empirical 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 model identification. A traditional plant identification test can take several weeks. The tests are done manually, which requires extremely high commitment from the engineers and operators. The quality of collected data depends heavily on the technical competence and experience of the control engineer and the operator as well as the circumstances of the plant test. After the test, due to the lack of a systematic identification approach, it can take another few weeks to analyse the data and to identify the models. While other ICT tools such as databases, user interfaces and internet/intranet have been improving dramatically, the way of doing MPC projects has not changed much in comparison.

There are several causes of the difficulties in current MPC identification. First, single variable tests make the test time unnecessarily long. Secondly, open-loop tests are used in industrial MPC projects. Often it is difficult to carry out open-loop tests without disturbing the unit operation. Finally, many industrial identification packages use or are based on a FIR (finite impulse response) model that is very costly (in test time) for slow processes.

In the academic control community, system (process) identification has been one of the most active branches in the last three decades; see e.g., Eykhoff (1973), Ljung (1987, 1999) and Söderström and Stoica (1989). Unfortunately, industrial MPC control engineers do not use most of the results developed in the last 30 years.

Recently, Zhu (1998) has developed a so-called ASYM method of identification. The method uses automated multivariable tests and parametric models. Both open loop and closed-loop tests can be used. The method has been applied in many MPC projects with success; see Zhu (1998) and Butoyi and Zhu (2001). Better models can be obtained and a significant amount of test and modelling time can be saved when compared with the traditional approach.

In this work, we will continue the development of Zhu (1998) and study closed-loop identification. In Section 2 we explain the motivation for closed-loop identification and discuss the four problems of model identification. In Section 3 the ASYM method is introduced where closed-loop test design and model validation will be emphasised. In Section 4, two case studies are used to show the feasibility and benefits of proposed approach. Section 5 contains the conclusions and perspectives.

2 The Identification Problems

In closed-loop identification, the 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 provide the motivation for closed-loop identification from both a process operation point of view and a theoretical control point of view. We will also discuss various issues around closed-loop identification. Although the method works for all continuous processing units, we will focus our discussion on hydrocarbon process industry (HPI) processes. This class of processes can be characterised as follows:

- Large scale and complex.
- Dominant dynamics are slow.
- High level and slow disturbances.

These characteristics require special attention in HPI process model identification. The discussion will be around the four problems of identification: test design, parameter estimation, model structure and order selection, and model validation.

1) Identification Test, Open- or Closed-loop

The current practice of the 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 problems with single variable step tests are:

1) the high cost in time and in manpower;

2) the data from a single variable test may not contain good information about the multivariable character of the process (ratios between different models) and step signals do not provide sufficient excitement of the dynamic character of the process; and

3) an open loop test may disturb unit operation.

Using automatic multivariable testing can solve the first two problems; see Zhu (1998). In an open-loop multivariable test, many, or, all manipulated variables (aka MV's) are perturbed using some test signals. However, HPI processes often suffer from high level disturbances and will be nonlinear if considered over a wide range. In such cases, identification tests can be done in closed-loop operation with part or all the controlled variables (aka CV's) under feedback control. There are many advantages of closed-loop test:

- **Reduce the disturbance to unit operation.** In a closed-loop test, the controller will help to keep the CV's within their operational limits.
- **Easier to carry out**. In an automatic multivariable closed-loop test, much less engineer or operator intervention is needed. Night shifts may be avoided.

- **Better model for control**. This can be explained in several ways. Under the same CV variance constraints, the model from a closed-loop test data will have higher control performance than the model from an open loop test; see Gevers and Ljung (1986) and Hjalmarsson *et. al.* (1996). The feedback will have additional advantage if the process is ill-conditioned meaning that several CV's are strongly correlated such as in high purity distillation columns. For the control of ill-conditioned processes, it is important to identify the model that has good estimate of the difference or ratios between the CV's, or, the low-gain direction. In order to amplify the power of low-gain direction, strong correlation between MV movements is needed. This correlation can be created naturally by feedback control; see Koung and MacGregor (1993) and Jacobsen (1994).

There are two circumstances under which identification is required: initial MPC development and MPC maintenance. In MPC development, a partial closed-loop test can be used since there is no existing MPC to exploit. The partila closed-loop control can be provided by one or more PID loops, which often already exist. In principle, all existing CV control loops can be closed during the identification test. Typical examples of these loops are: top and bottom compositions, temperatures (pressure compensated), and levels. In MPC maintenance, although no longer performing statisfactorily for high quality control, the existing MPC may still work reasonably well. It could be used for the test.

