NEW DEVELOPMENTS IN INDUSTRIAL MPC IDENTIFICATION

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Abstract: In industrial model predictive control (MPC), there is a demand for more efficient model identification methods. In this work we will review some recent developments in industrial MPC identification. The discussion will be around four fundamental issues of industrial identification: 1) test method, 2) parameter estimation, 3) order selection and 4) model validation/selection. Three industrial products will be discussed: 1) RMPCT identification package of Honeywell Hi-Spec Solutions, 2) DMCPlus™ identification package DMCplus Model of Aspen Technology, and 3) Tai-Ji ID, the identification package of Tai-Ji Control. To show the benefits of modern approaches, two applications of Tai-Ji ID will be presented: an open loop identification of a crude unit and a closed-loop identification of a deethanizer.

Keywords: Model predictive control (MPC), identification, plant test, parameter estimation, order selection, model validation, application.

1. INTRODUCTION

Dynamic models play a central role in MPC technology. Typically identified linear models are used in an MPC controller; also inferential models are used for product quality prediction. Industrial 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 quality of collected data depends heavily on the technical competence and experience of the control engineer and the operator who carried out the tests. After the test, it can take another two 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.

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

Recently, MPC vendors and other control technology companies have made some effort to improve the efficiency of MPC identification. In this work, we will introduce and discuss the identification packages of RMPCT controller of Honeywell Hi-Spect Solutions, DMCplus™ of Aspen Technology and Tai-Ji ID of Tai-Ji Control. In Section 2 we address the key issues of MPC identification. In Section 3 the three identification packages are described and their "modern" features are emphasized. In Section 4, two industrial cases are used to show the feasibility and benefits of the modern approach. Section 5 will discuss nonlinear model identification. Section 6 contains the conclusions and perspectives. The purpose of this paper is to inform the academic researchers about the needs and new developments in industrial MPC identification. The author is not in a position to evaluate the three packages and to give recommendations.Text of paper, 76 mm (3in) column width, with 8 mm (.3in) space between. Use full 253 mm (10 in) column length. Paragraphs should be justified, using single spacing, with no paragraph indentation. Use Times Roman font, 10 point. Leave one clear line between paragraphs within a section; two clear lines before a main or secondary heading.

2. KEY ISSUES IN MPC IDENTIFICATION

Hydrocarbon process industry (HPI) processes can be characterised as 1) large scale and complex, 2) dominant slow dynamics and 3) high level disturbances. They 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

In a traditional identification test, each MV is stepped manually and each MV is tested separately after each other. All the CV's are in open loop operation. The average step length is related to the estimated settling time of the process. The test is carried out around the clock and it will cost 15 to 20 days to test a large unit such as a crude unit and an FCCU. This approach has been very successful in the last 20 years. 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:

- High cost in time and in manpower.
- 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.
- An open loop test may disturb unit operation.

Using automatic multivariable closed-loop testing can solve these problems. There are many advantages of a multivariable 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. One or more PID loops can be used in a partial closed-loop test. 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 satisfactorily 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 Ljung (1999).

2) Model Structure and Parameter Estimation

In traditional MPC identification, first an MIMO FIR model is used to estimate using least-squares method. This often results in a model with non-smooth step responses. Model reduction or smoothing techniques are used to obtain smooth model responses. Optionally, SISO parametric models are estimated using data slices that only involve the movements of one MV-CV pair. This is not always feasible due to high-level disturbances and multiple movements of the MV's.

The following models/methods are common in identification literature:

- FIR (finite impulse response) model
- ARX (AutoRgressive with eXternal input) model, or, least-squares model
- Output error (OE) model
- ARMAX (AutoRgressive Moving Average with eXternal input) model
- Box-Jenkins model

These are special cases of the more general prediction error model family (Ljung, 1987). The model parameters are determined by minimising the sum of squares of the prediction error. In literature, ARX, OE, ARMAX and Box-Jenkins models are called parametric models and the FIR model is called a nonparametric model.

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 a state space model of a multivariable process directly from input/output data. For closed-loop identification, the choice of model structure (or estimation method) depends on three 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 are used in identification, a more compact model will be more accurate provided that the parameter estimation algorithm converges to a global minimum and the model order is selected properly. In general, a model structure or an estimation method that includes a disturbance model will be more accurate than a method without the disturbance model. Moreover, a model with a disturbance model will give a consistent estimate for closed-loop data, meaning that the effect of the disturbance will decrease when test time increases; whereas a model without a disturbance model will deliver a biased estimate when using closed-loop data.

