TOWARDS A LOW COST AND HIGH PERFORMANCE MPC: THE ROLE OF SYSTEM IDENTIFICATION

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Abstract

The high cost of model predictive control (MPC) technology has hampered its wide application in process industries beyond the refining/petrochemical industry. This work aims to increase the efficiency of MPC deployment. First a semi-automatic MPC system is introduced. It consists of three modules: an *MPC control module*, an *online identification module* and a *control monitor module*. The goal of the MPC technology is twofold: (1) to considerably reduce the cost of MPC commissioning and maintenance; and (2) to increase control performance. System identification plays important roles in all the three parts of the MPC system. In the identification module, the so-called ASYM method of identification is used. It is demonstrated with an industrial application. In the control module, adaptive disturbance model identification is developed for improving control performance; in the monitor module, a method of model error detection method is developed. Industrial applications and simulations are used to demonstrate the ideas. Finally, we comment on some industrial needs on MPC research and development.

Keywords

Model predictive control (MPC), system identification, control performance monitoring, disturbance model, model error detection

1 Introduction

In the last three decades, model predictive control (MPC) technology has been widely applied in the refining and petrochemical industry and is beginning to attract interest from other process industries (Cutler and Hawkins, 1988 and Qin and Badgwell, 2003). MPC technology can bring tremendous benefit for process industries by improving product quality and safe operation, reducing energy and material costs as well as pollution. Dynamic models play a central role in the MPC technology. The most difficult and time consuming work during an industrial MPC project is modeling and identification (Richalet, 1993, Zhu, 1998). In MPC maintenance, the main task is model re-identification. Besides model identification, understanding MPC control theory and tuning methods and control performance is not an easy task. This makes skilled MPC control engineers very scarce. Due to these technical and manpower difficulties, MPC applications in other (non-petrochemical) process industries are still very limited.

In the last 10 years, work has been done in the MPC industry to improve the efficiency and accuracy in model identification. Key improvements are

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- Automated multivariable plant test instead of single variable manual test.
- Closed-loop test instead of open loop test.
- The use of parametrical models.
- The use of model quality grading in model validation.

See Zhu (1998, 2006), Celaya et. al. (2004, 2005), Mantelli et. al. (2005) and Kalafatis et. al. (2006). Also, the user-friendliness of MPC software packages has been improved considerably. Even so, the MPC technology is still at the hands of few skilled control engineers and cannot be used by non control experts. In MPC applications, it is greatly desired to reduce the technical difficulties and the engineering effort.

Recently, Zhu and coworkers (Zhu et. al. 2008) have started the development of a semi-automatic MPC system that aims to considerably reduce the cost of MPC technology as well as to increase control performance. The MPC system consists of three parts: an online control module, an online identification module and a control performance monitor module. For a given MPC design, the adaptive MPC can perform controller commissioning and maintenance automatically. In this work, we will discuss how system identification plays the key role in the adaptive MPC. The recent versions of other MPC packages have embedded this philosophy as well. Market is heading towards this goal.

In Section 2, the architecture of the semi-automatic MPC is introduced. In Section 3 the identification module is discussed and an industrial application is presented. In Section 4 the control module is introduced where an adaptive disturbance model is used to increase control performance. In Section 5, the monitor module is discussed where an identification method is used in model error detection. Section 6 contains the conclusion and discussion.

This paper emphasizes methodology, technology and application. Due to space limitation, mathematical details are omitted and they can be found in the references.

2 The Architecture of the Semi-Automatic MPC

At present, a common MPC project approach has the following steps (Zhu, 2001):

(1) MPC controller design and benefit analysis.
(2) Pre-test.
(3) Identification test and model identification.
(4) MPC controller tuning and simulation.
(5) MPC controller commissioning.
(6) MPC controller maintenance. The main task of maintenance is to re-identify the process model.

Highly skilled control engineers with many years of experience are needed to perform the tasks and each step cost considerable time and effort. Different software packages are used in different steps, which is not convenient for the user.

In Zhu et. al. (2008) we have proposed a semi-automatic MPC controller. The goal of the MPC controller is to automatically and efficiently perform MPC implementation and maintenance, that is, steps (2) to (6) previously mentioned. The MPC controller consists of three modules: (1) an MPC Control Module, (2) an online Identification Module and 3) a Control Performance Monitoring Module. Figure 1 shows the block diagram of the semi-automatic MPC controller.

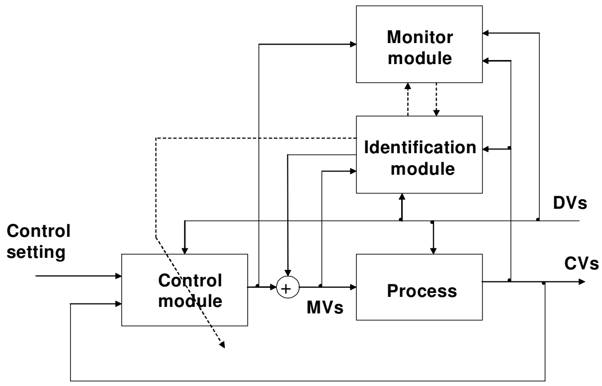

Figure 1. Block diagram of the semi-automatic MPC

Assume that an MPC controller design is given. During the MPC implementation, the Identification Module performs automated plant test and automatic model identification. During the plant test, when some identified models have good quality for control based on model validation, they will be used in the MPC Control Module and the corresponding manipulated variables (MVs) and controlled variables (CVs) will be turned on. As the test continues, more and more models will be loaded in the MPC Control Module and MVs and CVs turned on. When all expected models reached good fidelity and are used in the MPC Control Module, the Identification Module will stop and the MPC commissioning is finished. For an online MPC controller, the Monitor Module continuously monitors its performance. When the Monitor Module detects considerable control performance and model quality degradation, it will activate the Identification Module and plant test and model identification will start while the MPC controller is still on. During the test and identification, poor models will be gradually replaced with the new and good ones. When all the poor models are replaced, the identification module will stop and the MPC maintenance is finished.