Some researchers and engineers have mistakenly believed that the process is only identifiable when an open loop test is performed and when MV's are moved independently. It has been shown a long time ago that, if persistent excitation signals are added on the MV's and/or on the CV setpoints, the process will be identifiable in a closed-loop test; see Gustavsson et. al. (1977). It is true that some model structures and 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 nomenclature. Given a multivariable process with *m* manipulated variables (MV's or inputs) and *p* controlled variables (CV's or outputs). Denote the data sequence collected from an identification test as

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

where $u(t)$ is m-dimensional input vector (MV's), $y(t)$ is p-dimensional output vector (CV's) 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 $H^o(z^{-1})e(t)$ represents the unmeasured disturbances acting at the process outputs.

The model to be identified is in the same structure as in (2.2):

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

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

FIR (finite impulse response) model

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

where B_k is a constant matrix.

Box-Jenkins model

$$y(t) = A^{-1}(z^{-1})B(z^{-1})u(t) + D^{-1}(z^{-1})C(z^{-1})e(t) \tag{2.5}$$

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, the Box-Jenkins model is called a parametric model and the FIR model a nonparametric model. The difference between the two types of models is that parametric models are much more compact than nonparametric models and need many fewer parameters to describe the same dynamic behaviour. Let us use the degree of the polynomial matrix as a measure of model compactness. Then a model is said to be more compact if the polynomial degree is lower.

For closed-loop identification, the choice of model structure depends on three and often conflicting 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 the 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. Among the parametric models, one would like to have the model that is most accurate or, in identification terms, 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 belong to the first class; while the output error criterion used by the FIR model belongs to the second class. Moreover, the prediction error method and the maximum likelihood method will give consistent estimates for closed-loop data meaning that the effect of the disturbance will decrease when test time increases; while the output error criterion will deliver biased models when using closed-loop data. However, a more compact model needs more complex parameter estimation algorithms. To estimate a Box-Jenkins model, nonlinear optimisation routines are needed which often suffer from local minima and convergence problems when identifying a multivariable process. In the FIR model, the error term $e(t)$ is linear in the parameters; see (2.4). Due to this property, the linear least-squares method can be used in parameter estimation that is numerically simple and reliable; with no problems of local minimum and non-convergence.

It is clear that the Box-Jenkins model is the best candidate for closed-loop identification, provided that parameter estimation and order selection problems can be solved.

3) Order Selection

In the 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 (2000) for more details. 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 advice 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, doing a whiteness test of model residuals, and testing the independence between the residuals and past MV's. These methods only tell how well the model agrees with the test data. They can neither quantify the model quality with respect to control, nor can they give good advice for re-identification. Simulation is a common validation tool in many industrial packages. This approach is very questionable for closed-loop data, because it is known that it is very easy to fit measured CV's with simulated CV's when there is no persistent excitation and the model converges to the inverse of the controller rather than to the process.

To solve these four problems in a systematic manner is a challenging task. In the next section the so-called ASYM method of identification is introduced that provides the solutions to the problems.

3 Asymptotic Method of Identification

The asymptotic method (ASYM) of identification was developed for the purpose of model based control; see Zhu (1998). The method is based on the asymptotic theory of Ljung (1985) which was extended in Zhu (1989). In the following, we will outline the ASYM method that makes extensive use of the asymptotic theory.

1) Identification Test

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 (see also Zhu, 1998):

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 MV's. The initial planned test time is in the range of 10 ~ 15 times the process settling time. The final test time is determined by model validation; see the later part of this section. 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 requires a much longer test; see Zhu et. al. (2000).

b) Partial closed-loop test. Often some CV's are sensitive and have tight constraints. In this situation, closed-loop testing will be used with these CV's being controlled by some single loop PID controllers. The test signals are applied to the MV's which are not under closed-loop test (are on local or operator setpoint) and the setpoints of the CV's which are under control. If an MV which is in a closed-loop does not move sufficiently due to too slow control action, an additional test signal can be added at the MV set-point itself.

c) Total closed-loop test. When an MPC controller exists which still does a reasonably good job, though no longer optimal, one can test the process while keeping the MPC on. This will in general stabilise the operation. In this situation, the test signals are applied to the setpoints of the CV's. When some CV's are configured as constraint boundries, one can pin the boundaries and move them accordingly. If MV's do not move sufficiently due to slow control action, test signals can be added at MV positions. One can also perform a partial closed-loop test using an MPC with part of the MV's and CV's on.

d) Forms and spectra of test signals. The optimal spectra of test signals are designed to minimise the sum of the squares of the simulation error (often called prediction error in MPC terminology). The guideline is to put the energy of the test signal at frequencies where the model will be used and where disturbance level is high; see Ljung (1985) and Zhu and van den Bosch (2000). The spectra of the test signals are approximated using GBN (generalised binary noise) signals; see Tulleken (1990). Namely, the mean switching times of the GBN signals are set to realise the required signal spectrum. Also filtered white noise and multiple sinusoids can be used.

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

$$\hat{A}^n(z^{-1})y(t) = \hat{B}^n(z^{-1})u(t) + \hat{e}(t) \tag{3.1}$$

where $\hat{A}^n(z^{-1})$ is a diagonal polynomial matrix, $\hat{B}^n(z^{-1})$ is full polynomial matrix, and $\hat{e}(t)$ is called equation error.