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. In FIR and ARX models, the error term is linear in the parameters. Due to this property, a linear least-squares method can be used in parameter estimation that is numerically simple and reliable. This explains partly why the 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.

To summarise the discussion, the following table compares the advantages and disadvantages of various model structures or parameter estimation methods.

Table 2.1 Comparison of various model structures and estimation methods

Model structure or estimation method	Numerical difficulty	Accuracy	Consistency for closed-loop
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	?

For multivariable processes, model parametrization (SISO, MISO or MIMO) will also play a role in determining model accuracy for control; see Zhu and Butoyi (2002).

3) Order Selection

In traditional MPC identification, for an FIR model, the estimated settling time is used as the model length or "order" of the model. This is theoretically simple, but it is not easy to use in practice. A phenomenon that often occurs is that, when the disturbance level is high, the model gains will change when the model length changes. For SISO model estimation, usually first order or second order plus delay models are tried and the choice is made based on simulation and/or process knowledge.

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; in the frequency domain, this requires that the total error is minimal. See Zhu (2001) for more details.

4) Model Validation

In traditional MPC identification, the model validation and selection are done based on process knowledge on the gains and on the fits between simulated CV's and their measurements.

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. Simulation approach is very questionable for multivariable closed-loop test data because a good fit of a CV cannot guarantee that models from all MV's are equally good and a poor fit of a CV does not imply that all the models for that CV are bad. A more useful model validation method should provide information of model accuracies of each transfer functions and relationship between model accuracies and test variables such as signal amplitudes and test time.

3. THE THREE IDENTIFICATION PACKAGES

3.1 RMPCT Identification Package

This software is part of Honeywell Hi-Spec's Profit Suite family of products. The identifier has been historically used to perform off-line identification for the RMPCT controller (now referred to as Profit Controller) using data collected from identification tests.

1) Identification Tests

As there is no restriction on the source of input data, the Identifier accommodates both conventional and automatic tests. Automatic test signals are generated using either a phased Schroeder or PRBS based approach. The Schroeder signals are finite frequency (power at designed frequency points) signals that are univariate in nature. These signals are more appropriate for the PEM class of models. The PRBS approach used is a multivariable design, which allows the movement of simultaneous MVs. Historically, however, engineers have preferred using the sequential PRBS (single variable at a time) approach. While the PEM class of models (Box-Jenkins) can accommodate closed loop identification, most historical ID has been open loop.

2) Model Structure and Parameter Estimation

Both FIR and the general PEM model class (see Ljung 1987) are supported. The default PEM structure is Box-Jenkins. As discussed before, Box-Jenkins is one of the most advanced model structure. On the other hand, for a large-scale process with many MVs moving simultaneously, numerical optimisation is difficult for this model structure.

Both FIR and PEM models accommodate simultaneous inputs and contaminated and/or discontinuous data.

Irrespective of the model type, a model reduction step is applied to obtain a low-order-plus-delay model for each transfer function. The max “order” of this low order model is user configurable

3) Order Selection

For the FIR model, the estimated settling time is used as the model order. For the PEM models, several candidate orders are tried, the final model orders are determined based on statistics (new feature) and how good the simulated CV’s fit the their measurements.

The order of each low-order-plus-delay model is determined based on how good its step response fits that of the FIR or PEM model. This goodness of fit is checked by visual inspection for the output error (OE) and prefiltered ARX models (ARX models are automatically prefiltered to remove bias). The order is automatically selected (up to third order) for the Laplace model. The order reduction step will try OE, ARX and Laplace models to automatically determine the best structure based on goodness of fit. If the OE or ARX structure is selected, then this discrete time model is converted to the Laplace (continuous) domain. The final low order model is always saved in the Laplace domain and is visually displayed in transfer function form.

4) Model Validation

Model validation is performed on full order models in terms of; confidence limits, noise bounds, null hypothesis tests and step response sensitivities. The latter metric is based on model perturbations. Model rankings are automatically determined based on the above-mentioned statistics. Rankings are given values 1 through 5 with 1 being excellent and 5 being useless. Full order model ranks can be used to automatically null corresponding reduced order models. This feature is user selectable.

Finally, reduced order model verification and selection are done based on process knowledge on the gains and on the fits between simulated CV’s and their measurements.