The semi-automatic MPC performs the plant test, model identification, control simulation and control commissioning in a parallel manner and, therefore, it can considerably reduce the cost of MPC deployment. Most of the time plant tests are performed in closed-loop; therefore, disturbance to process operation is reduced. Almost all steps in MPC commissioning and maintenance are done automatically and it can be used by control non-experts such as operators. Hence the engineering cost can be reduced. The improvement in MPC efficiency can be shown as follows:

1) The Old Way: Series steps, 3 to 4 software packages

Pre-test	**Step test & model ID**	**Simulation**	**Commission**

2) With New Identification: Series steps, 3 to 4 packages

Test & model ID	**Simulation**	**Commission**

3) The Integrated MPC: Parallel procedure, 1 package

Test & model ID
Simulation
Commission

A prototype of the semi-automatic MPC controller has been developed which contains two modules: the Control Module and the Identification Module. It has been applied successfully to a PTA (pure terephthalic acid) unit; see Zhu et. al. (2008). The development of the Monitor Module is in progress. In the following we will discuss how system identification plays a key role in all the three modules.

3 Identification Module

The Identification Module uses the so-called asymptotic method (ASYM); Zhu et. al. (1991) and Zhu (1998). The approach is based on the asymptotic theory of identification developed by Ljung and Yuan; Ljung (1985) and Ljung and Yuan (1985). The technical detail of the method has been discussed in Zhu (1998, 2001). Here, we will outline how to use the method to achieve automated online identification of industrial processes.

(1) Test signal design and identification test

The spectra of the optimal test signals can be derived using the asymptotic theory. The optimality roughly means that the identified model is optimal for MPC control. The spectra of the test signals are realized by modified GBN (generalized binary noise) signals (Tulleken, 1990). The character of a GBN signal can be determined by its average switch time and its amplitude. The amplitudes of GBN signals are closely related to the MV step sizes moved by the operator during manual control. Studies show that the optimal average switch time of signals can be related to the process time to steady-state (settling time).

A test program carries out plant test by automatically writing out the test signals. The test data is collected and stored for use in identification. It is a multivariable test, meaning, that in general, all MVs will be excited (tested) simultaneously. For each MV, the test can be open loop or closed-loop. If an MV is in open loop test, the test program writes the total MV signal to the process; if an MV is in closed-loop test, the test program only writes the test signal and the MPC controller will write the mean value of the MV. During the plant test, an MV can be switched from open loop to closed-loop test.

2) Parameter estimation

The parameter estimation is done in two steps: (1) Estimate a high order ARX (equation error) model and (2) Perform frequency weighted model reduction. It can be shown that this approach can result in maximum likelihood estimate, that is, most accurate model for the given data. It can also be shown that the estimation will give unbiased model for closed-loop test.

3) Order selection

The best order of the reduced model is determined using a frequency domain criterion. The basic idea of this criterion is to equalize the bias error $(E\hat{G}(e^{i\omega}) - G^o(e^{i\omega}))^2$ and variance error $E(\hat{G}(e^{i\omega}))^2$ of each transfer function in the frequency range that is important for control. Here E denotes the expectation, $\hat{G}(e^{i\omega})$ and $G^o(e^{i\omega})$ are the frequency responses of the model and of the process.

4) Error bound matrix for model validation

Based on the asymptotic theory, a 3σ error bound can be derived for each transfer function of the identified model. In the following we will give an *engineering* solution to the model validation problem based on the derived error bounds.

Grading the Models. This is done by comparing the relative size of the bound with the model over the low and middle frequencies. Identified transfer functions are graded in A (very good), B (good), C (marginal), and D (poor, or, no model exists). Based project experience, A grade and B grade models can be used in the controller. C grade and D grade models are treated as follows:

1) Zero them when there are no models expected between the MV/CV pairs.
2) If a transfer function is expected and needed in the control, modify the ongoing test in order to improve the accuracy of these models.

Modify the Test. There are several ways to modify the ongoing test for improving model quality:

- Increase the amplitudes of test signals will in general decrease model errors
- Increase the test time will reduce model errors
- Increasing the GBN switch time will reduce model errors in the low frequency band; decreasing

switch time will reduce model errors in the high frequency band.

Model identification and validation is carried out at a given time interval, for example, at each 100 samples, and the test may be modified according to model results. When most of the expected models are with grade A, and grade B, the identification test will be stopped.

The online identification module is also a standalone package and has been applied many times in the industry; see, e.g., Celaya et. al. (2004, 2005) and Kautzman et. al. (2006). The following is an industrial application.

Subspace method is also used in some MPC packages. However, subspace method is not yet mature enough to achieve automated identification and automated model validation and selection; its performance in closed-loop identification is also questionable.

An Industrial Application of the Identification Module

The process under consideration was a crude unit at the Ras Tanura Refinery of Saudi Aramco in Saudi Arabia, Figure 2. The existing controller had been in service for almost 5 years. Process revamps had resulted in loss of model fidelity and therefore, a controller revamp (maintenance) was undertaken. The model predictive controller was running on a Honeywell TDC 3000 distributed control system (DCS) on a standalone application server. The controller had 18 MVs, six disturbance variables (DVs) and 35 CVs. The process time to steady state was 2 hours. With conventional step testing approaches the estimated time was 2 to 3 weeks of open loop testing followed by modeling activities. With the automated step testing/modeling approach based on the ASYM method, the actual step testing time was 4.5 days.

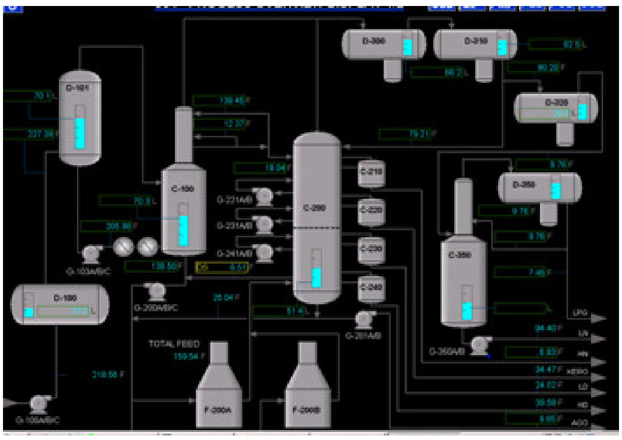

Figure 2. Schematic of the crude unit

To facilitate the closed loop step testing, additional points were built on the DCS to do the summation of the controller and the test signals. The step testing package has hosted on a standalone machine and communicated with the DCS via OPC (Ole for process control) protocol. The integration activities consumed about 1-2 days of preparation time. The integration logic was left in place following the step test to carry out future step testing. A master switch enforced zeroing of all the bias signals during normal operation. Operating data and the original step test data was reviewed to obtain initial estimates of the step sizes for the different MVs.