3) Perform frequency weighted model reduction (ML estimate)

The high order model in (3.1) is practically unbiased, provided that the process behaves linearly around the working point. The variance of this model is not minimal due to its high order. Model reduction on the high order model can reduce the variance. 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. See Zhu (1998) for details.

4) Use asymptotic criterion 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 (1998). The basic idea of this criterion is to minimize the total model error by equalizing the bias error and the variance error of each transfer function in the frequency range that is important for control.

5) Model validation using error bound matrix

Based on an asymptotic theory (Ljung 1985 and Zhu 1998), a 3-δ bound can be derived for the model frequency response between *i*th CV and *j*th MV as:

$$\left|G_{ij}^o(e^{i\omega}) - \hat{G}_{ij}^n(e^{i\omega})\right| \le 3\sqrt{\frac{n}{N}[\Phi^{-1}(\omega)]_{jj}\Phi_{v_i}(\omega)} \quad \text{w.p. } 99.9\% \tag{3.2}$$

where $\Phi(\omega)$ is the spectrum matrix of inputs and prediction error residual $col[u^T(t), \hat{e}^T(t)]$, $\Phi_v(\omega)$ is spectrum matrix of unmeasured disturbances.

In model validation, the relative size of the error bound is compared with the model frequency response over the low and middle frequencies. Then each transfer function is graded either an A (very good), B (good), C (marginal) and D (poor). In general, A and B models can be used in MPC control and C and D models should be treated as follows:

1) Zero them when there is no transfer between the MV/CV pairs. This can be determined by using 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 the upper bound formula (3.2), we can easily give some guidelines for improving the test design:

- Doubling the amplitudes of test signals or quadrupling the test time will half the error over all frequencies;
- Doubling the mean switching time of GBN signals will half the model error at low frequencies and double the error at high frequencies. Halving the mean switch time of the GBN signal will do the opposite.

Because ASYM provides systematic solutions to the four identification problems, it can be made very user friendly for non-expert users. Recently, ASYM has been implemented in the automated identification software Tai-Ji ID.

4 Case Studies

In order to study the feasibility and benefits of the proposed methodology, two case studies are carried out. The first one is a partial closed-loop identification of two distillation columns in a chemical plant. The second one is a total closed-loop identification of a simulated distillation column.

4.1 Partial Closed-loop Identification of Two Distillation Columns

Process description: This double shell column is part of an aromatics processing unit. The columns separate an aromatic intermediate stream into fractions useful in downstream processing units which ultimately make the aromatic products. The 2 columns effectively act as one large column. It has 2 feed streams of different composition, 2 reflux streams (one top, one middle), an overhead product, a bottoms product, one liquid sidestream product, and one vapor sidestream product.

MPC configuration

MV tags	**Description**
T_C3FD.SP	Upper feed temperature
F_C3IR.SP	Upper internal reflux flow
MW_REB.SP	Reboiler duty
F_MIDP.SP	Vapor Sidestream flow rate
F_MGAS.SP	Liquid sidestream flow rate
F_C2IR.SP	Lower Internal reflux flow
F_BOTP.SP	Bottoms product flow
P_TOWR.SP	Tower Pressure
F_C2FD.SP	Tower Heavy Feed rate

DV tags	**Description**
F_C3FD.PV	Tower light feed rate

CV tags	**Description**
T_2UTR.PV	Lower column tray #1 temperature
T_M98P.PV	Middle column tray temperature
A_LNA8PV	Sidestream product light key analyzer
T_C3TR.PV	Upper column tray temperature
A_C9OH.PV	Overhead product heavy key analyzer
DP_C2_.PV	Column delta pressure
T_2LTR.PV	Lower column tray #2 temperature
L_2BOT.PV	Column bottoms level
F_2OVH.PV	Sum vapor sidstream + lower reflux rate
F_POVR.SP	Liquid flow from upper column to lower column

The MPC controller has been in operation for many years and was commissioned using the conventional identification approach. After a unit revamp, the models were no longer valid and a new identification was necessary for the MPC controller. Tai-Ji ID was used for the test signal design and for model identification. Based on process knowledge, a four day test was planned with all MV's being moved by a test program. The test program read the test signals created from Tai-Ji ID and moved the MV and CV setpoints accordingly.

Tray temperature on the upper column (T_C3TR.PV; a CV in the MPC) was an important variable. Experience had shown that the unit will operate smoothly if this tray temperature stays within a given range and a variation too large will cause operational problems. There existed a PID controller for the temperature that used the column reflux (an MV in the MPC). In order to maintain stable operation, this temperature control loop was closed during the test. A GBN signal was applied to the setpoint of the temperature. All open loop MV's were moved by GBN signals. Figure 4.1 shows the MV signals used for the test. Note that the signals are scaled.