In addition to the RMPCT identifier, the Profit Suite family of products support the newly released product, Profit Stepper. This stand-alone product performs on-line open-loop identification in an automated fashion. The design test signal moves one MV at a time. As the models are developed, the input signal is modified to enhance data information content as required. All models are generated automatically and ranked according to estimated performance. Final models are generated in the Laplace domain and can be imported directly into the Design Studio for RMPC or PID control building. Once in the Design Studio the Identifier can also be used for any desired manipulations.

3.2 DMCplus™ Model

DMCplus™ Model is the model identification package for DMCplus™ controller of Aspen Technology Inc.

1) Identification Tests

Normally traditional step test approach is used to carry out identification tests. All CV’s are in open loop, step signals are applied at each MV’s sequentially, and the test is carried out manually around the clock.

Remark: Recently, a test program called SmartStep™ was developed. The SmartStep™ is an automatic online test program that works together with an existing DMCplus™ controller. SmartStep™ can be configured to perform different patterns of test: traditional one step for one MV or simultaneously stepping multiple MVs. It is user's choice what way he wants to go. The existing DMCplus controller is set in range control mode that is used to stabilize the unit operation. Because SmartStep™ needs an existing DMCplus™ controller, it is more suitable for use in controller maintenance than in new controller commissioning. SmartStep™ generates both closed-loop and open loop data. That is because unmeasured disturbance and model uncertainty will always have tendency to drive the process out of a constraint and SmartStep™ will use feedback to correct the process.

2) Model Structure and Parameter Estimation

FIR model is used in parameter estimation. Some smoothing technique is used to reduce the randomness of the FIR coefficients.

Recently, as an option, subspace method is introduced that estimates state space model. As discussed before, state space model is a compact model structure numerical solution is simple in subspace method. However, there is no general consistence proof for the class of subspace methods using closed-loop data.

3) Order Selection

For the FIR model, the estimated settling time is used as the model order. The smoothing factor used in the method can be considered as a measure of the "order". The smoothing factor is determined by visually inspecting the smoothness of model step responses.

When state space model is used in subspace method, the order or the state dimension is determined on how good the simulated CV's fit the their measurements.

4) Model Validation
Model validation and selection are done based on process knowledge on the gains and the shapes of step responses and on the fits between simulated CV's and their measurements.

3.3 Tai-Ji ID

Tai-Ji ID is a model identification package developed by Tai-Ji Control. The method is based on the ASYM method; see Zhu (1998, 2001).

1) Identification Test
Tai-Ji ID uses automatic test. It generates GBN (generalised binary noise, Tulleken, 1990) as test signals. Tai-Ji ID tests are multivariable, which means that many MV's are moved simultaneously using GBN signals. Both open loop and closed-loop test can be used. In an open loop test, typically, up to 10 MV's are moved; in a closed-loop test, typically, all MV's will be moved. The existing controller can be PID loops, or an MPC controller. The duration of a Tai-Ji ID test is much shorter than a traditional step test. It will take 5 days to test a crude unit or an FCCU using Tai-Ji ID approach.

2) Model Structure and Parameter Estimation
Tai-Ji ID first estimates a high order ARX model and than perform a frequency domain model reduction. The reduced model is in a Box-Jenkins format.

3) Order Selection
Tai-Ji ID uses a frequency domain criterion for order selection so that the total model error (bias part plus variance part) is minimal; see Zhu (1998, 2001). The order selection is done automatically without user intervention.

4) Model Validation
Based on an asymptotic theory (Ljung 1987 and Zhu 2001), an upper error bound can be derived for the model frequency response of each transfer functions. The relative size of the error bound is compared with the model frequency response over the frequency range that is important for control. Each transfer function is graded an A (very good), B (good), C (marginal) or D (poor). In general, A and B models can be used in MPC controller.

The upper bound has a clear relationship with the test variables such as test time and signal spectrum and amplitude. For example, the following simple rules can be derived and used to adjust the on going test: 1) Doubling the amplitudes of test signals or quadrupling the test time will halve the error over all frequencies; 2) doubling the mean switching time of GBN signals will half the model error at low frequencies and double the error at high frequencies.

4. INDUSTRIAL CASE STUDIES

All three methods have been applied to many HPI processes in industrial MPC projects. The purpose here is to show that the new developments in MPC identification can improve the MPC project efficiency considerably. The first case shows that the test time can be reduced considerably (70%) by using automatic multivariable test and parametric models; the second case shows that the disturbance to unit operation can be reduced considerably by using (partial) closed-loop test.