All the MVs were moved simultaneously under closed loop conditions. Figure 3 shows a snapshot of some of the MVs and CVs during the step test. Where possible, DVs were moved through the operator. Models were built from the step test data daily. The model qualities were reviewed with the site engineers and changes were made to the step sizes based on the estimated model qualities.

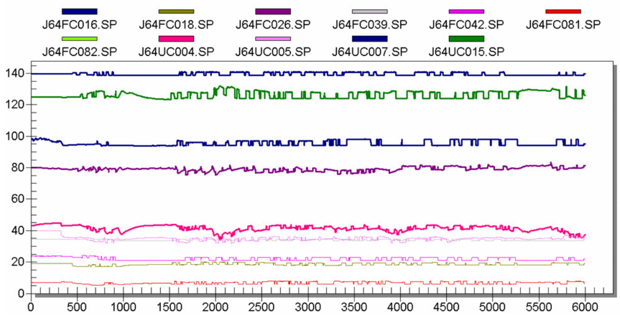

Figure 3. Step testing trends for a section of the MVs

Figure 4 shows the step responses for a section of the MVs/CVs. The color background is used to indicate A/B quality models (white background), C/D models (pink background) and grey background indicating where no relationships are expected. Model identification was done in a multivariate sense with very little user input. Delays/orders were automatically estimated.

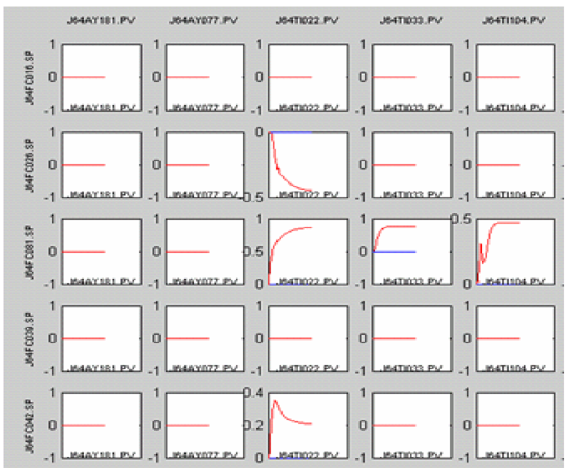

Figure 4. Models estimated from closed loop data for a section of the controller

Figure 5 shows a comparison of the models estimated after days 1 and 4. The step test was concluded after 5 days of testing. A number of new models were identified in the multivariable step test as a result of larger number of moves per MV and a more accurate identification method.

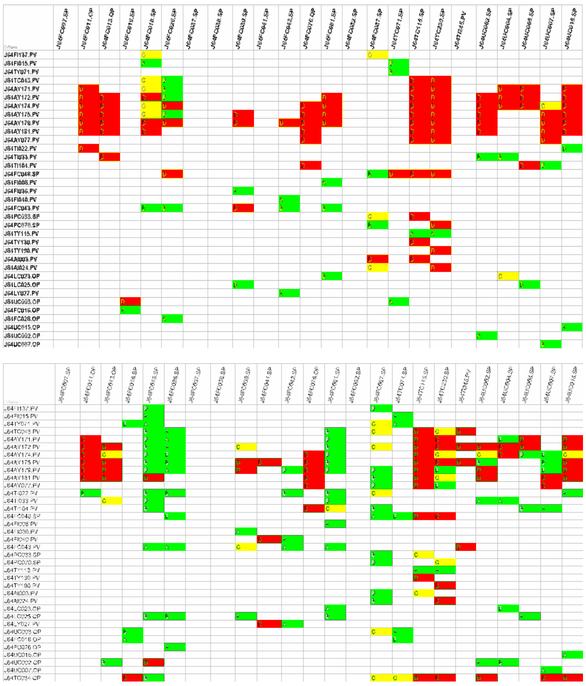

Figure 5. (Upper) Model qualities after day 1 of step testing and (Lower) after 4 days of step testing. Red – D quality models, Yellow – C quality and Green – A/B quality models. Blank entries in the matrixes means that there is no model expected

The progress of the model quality was tracked every day and the step test was concluded once the critical MV/CV relationships were identified to a satisfactory accuracy. Certain MV models could not be identified accurately due to process issues such as potential fouling. This is why some columns in the model matrix are empty. Table 1 shows the overall progression of the model quality vs the number of models identified during the step test. Apart from a number of new relationships being identified during the multivariable step test, some of the existing ones were flagged as uncertain. This was due to the fact that the accuracy of each model was now being quantified. Previously there were no hard measures available for judging model quality and this often led to questionable models being included in the overall controller model.

Table 1. Model quality progression on a daily basis

	Day 1	Day 2	Day 3	Day 4
No of A Models	12	21	29	32
No of B Models	20	29	50	54
No of C Models	10	13	22	20
No of D Models	82	67	59	63
Total Models	124	130	160	169
% A/B models	26	38	49	51

Figure 6 compares the previous and the newly estimated models from the closed-loop step test. A thorough review of the identified models was carried out prior to adpating the new models in the controller.