Identification was carried out after about 24, 48 and 72 hours of testing. These intermediate results were used to verify if the test was going well and if all MV signal amplitudes were properly set. The model validation outlined in the previous section was used for this purpose. One can see that the amplitudes of four MV's were increased during the test. Also some manual control took place during the test which changed mean values of MV signals; see Figure 4.1. According to model validation, models obtained from the three day test were good enough, because most required models are in grades A and B. Indeed the models from the total four day test were nearly the same as those of three day test. Model step responses are shown in Figure 4.2; frequency responses and error bounds are shown in Figure 4.3; and simulation and model fit are shown in Figure 4.4.

The models are being used in the MPC controller and the control performance was good.

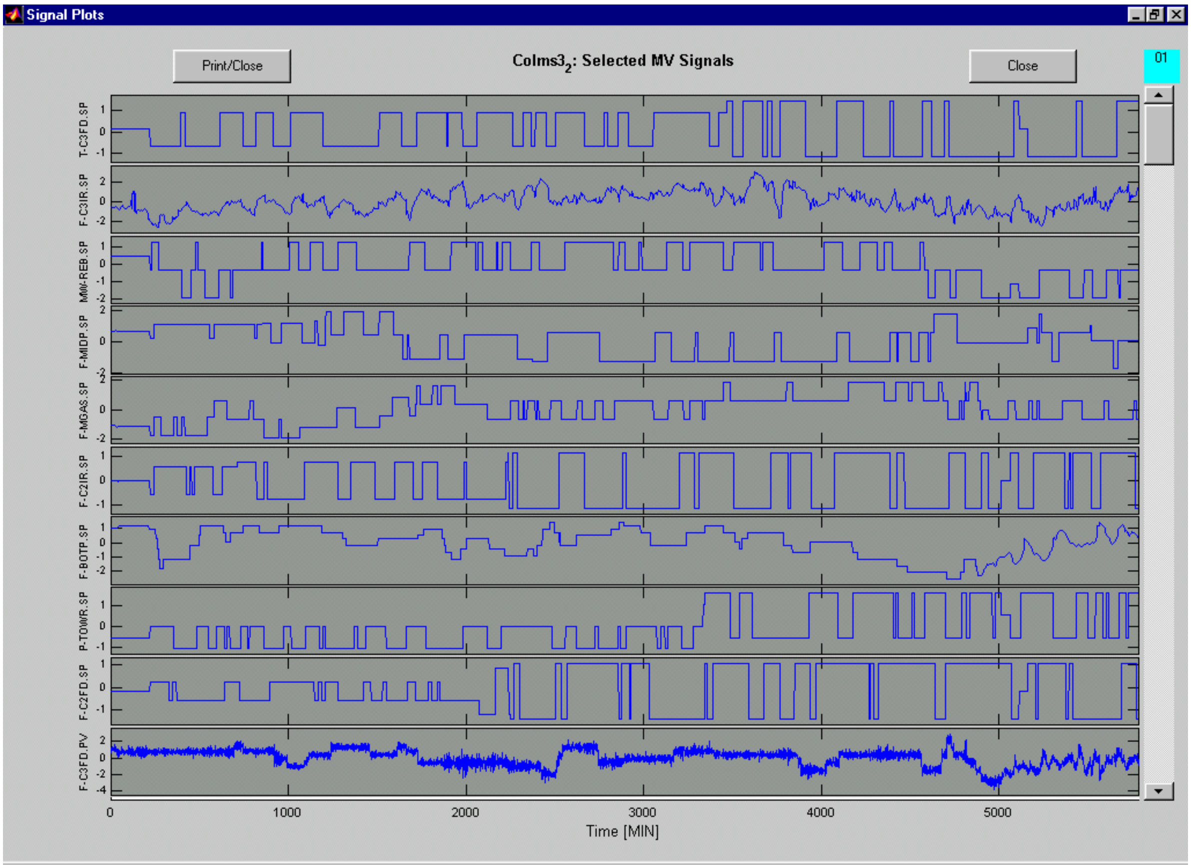

Figure 4.1 MV signals during GBN test, signals are scaled

Figure 4.2 Model step responses

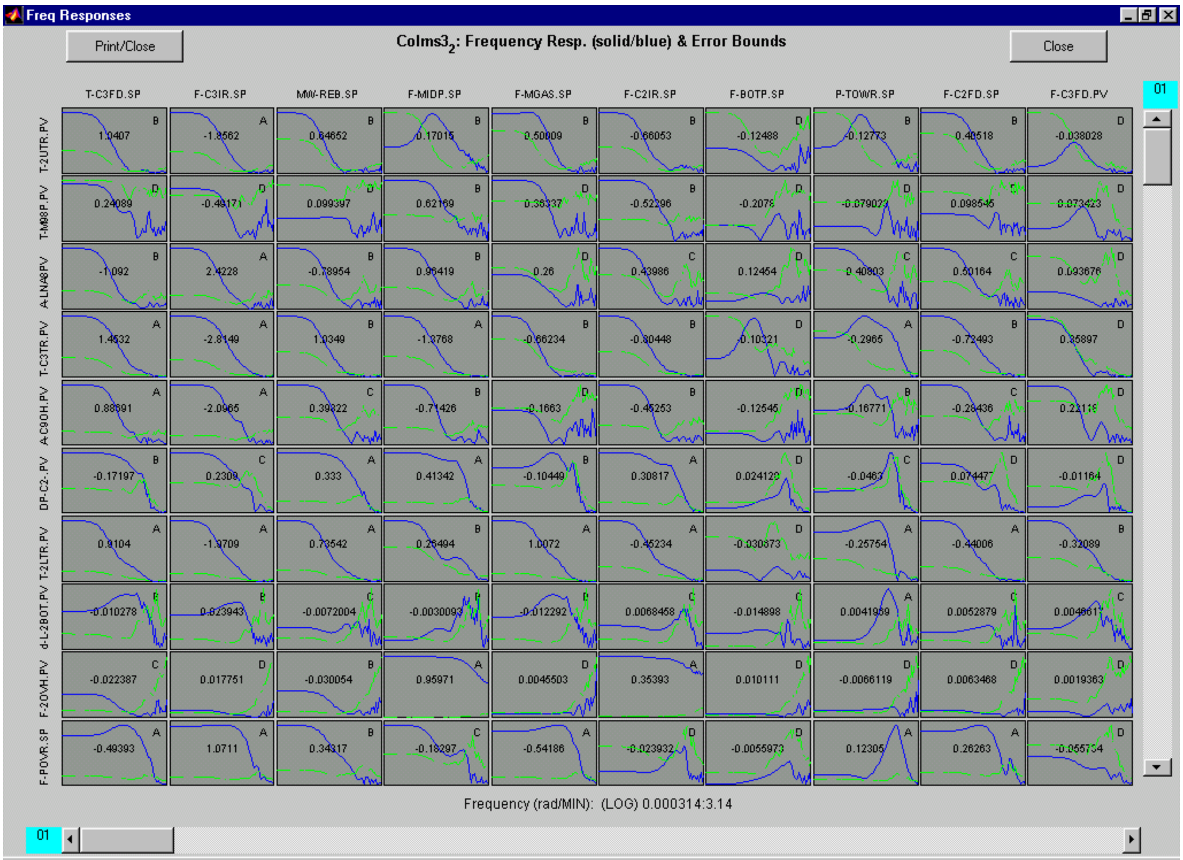

Figure 4.3 Model frequency responses and upper error bound

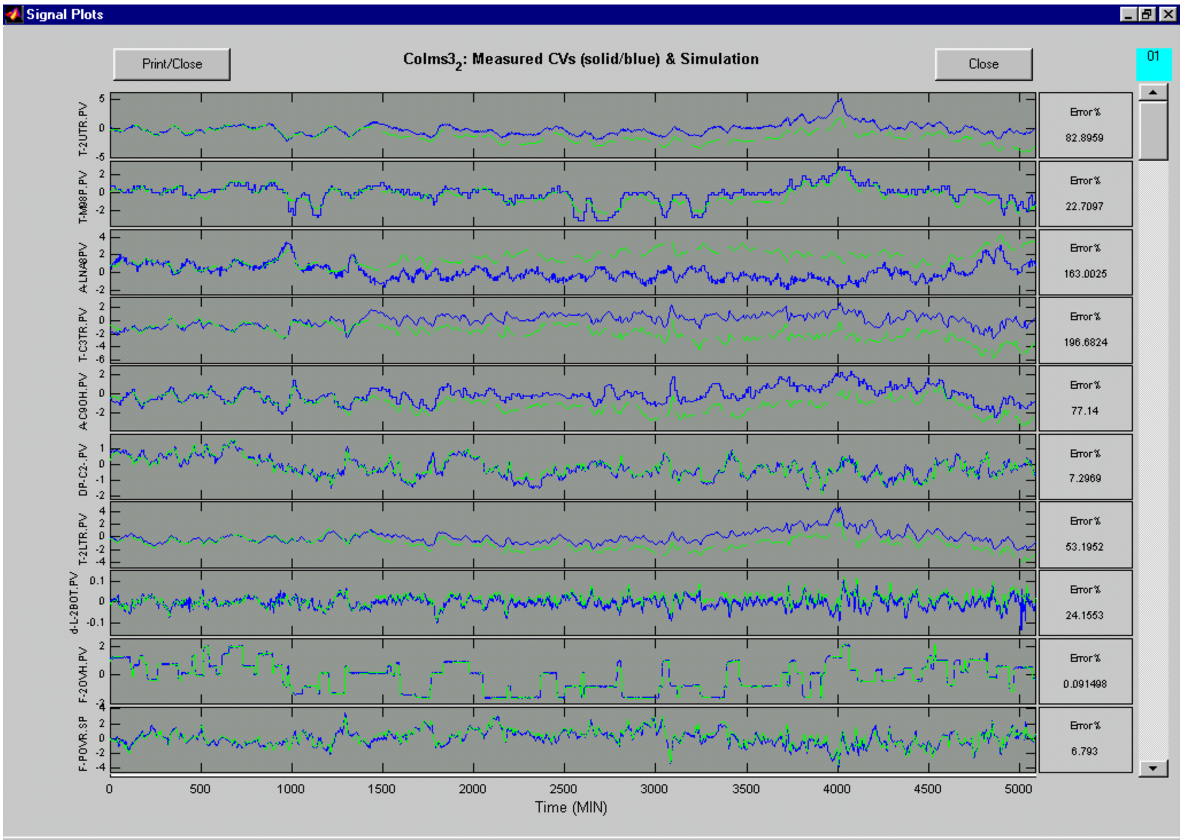

Figure 4.4 CV's and their simulations