4.1 Identification of a Crude Unit

The crude unit consists of three distillation columns in series: an atmospheric tower, a splitter and a stabilizer column. Two DMC controllers have been installed for the crude unit, one for atmospheric column and one for splitter/stabilizer. In this paper we will only discuss the first controller. Figure 4.1 shows a simplified process flow diagram of the atmospheric tower.

The column performs the initial distillation of the crude oil into various boiling range fractions. The column has four side draws each with its own side draw stripper. The column has whole straight run naphtha (WSR) as top product and a bottom residue is the feedstock for the vacuum unit. Moreover the column has a top reflux flow and three pump around flows of which the TPA and BPA exchange heat with stabilizer and splitter columns respectively.

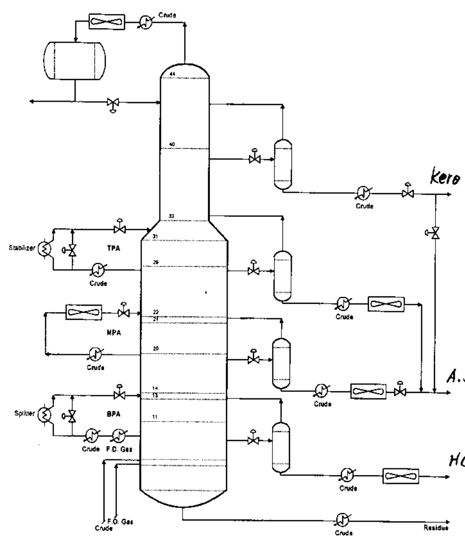

Figure 4.1 Simplified flow diagram of crude unit atmospheric distillation column

In order to achieve various control objectives, A DMC controller with 19 MVs, 3 DVs and 36 Cv6 was configured.

Initially a single variable step test approach was used for model identification. The step test took about 14 days. The identified model was used in the DMC controller and the control performance was not satisfactory. It was believed that model quality was one of the causes of control problems.

A) ASYM Identification Tests

It was decided that 13 of the 19 MVs will be tested and their models identified using ASYM. GBN signals are used as test signals. Two open-loop tests were designed and carried out. Each test lasted for about two days, so the total test time was 4 days. The tests did not cause any product quality problems. Figure 4.2 shows the plots of part of the 8 MVs during some of CVs during PRBS Test 1. During the test the operators have adjusted the average setpoints for many MVs in order to maintain stable unit operation. Note also that the step sizes of some MVs were increased during the test.

B) Process Models and Model Validation

In Figure 4.3 the model step responses of 8 CVs for Test 1 are plotted, in Figure 4.4 their frequency responses and upper error bounds are plotted. The models are graded according to the relative size of their upper bounds. The result of model validation agreed very well with process knowledge. Model validation results using upper error bounds agreed very well with the process knowledge. Most of the A and B grade models are used in the DMC controller.