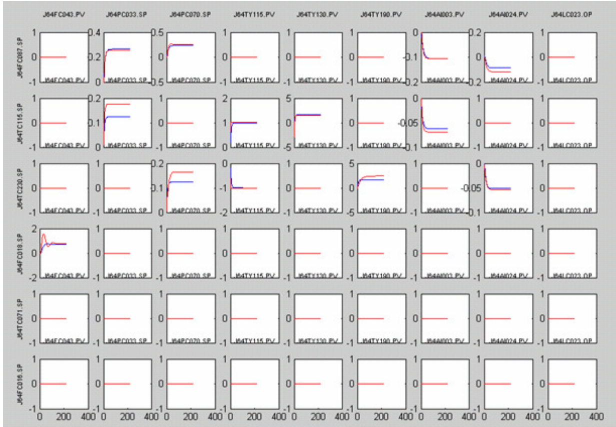

Figure 6. The old (blue) and the new (red) models for a section of the MV/CVs

Some of the key lessons learned from the multivariable closed-loop step test and remodeling initiative were:

(1) Closed loop identification and multivariable step testing are definitely viable alternatives to traditional single variable open loop test approach, especially for revamp (maintenance) projects.

(2) For grassroots MPC implementations, the opportunity to truly "learn" the process dynamics is diminished if one is moving all MVs simultaneously; however, it may still be feasible to apply this approach on units which are well understood – such a distillation column or a furnace.

(3) Closed-loop identification and model uncertainty quantification in particular offer precise insight into the quality of the model which is often the key "tuning" parameter in a model predictive controller. More work could be done in the direction of using this information to determine optimal controller tuning parameters, such as weights, for a given level of process uncertainty.

4 Identification in the Control Module: An Adaptive Disturbance Model

The MPC Control Module performs MPC auto-tuning (for the dynamic control layer only), MPC simulation and online control. The MPC control algorithm uses a multi-objective layered optimization method; see Wu and Qian (2005). Each CV can be controlled to its setpoint or within a zone (range); when there is not enough freedom to control all CVs, priorities and/or weightings can be used; for economic optimization, both linear programming (LP) and quadratic programming (QP) can be used and ideal resting value (IRV) can be assigned to each MV and CV.

At each control sampling interval, the MPC control algorithm consists of three steps: (1) prediction, (2) steady state optimization and (3) dynamic control. In prediction, the identified process model is used together with the MVs, DVs and CVs up to current time to calculate the future values of CVs. The predicted values will be used in steady-state optimization and dynamic control.

In steady-state optimization, first feasibility analysis is performed, then, economical optimization is carried out. Feasibility analysis is to check if there is enough degree of freedom to control all CVs. If enough degree of freedom is not available, CV priorities and/or weightings will be used to resolve the conflict. When there are degrees of freedom left after meeting all CV control requirements, economic optimization will be performed. The economic optimization is realized by using combined LP and QP.

We assume that all the parameters in the steady state optimization are determined in the MPC design. The results (output) of the steady-state optimization are the steady state values of MVs and CVs.

The dynamic control part of the MPC algorithm uses the prediction values and process model to calculate the MV control actions that will drive the process to its steady state which is determined by the steady state optimization. The dynamic control calculation is again a QP

To achieve semi-automatic MPC control, the MPC Control Module must able to (1) automatically select and use identified models in control and (2) automatically tune the MPC control parameters.

Automatic Model Selection

For a large scale industrial MPC controller with many MVs and CVs, not all MVs and CVs have relations, meaning that there are many zeros in the model transfer function matrix; also only good individual models will be used in the MPC control. Model selection determines which individual model will be used in the MPC control module. Model selection can be done automatically using the model validation results of the identification module and process knowledge given in a so-called e*xpectation matrix.* An expectation matrix is a matrix where columns relate to MVs and rows to CVs. The elements of the matrix contains "+" or "-" or "?" or "No". A "+" element means that a model with positive gain is expected between the corresponding MV and CV. Similarly, a "-" element means that a model with negative gain is expected. A "?" element means that the user is unsure about the existence of a model for the corresponding MV and CV. "No" means that the user is sure that no model exists between the MV-CV pair.

Now the following model selection rule is used: If an individual model has a grade A, B or C and the sign of the model gain is the same as that in the expectation matrix, then use the model in MPC control. Other wise, do not use the model.

Automatic Control Parameter Tuning

The goal of automated MPC tuning is to obtain a default tuning that has good and robust control of the given process. This is only done for the dynamic control part of the MPC algorithm as the parameters of the steady state optimization are assumed to be given in the MPC controller design. An MPC controller with auto-tuning can be used by a non-control expert, for example, an operator, which will considerably reduce the engineering cost of MPC technology. The tuning rule depends heavily on control requirements and can differ from one industry to another industry. Based on many simulation studies and industrial experience, an auto-tuning rule is derived which are suitable for MPC control in the refining/petrochemical industry. The tuning parameters are the closed-loop speed of all the CVs and weighting factors in the QP. These parameters are determined as functions of the open loop CV response times and variations of MVs and CVs which can be obtained from the model and testing data.

Experience has shown that this tuning rule will give good and robust MPC control for major units in the refining/petrochemical industry, and may also be good for other process industries. To optimize the control performance, a control expert is needed to perform the tuning.

Adaptive Disturbance Model Identification

Here a technique for improving the performance and robustness of the MPC Control Module is discussed. In industrial MPC applications for continuous process units, we have observed that the process dynamics from inputs to outputs do not change for a long period of time; but the character of unmeasured disturbances change frequently. These variations cannot be modeled as stationary stochastic processes. In Xu et. al. (2010) we have developed an MPC technique that uses a fixed process model and an adaptive disturbance model. The process model is identified using externally excited input-output data. The unmeasured disturbances at the outputs are modeled as a time varying process filtered by an integrated white noise sequence; a time series ARMA model is used to describe the dynamics of the disturbances.

Figure 7 shows the scheme of the MPC with adaptive disturbance model. Traditional adaptive MPC controllers update both process model and disturbance model sample-wise and may suffer from poor excitation conditions if no test signals are applied. For the proposed method no persistent excitation problem will occur as input signals are not used here.

The disturbances at outputs are assumed uncorrelated. Hence each disturbance can be modeled as single variable time series. This simplifies the model estimation problem.