4.2 Total Closed-loop Identification of a Simulated Distillation Column

The process is a simulated distillation column, a simple 2 product fractionation column. It separates C3 and lighter from C4 and heavier.

MPC configuration

MV's

Column Feed rate	F018.SP
Column Tray 10 Temperature	T014.SP
Column Pressure	P015.SP
Column Overhead Product Rate	F020.SP
Column Reflux Rate	F019.SP
Column Overhead Drum Vent flow	F022.SP

Key CV's

Overhead Product Heavy Key Analyzer	AC003
Bottoms Product Light Key Analyzer	AC002
Pressure Controller Valve Position	P015.OP
Overhead Drum Level	L008
Column Bottoms Flow Rate	F023

Open Loop Identification and MPC Tuning

First, a traditional single variable open loop test was performed. Disturbances (random noise plus slow drifts) were added to the feed composition and feed temperature that act as unmeasured disturbances. Models were identified using Tai-Ji ID. Model qualities were good according to model upper bounds and model simulation. Figure 4.5 shows the model step responses; Figure 4.6 shows the model fit. One can see that the model cannot fit the data perfectly due to the nonlinearity and disturbances. The identified models were then used in a MPC controller. After some tuning, the MPC performed properly. The second use of the model from the open loop test is to verify the model from closed-loop identification.

Closed-loop Identification

Then a closed-loop test was performed with the MPC on control. All the MV's and part of the CV's were perturbed using GBN signals created by Tai-Ji ID. The same disturbances on the feed composition and feed temperature used in open loop test were also used in the closed-loop test. The CV variations during the closed-loop test are similar to those during the open loop test. Then models were identified using Tai-Ji ID. According to model validation, model qualities are good. Figure 4.7 shows the model step responses.

Verify the Closed-loop Model

In order to make sure that the models from the closed-loop test data indeed have good qualities, we need to find a way to verify them. Since we know that the open loop models have good quality, we can then compare the models from the two tests. From step response plots, we can see that most model gains and settling times are very close. Table 4.1 shows the significant model gains of both open loop and closed-loop models. Again we find that the gains of the two models are close. From project experience, we are certain that the models identified from the closed-loop test will perform well when used in the MPC controller.