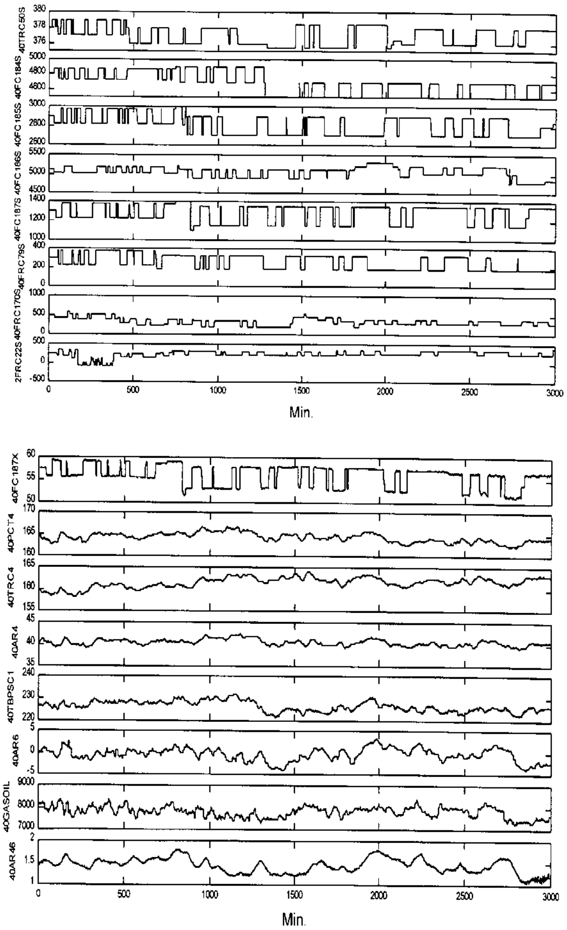

Figure 4.2 Trends of part of moved MVs and CVs during PRBS Test 1

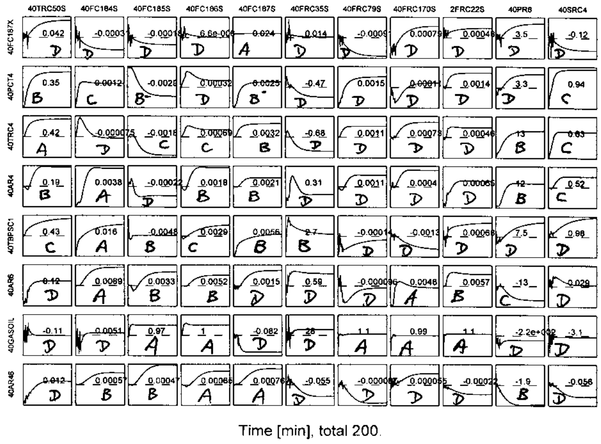

Figure 4.3 Step responses of the models of 8 CVs from Test1

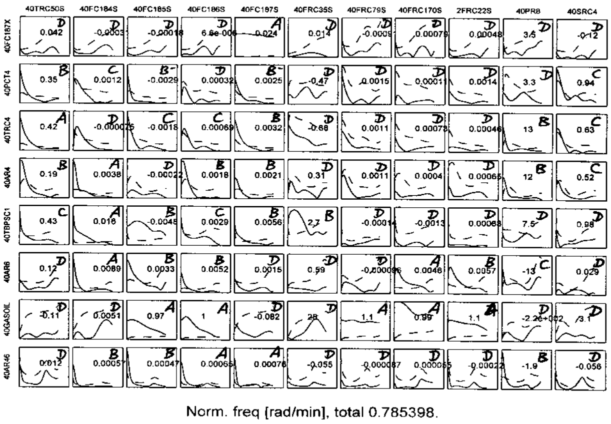

Figure 4.4 Frequency response plots (solid) and error bounds (dashed).

C) DMC Commissioning and its Performance

The ASYM models are very accurate for the working range tested. As a result the controller can be tuned very fast. This time, it took only two weeks to commission the atmospheric column DMC controller. Control results are pointing at a much higher yield pattern at the expense of residue. The variance of the product qualities has been reduced dramatically.

4.2 Open and (Partia)l Closed-loop Identification of a Deethanizer

The process is a Deethanizer which is a distillation column that separates C2 and lighter components from C3 and heavier components. 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. An MPC controller was designed and was going to be commissioned as part of an advanced process control and optimization project. The purpose of the Deethanizer MPC is to reduce the variations of product qualities while respecting process operation constraints.

The inputs of the controller:
- Reflux: Reflux flow setpoint
- Steam: Reboiler steam flow setpoint
- Preheater: Feed preheater flow setpoint

Feedforward variable:
- Feed: Column feed flow

Main outputs of the controller:
- OverheadC3: Overhead C3 composition
- DeltaPress: Column pressure difference
- BotTemp: Bottom temperature
- TopTemp: Top temperature
- TrayTemp: A tray temperature

The identification is a challenging problem. The main reason is that the column is operating in a high purity mode and is very sensitive. The tray temperature TrayTemp is an important variable which should be controlled within 6 degrees (^{o}C) for normal operation. When it becomes too low, there will be off-spec overhead product and the column will be difficult to control. When the variation of the tray temperature becomes too large, nonlinear behaviour will be introduced and it will be difficult to control the column.

Initially, an open loop multivariable test has been carried out; see Figures 4.5 and 4.6. GBN signals were used as test signals. The test lasted 55 hours.

The following have happened during the open loop test:

- The tray temperature TrayTemp varied over a range of about 20 degrees, which is far beyond the normal operation range. The signal amplitudes determined during the pre-test turned out to be too large.

- 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.

- The preheater flow could not be moved during most of the test period due to the high level of disturbance.

- The column pressure difference became too large after sample 2200, which indicates the column was in flooding. The overhead C3 composition increased during this period.