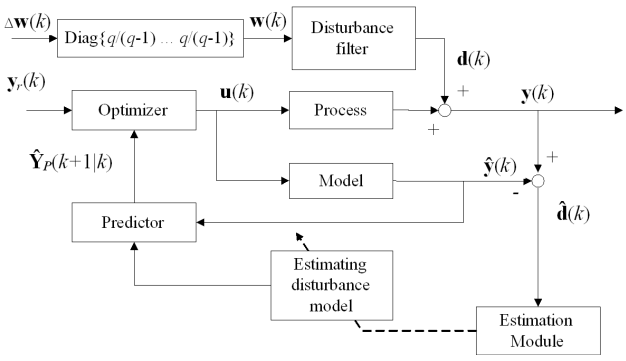

Figure 7. MPC controller with the adaptive disturbance model

Denote $u_j(t)$ as the j-th input at time t, $y_i(t)$ and $\hat{y}_i(t)$ as the i-th output and its simulation. Define the simulation error (or output error residual) as

$$\begin{aligned}\hat{d}_i(t) &= y_i(t) - \hat{y}_i(t) \\ &= \sum_{j=1}^{n_u}[G_{i,j}(q) - \hat{G}_{i,j}(q)]u_j(t) + H_i(q,t)w_i(t)\end{aligned} \qquad (1)$$

where $G_{i,j}(q)$ is the (i, j) transfer operator of the process and $\hat{G}_{i,j}(q)$ its model, q^{-1} is the unit delay operator and $H_i(q,t)$ is the time-variant disturbance filter.

If the process model quality is good, the simulation error is a good estimate of the unmeasured disturbance. Then (1) can be approximated as

$$\hat{d}_i(t) \approx \hat{H}_i(q,t)w_i(t) \qquad (2)$$

Assume that $w_i(t)$ is an integrated white noise. Then from (2) we have:

$$\Delta\hat{d}_i(t) \approx \hat{H}_i(q,t)\Delta w_i(t) \qquad (3)$$

The dynamics of $\Delta\hat{d}_i(t)$ can be described by an ARMA process:

$$H_i(q,t) = \frac{1 + c_{i,1}(t)q^{-1} + \ldots + c_{i,n}(t)q^{-n_i}}{1 + a_{i,1}(t)q^{-1} + \ldots + a_{i,n}(t)q^{-n_i}} \qquad (4)$$

Here n_i is the order of the ARMA model.

Traditional recursive identification method for the ARMA model performs a single iteration through a descent direction when a new data sample is available. It is well-known that multi-iteration is needed in nonlinear optimizations and the single iteration used in traditional recursive identification methods will lead to low accuracy and slow convergence. Based on this observation, a novel multi-iteration pseudo-linear regression (MIPLR) method is developed and used which is more accurate and has faster convergence than traditional recursive identification methods. Figure 8 compares the speeds of parameter convergence of the new MIPLR and of the traditional PLR in a simulation.

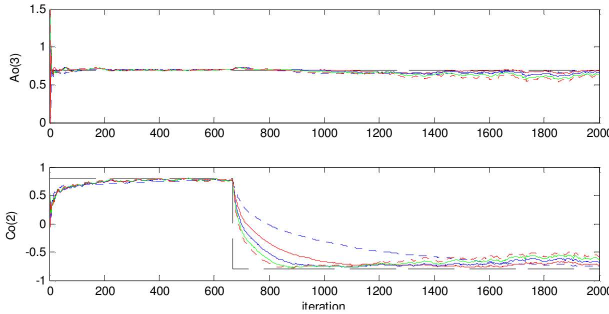

Figure 8. Parameter plots in the simulation study. Parameter c_2 jumped at sample 660. The blue dashed lines are the parameters estimated using traditional PLR, other lines are the parameters estimated using the new MIPLR with increasing iteration number

The MPC method using the adaptive disturbance model is tested on an industrial distillation column; see Xu et. al. (2010). The test results show that the proposed MPC scheme can not only increase control performance, but also increase robustness against model errors. Is this a *free-lunch in control*? In Figure 9 the prediction errors of two MPC controllers are shown for the two CVs of the process. One can see that the disturbance model improves the prediction accuracy.

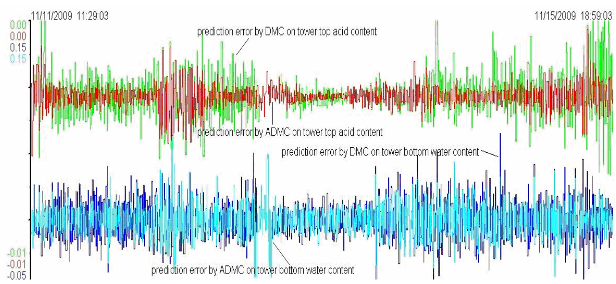

Figure 9. Prediction errors of the new MPC (red and light blue lines) and those of the old MPC (green and light blue lines)

More simulation studies have shown that the adaptive disturbance model is particularly useful for control during large disturbance events such as crude switches of crude units, drum switches of delayed coker and load changes of power plants. Here a simulation study of crude switch control is presented briefly. The process is a small part of an identified crude tower distillation column; studied in Zhu (1998). It has five MVs and five CVs. MV1 and MV2 are temperature setpoints, MV3 is a flow setpoint, MV4 and MV5 flow ratio setpoints. CV1 is a temperature difference, CV2 to CV5 are product qualities from online analyzers. Disturbance source signal mimic four crude switches in two days, where each crude switch is represented as a 1-hour ramp step plus random noise. The disturbance source signal is filtered using process models which resulted in five disturbance signals and each one acts as the unmeasured disturbance at a CV.

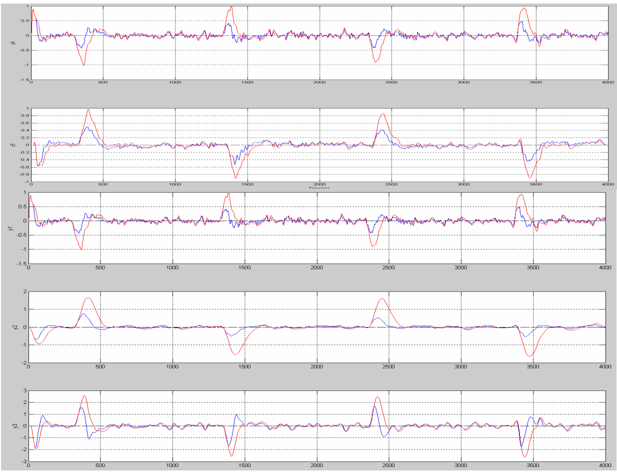

Figure 10. CVs of the old MPC (red lines) and that of the new MPC (blue lines). CV peaks can be reduced 50%.