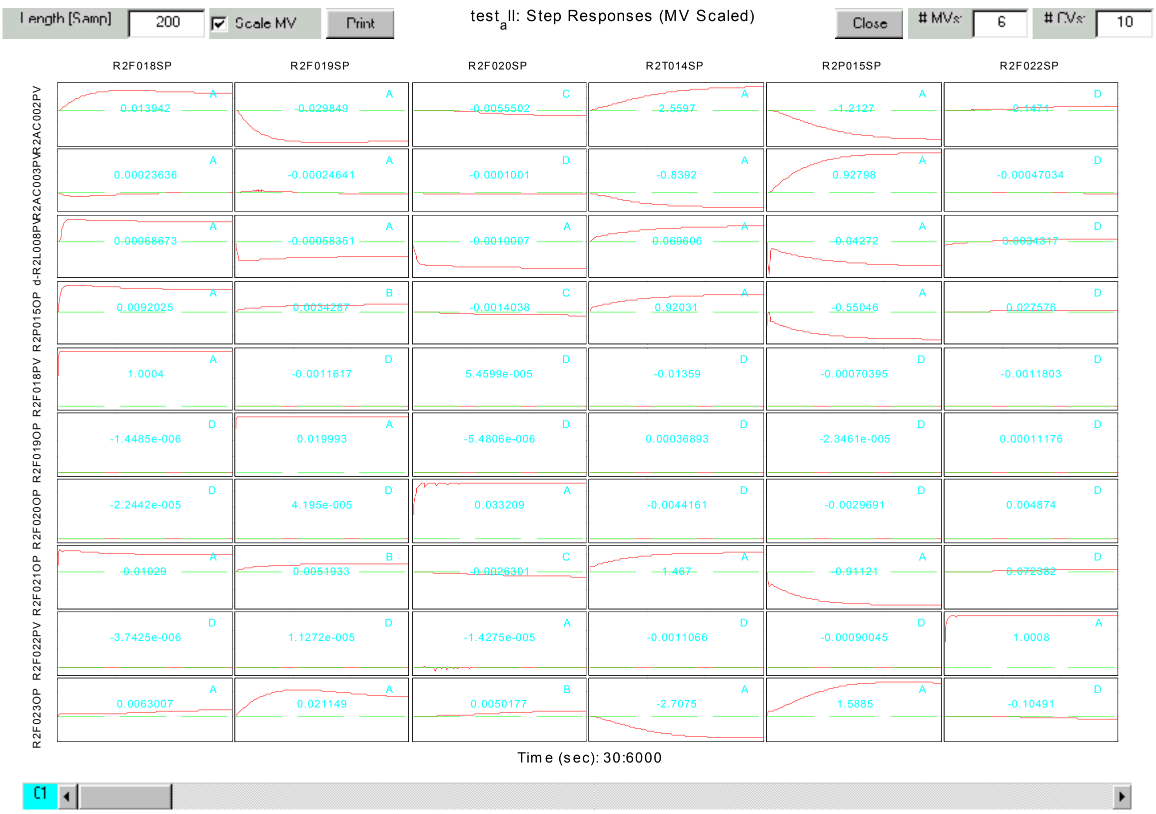

Figure 4.5 Model step responses, open loop identification,

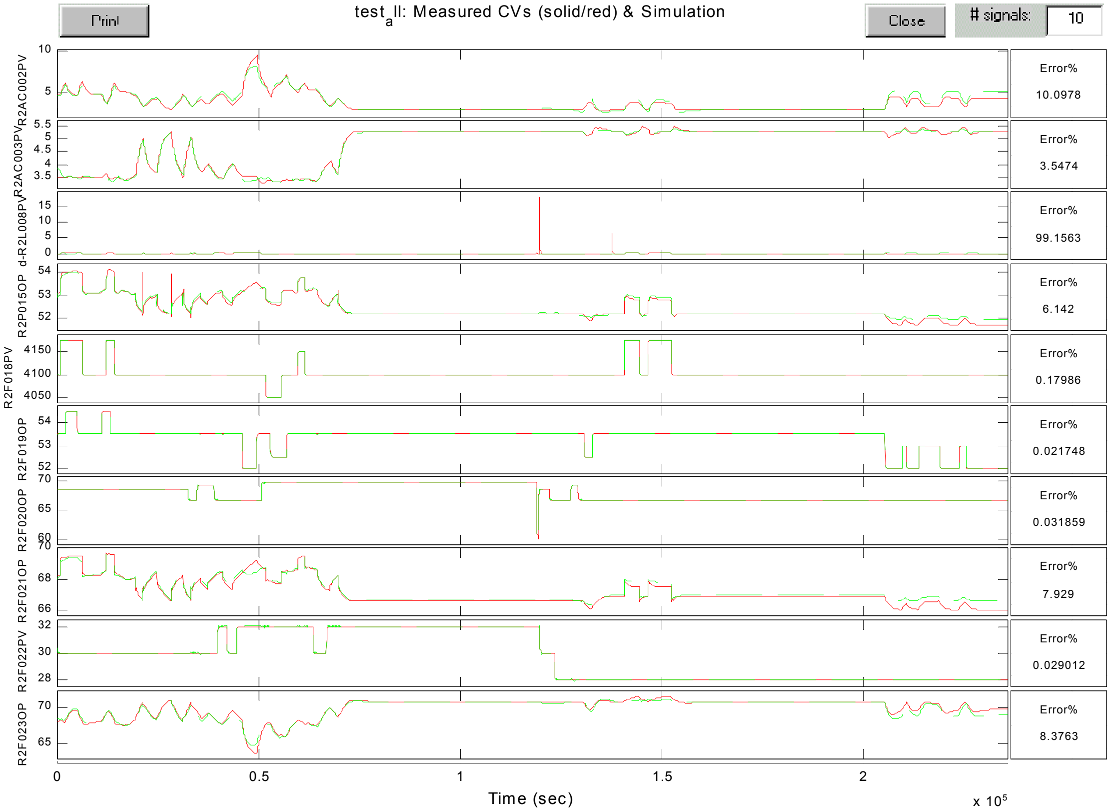

Figure 4.6 Model fit, open loop identification

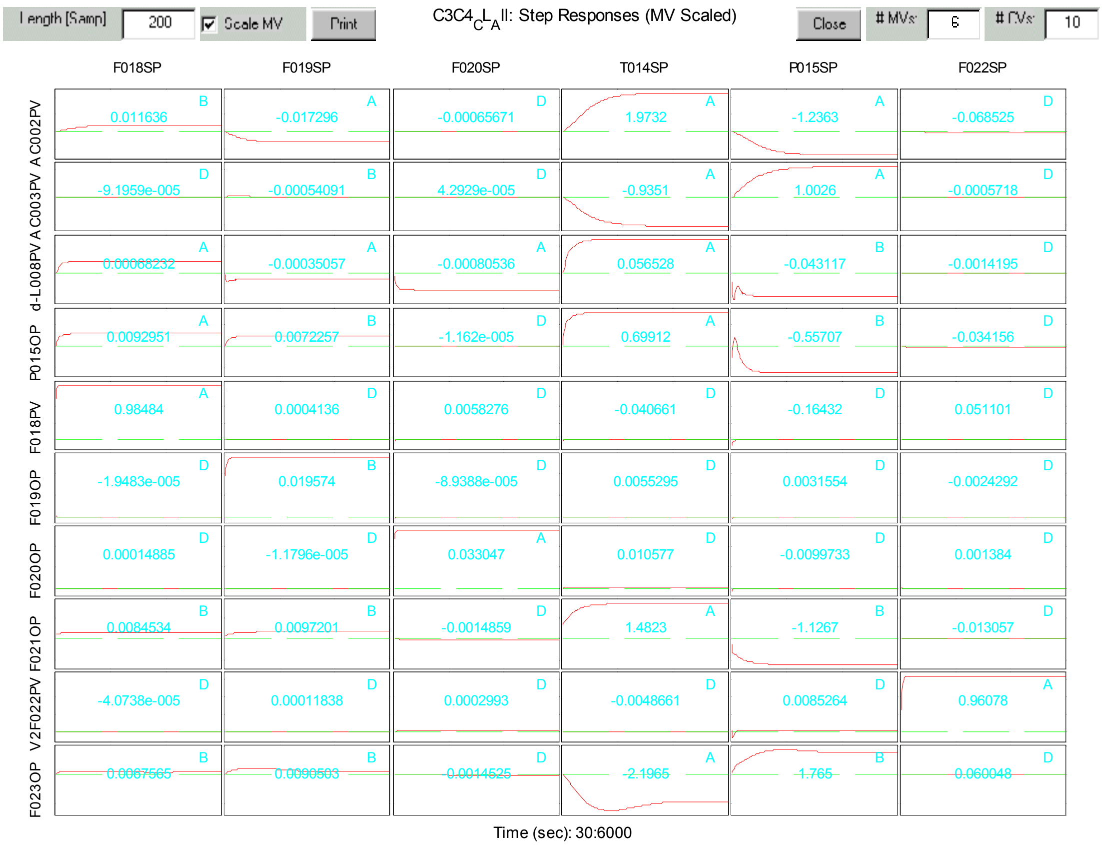

Figure 4.7 Model step responses, closed-loop identification

Table 4.1 Significant gains of open loop model (upper) and closed-loop model (lower)

MV / CV	F018SP	F019SP	F020SP	T014SP	P015SP	F022SP
AC002PV	0.01394 0.01164	-0.0298 -0.0172	2.5597 1.9732	-1.2127 -1.2363		
AC003PV				-0.8392 -0.9351	0.9280 1.0026	
d-L008PV	0.00069 0.00068	-0.00058 -0.00035	-0.00100 -0.00080	0.0696 0.0565	-0.4272 -0.4312	
P015OP	0.0092 0.0093	0.00343 0.00723	0.9203 0.6991	-0.5505 -0.5571		
F018PV	1.0004 0.9848					
F019OP		0.0200 0.0196				
F020OP			0.03321 0.03305			
F021OP	0.0103 0.0085	0.0052 0.0097		1.4670 1.4823	-0.9112 -1.1267	
F022PV						1.0008 0.9608
F023OP		0.0211 0.0091	-2.7075 -2.1965	1.5885 1.7650		

This simulation study shows that total closed-loop identification test with an MPC online is feasible.

5 Conclusions and Perspectives

In this work we have studied multivariable closed-loop identification for use in MPC. The ASYM method is introduced to solve the problem. Two case studies are used to demonstrate the method. We have shown that closed-loop tests have many advantages over open-loop tests. Many 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. Using closed-loop control and manual intervention during the test reduces the disturbance to unit operation. The cost of identification is significantly reduced; reduction of both test time and data analysis time by 70% can be realised. Initial experience with closed-loop testing shows the possibility to eliminate the night shifts during the test. This will further reduce the cost of manpower. Total closed-loop testing is not only important for MPC maintenance; it can also be used in controller diagnosis and performance monitoring.

Further performance improvement and project cost reduction may call for adaptive MPC. Closed-loop identification plays a central role in adaptive control. Another new direction worth considering is the use of nonlinear models in MPC. Some new results have been developed in this regard; see Zhu (2001)

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