The data have been used for identification using several software packages. Data slicing was used to remove the portion during column flooding. When the identified models were used in the MPC controller, the closed-loop performance was not satisfactory. It was decided that the best solution would be to retest the plant to get a better data set.

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. In the test, a GBN signal was applied at the setpoint of the tray temperature and the two GBN signals were applied at the reflux and the preheater flow. Figures 4.5 and 4.6 show the test data. The test lasted for 53 hours.

The closed-loop test can be summarised as follows:

- Controlled variable variations were much smaller than their variations during the open loop test. The tray temperature is within a range of 7 ^{o}C during the test. All the three inputs could be tested according to plan. The test did not disturb normal operation. See Figures 4.5 and 4.6.

- Much less operator intervention took place, which implies an 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 by cutting the reflux and preheater flow, thanks to the tray temperature controller.

Tai-Ji ID was used to identify the models using the closed-loop data. The disturbance to the key process variable TrayTemp is reduced by a factor of 3 and normal operation is easily maintained during the closed-loop test, which has made the identification test much more acceptable to the operation personnel. From a control point of view, the closed-loop data contains much less nonlinearity and more information around the normal process operation range. This will make the identified model more suitable for control.
The MPC controller commissioning using the closed-loop model went smoothly and the Deethanizer controller has been online ever since without major problems. The MPC system is stable and the variances of the controlled variables have been reduced considerably.

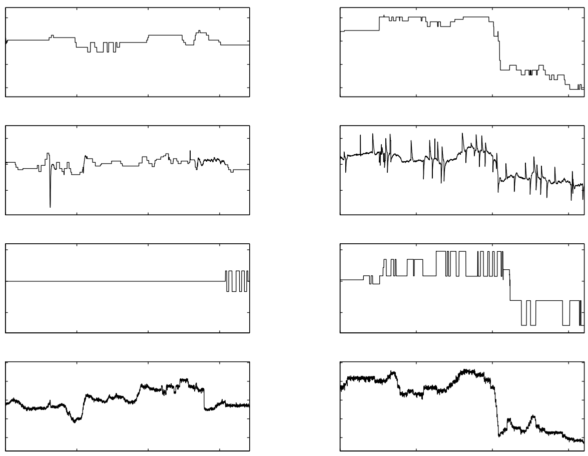

Figure 4.5 MV plots of the open loop test (left) and closed-loop test (right). The data are normalised. For each input, the same scaling factor is used for both open loop test and closed-loop test.

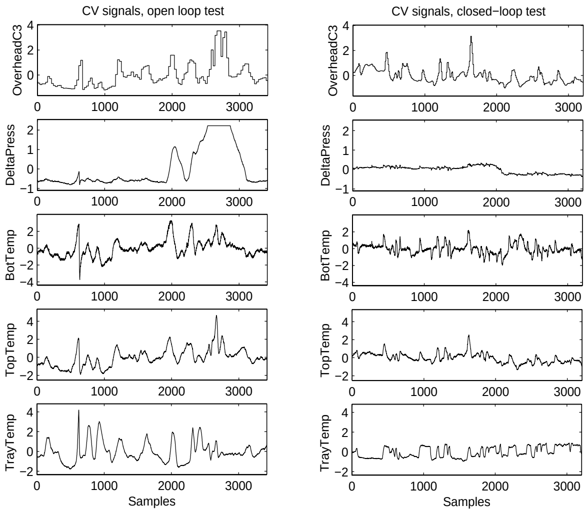

Figure 4.6 CV plots of the open loop test and closed-loop test. The data are normalised. For each output, the same scaling factor is used for both open loop test and closed-loop test.

5. CONCLUSIONS

New developments of industrial MPC identification have been reviewed. First the important issues of MPC identification have been addressed. Then three industrial identification packages have been introduced. The new developments include automatic identification test, multivariable and closed-loop test, the use of compact/parametric models and the use error bounds in model validation. The two case studies demonstrated the benefits of new technologies: considerable test time and manpower can be saved and, at the same time, the disturbance to unit operation can be reduced. Although most MPC projects are still performed using traditional identification method, applications of new methods grow steadily. Experiences with closed-loop tests show the possibility to eliminate night shifts during tests. This will further reduce the cost of manpower. Good experience with automatic closed-loop tests and automatic identification software is pointing at the possibility of self-adaptive identification/MPC.

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