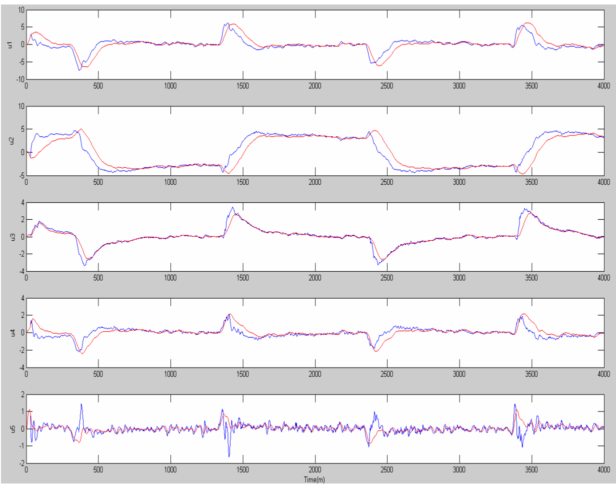

Figure 11. MVs of the old MPC (red lines) and that of the new MPC (blue lines). MVs of the new MPC moves ahead of that of the old MPC

Next, two MPC controllers are compared for crude switch control: the traditional MPC without using disturbance model (will be called old MPC) and the new MPC using the adaptive disturbance model. To test the robustness of the methods, both controllers use models that have 30% gain errors. Figure 10 shows that CV peak values during crude switches can be reduced 50% using the new MPC. Figure 11 shows that the MV moves of the new MPC are ahead of that of the old MPC during crude switches, which is due to better predictions.

5 Identification in the Monitoring Module: A Method of Model Error Detection

The monitor module monitors the performance of the MPC control as well as model quality. Four major indicators are used to monitor the MPC controller performance:

(1) On/off status of MVs and CVs. When the MPC controller does not perform well, some of the MVs or CVs may be turned off by the operator or by the MPC controller itself. The on/off status of MVs and CVs will be checked continuously.

(2) Oscillations of MVs and CVs. When the MPC controller performs poorly, MV and CV oscillations often exist. Oscillation detection is performed using signal spectrum analysis.

(3) CV standard deviations. Immediately after the MPC controller is commissioned or maintained, the monitor module will calculate standard deviations of all CVs for a time interval and use them as benchmarks for CV variations. The CV standard deviations will be calculated repeatedly and compared to their benchmarks. Denote std(CVi) as the standard deviation in a calculation period for CVi and $std(CVi)_{BM}$ as its benchmark. If ratio $std(CVi)/std(CVi)_{BM}$ is much greater than 1, it will indicate that control performance for CVi can be poor. A threshold for the ratio is used to indicate that the control performance for the CV is very poor; the value can be 2, 3 or 5, depending on the application. Similar benchmark is also proposed in Yu and Qin (2008a) using more complex calculations.

(4) Model quality. The model quality information is obtained using a model error detection method as described below.

The poor performance of an MPC controller can be caused by: (1) large model errors, (2) large unmeasured disturbances, and (3) improper MPC setting. When diagnosing control performance degradation, it is important to know the size of model error. Only when the large model error is the cause of the control degradation, model identification will be used to re-identify a new model of the process. So an area of MPC performance monitoring involves the search of the root cause of the control performance degradation, or, diagnosis (Qin, 1998 and Patwardhan and Shah, 2002). Some methods have been developed for diagnosis, e.g., Kesevan and Lee (1997), Yu and Qin, (2008) Harrison and Qin (2009), Badwe et al., (2009) and Badwe *et. al.*, (2010). A common problem of these methods is the lack of excitation when using closed-loop normal operation data, which often leads to inconclusive results. Another problem is that these methods usually do not assess the accuracy of their calculations and estimates.

In Zhang et. al. (2011), we have developed a method of model error detection for MPC performance monitoring and diagnosis. Here we will briefly discuss the main ideas of the method and show a simple example.

In this approach, three small amplitude sinusoids test signals are used as test signals to provide accurate estimates of the process frequency responses at the three frequency points; then the differences of the estimated frequency responses and those of the current MPC model are used as a measure of model errors. If the differences are larger than some threshold, then a warning message can be issued for too big model mismatch. This message will alert engineers the need to re-identify all or some models of the process, or, to activate the identification procedure automatically.

The following procedure is proposed for closed-loop test. Choose three frequency points for the given process: low frequency ω_1, medium frequency ω_2, and high frequency ω_3; construct the multiple sinusoidal test signal for *j*-th setpoint

$$r_t^j(t) = \alpha_1^j \sin(\omega_1 t + \varphi_1) + \alpha_2^j \sin(\omega_2 t + \varphi_2) + \alpha_3^j \sin(\omega_3 t + \varphi_3) \quad (5)$$

The three frequencies are determined automatically based on the process bandwidth; the amplitudes α_1^j, α_2^j and α_3^j are chosen so small that $u_t^j(t)$ will not disturb process outputs (CVs).

Apply the test signal $u_t^j(t)$ to *j*-th setpoint and keep other setpoints constant, record the all the signals of the closed-loop system. This will be called one sub-test. Repeat the sub-test for all the setpoints and collect the data.

Assume that the process has *m* inputs (MVs) and *p* outputs (CVs). Applying discrete Fourier transforms to a multivariable linear process we have

$$\mathbf{Y_N}(\omega) = \mathbf{G}(e^{i\omega})\mathbf{U_N}(\omega) + \mathbf{V_N}(\omega) \quad (6)$$

where $\mathbf{Y_N}(\omega)$, $\mathbf{U_N}(\omega)$ and $\mathbf{V_N}(\omega)$ are the discrete Fourier transforms (DFT) of output (CV) vector **y(*t*)**, input (MV) vector **u(*t*)** and unmeasured disturbance vector **v(*t*)**.

At test *j* and at one of the test frequency ω_k $(k = 1, 2, 3)$ we get from (6)

$$\mathbf{Y_N^{\mathit{j}}}(\omega_k) = \mathbf{G}(e^{i\omega_k})\mathbf{U_N^{\mathit{j}}}(\omega_k) + \mathbf{V_N^{\mathit{j}}}(\omega_k) \quad (7)$$

where $j = 1, 2, ..., m$, means the time of sub-tests. After performing all the m tests, one can put DFT data in matrixes as

$$\mathbf{Y_W}(\omega_k) = \left[\mathbf{Y_N^1}(\omega_k) \quad \mathbf{Y_N^2}(\omega_k) \quad \cdots \quad \mathbf{Y_N^{\mathit{m}}}(\omega_k) \right]_{p\times m}$$
$$\mathbf{U_W}(\omega_k) = \left[\mathbf{U_N^1}(\omega_k) \quad \mathbf{U_N^2}(\omega_k) \quad \cdots \quad \mathbf{U_N^{\mathit{m}}}(\omega_k) \right]_{m\times m}$$
$$\mathbf{V_W}(\omega_k) = \left[\mathbf{V_N^1}(\omega_k) \quad \mathbf{V_N^2}(\omega_k) \quad \cdots \quad \mathbf{V_N^{\mathit{m}}}(\omega_k) \right]_{p\times m}$$

Then from (7) one obtains

$$\mathbf{Y_W}(\omega_k) = \mathbf{G}(e^{i\omega_k})\mathbf{U_W}(\omega_k) + \mathbf{V_W}(\omega_k) \quad (8)$$

Note that each column of matrix $\mathbf{U_W}(\omega_k)$ consists of the DFT of the control inputs during one sub-test. Assume that none of any two outputs have identical models (if two outputs have the same or almost the same models, only the models of one output are analyzed.) Then, none of the two columns of $\mathbf{U_W}(\omega_k)$ will be linearly dependent. Moreover, the probability that any two rows of $\mathbf{U_W}(\omega_k)$ are linearly dependent is practically zero. Therefore, we can assume that $\mathbf{U_W}(\omega_k)$ is a nonsingular matrix. We can estimate process frequency response matrix $\mathbf{G}(e^{i\omega_k})$ using

$$\hat{\hat{\mathbf{G}}}_\mathbf{N}(e^{i\omega_k}) = \mathbf{Y_W}(\omega_k)\mathbf{U_W^{-1}}(\omega_k) \quad (9)$$

Because the disturbance vector is a stationary stochastic process, the norm of matrix $\mathbf{V_W}(\omega_k)$ is finite for any *N*; however, the input vector **u**(*t*) has sinusoids at frequency ω_k, and the norm of $\mathbf{U_W}(\omega_k)$ is in proportional to $\sqrt{N}$. Therefore, the norm of the estimation error is in proportional to $1/\sqrt{N}$. See Ljung (1999, Chapter 6) for detailed analysis. Therefore, we can say that the estimate (9) is consistent, or,

$$\hat{\hat{\mathbf{G}}}_\mathbf{N}(e^{i\omega_k}) \to \mathbf{G}(e^{i\omega_k}) \quad as \quad N \to \infty \quad (10)$$

Note that in the closed-loop test $p \geq m$ is a necessary condition to ensure that matrix $\mathbf{U_W}(\omega_k)$ is nonsingular. In order to access the quality of the frequency response estimate (9), an 85.7% upper error bound is derived; see Zhang *et. al.* (2011).

Model Error Index Matrix

Given the three frequency response estimates obtained

$$\hat{\hat{\mathbf{G}}}_\mathbf{N}(e^{i\omega_k}),\ k = 1,\ 2,\ 3 \quad (11)$$

Assume that the error of the estimates are small, which can be verified using the 85.7% upper error bound. Calculate the three frequency response of the current MPC model and denote them as

$$\hat{\mathbf{G}}_\mathbf{N}(e^{i\omega_k}),\ k = 1,\ 2,\ 3 \quad (12)$$

Then calculate the relative differences of the two frequency responses of each model

$$\frac{\left|\hat{\hat{G}}_{Nhj}(e^{i\omega_k}) - \hat{G}_{Nhj}(e^{i\omega_k})\right|}{\left|\hat{\hat{G}}_{Nhj}(e^{i\omega_k})\right|},\ k = 1, 2, 3 \qquad (13)$$

where $\hat{\hat{G}}_{Nhj}(e^{i\omega_k})$, $\hat{G}_{Nhj}(e^{i\omega_k})$ are the h-output j-input frequency response of estimate and that current MPC model.

Define a model error index matrix ERR as

$$\mathrm{ERR}_{hj} = 0.4\frac{\left|\hat{\hat{G}}_{Nhj}(e^{i\omega_1}) - \hat{G}_{Nhj}(e^{i\omega_1})\right|}{\left|\hat{\hat{G}}_{Nhj}(e^{i\omega_1})\right|} + 0.4\frac{\left|\hat{\hat{G}}_{Nhj}(e^{i\omega_2}) - \hat{G}_{Nhj}(e^{i\omega_2})\right|}{\left|\hat{\hat{G}}_{Nhj}(e^{i\omega_2})\right|} \qquad (14)$$
$$+0.2\frac{\left|\hat{\hat{G}}_{Nhj}(e^{i\omega_3}) - \hat{G}_{Nhj}(e^{i\omega_3})\right|}{\left|\hat{\hat{G}}_{Nhj}(e^{i\omega_3})\right|}$$

where higher weightings are used at low and medium frequencies to reflex their importance for MPC control. The index matrix MPM can be monitored by the MPC user and compared to some threshold, say 50%, for issuing model error warning messages.

Model Error Detection Procedure

(1) Perform small sinusoidal tests and estimate process frequency responses at the three frequencies.
(2) Calculate the 85.7% upper error bounds (see Zhang et. al., 2011) of the three point frequency response estimates. If all the error bounds are less than 10%, go to next step; if the error bounds are greater than 10%, wait for longer test data.
(3) Calculate the differences between the three-point frequency responses estimates and those of the current MPC model and show them graphically to the MPC user.
(4) Calculate the model error index matrix ERR. If some element of ERR is greater than the threshold (for example 50%), an alarm will be generated; alternatively, an automatic process identification test will be activated.

This approach is motivated by the following observations:

- The test signal energy is very small, which causes small or no disturbance to process operation; however, the test signal power at the three frequencies is very high for large number of data, thereby, the three point frequency response estimates are very accurate. A full identification step test is much more disturbing than the small sinusoidal test. Before performing a full step test, we first want to make sure some key models are with large errors.
- Most transfer functions can be well approximated by first or second order plus delay models. Therefore, if the errors of the current MPC models at all three frequencies are big, then the model errors are big.

Simulation Example

The model error detection method is tested in an MPC control system which is a simulation using the MPC Toolbox of MATLAB®. The real process is given as:

$$G(q) = \frac{q^{-1} + 0.5q^{-2}}{1 - 1.5q^{-1} + 0.7q^{-2}}$$

The MPC model used in control is:

$$\hat{G}(q) = \frac{q^{-1} + 2.4q^{-2}}{1 - 1.2q^{-1} + 0.7q^{-2}}$$

The unmeasured disturbance $v(t)$ is generated by filtering a white noise $e(t)$ using the following low-pass filter. The variance of $v(t)$ is 10.

$$v(t) = \frac{1}{1 - 0.95q^{-1}} e(t)$$

The small test signal is

$$r_t = 2.4\sin(0.015 * 2\pi t) + 2.68\sin(0.067 * 2\pi t - \pi)$$
$$+1.18\sin(0.13 * 2\pi t - 1.5\pi)$$

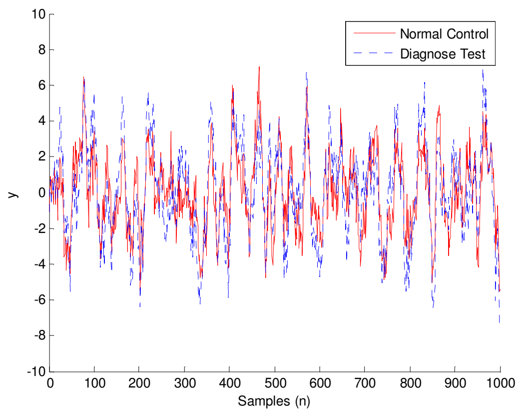

Figure 12. Output of normal MPC control (red solid line) and output of MPC control with diagnose test (blue dashed line)

In Figure 12, 1,000 points of normal control performances and diagnose test outputs are plotted. One can see that small period test signal does not increase the output fluctuations very much. The standard deviations of the two signals are 2.15 (normal operation) and 2.63 (using test signal) respectively. This means that the test signal only caused the 22% increase in output standard deviation.

This is very small disturbance indeed. In our industrial experience, a normal identification test will increase the output standard deviation by 200%.

When the system is stabilized, 20,000 data samples are used to perform frequency domain analysis. The frequency responses are shown in Fig. 13. The blue curve represents the frequency response of MPC model; the red curve is the frequency response of the current production process; three blue '+' in the figure are the estimated frequency response points; red '*' in the figure are the error of estimation and real process (in the normal test, the red curve and red '*' can not be obtained); three thick blue lines are the upper error bound.

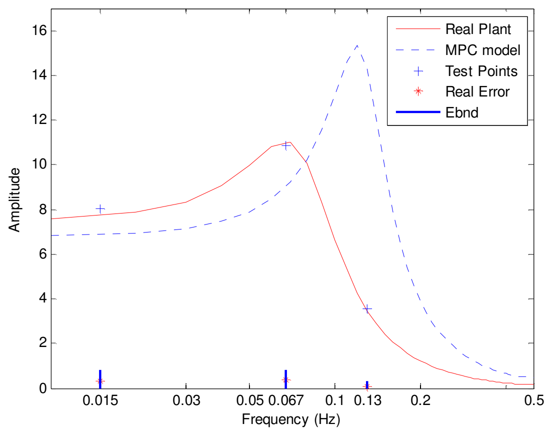

Figure 13. Frequency responses of the process (red line) and that of the MPC model (blue line)

The results of process frequency response estimation and model error calculation are given in Table 2. One can see that the model error estimation is accurate and the current MPC model has very large model error. The model error index in (21) can be determined as

$$\begin{aligned}\mathbf{ERR} &= 0.4\times 15.27\% + 0.4\times 65.32\% + 0.2\times 319.73\% \\ &= 96.18\%\end{aligned}$$

This is quite a big number and one may conclude that the model error is big and model re-identification is necessary in order to improve the MPC performance.

Table 2. Model error detection for the MPC system

	0.015Hz	0.067Hz	0.13Hz
Error of process freq. resp. estimate	4.24%	3.40%	2.23%
Error bound	9.95%	7.38%	9.53%
Estimated errors of the MPC model	15.27%	65.32%	319.73%
True errors of the MPC model	11.74%	62.82%	328.73%

A multivariable simulation exampple can be found in Zhang *et. al.* (2011).

6 Conclusion, Discussion and Perspective

In recent years we have worked on the development of a new generation MPC system to reduce the cost of deployment and to increase control performance. In the new MPC system the importance of system identification cannot be over stated. In the Identification Module, a multivariable closed-loop identification method is used which can identify process models efficiently; in the Control Module, a novel adaptive disturbance model identification method is used to improve the control performance and robustness; in the Monitor Module, a frequency domain identification method is used for model error detection. Industrial case studies and simulations have shown the effectiveness of the developed identification methods.

Each of the methods used was one or more research topics with real application background. We strongly believe that research and application (theory and practice) can be mutually supporting instead of conflicting. There are many interesting and challenging research problems in developing the new generation MPC technology. For researchers who like to contribute to the MPC technology, the following research topics could be considered:

- How to auto tune an MPC controller?
- How to relate MPC tuning to model uncertainty?
- Prove the (robust) stability of MPC with adaptive disturbance model of Section 4.
- Prove the existence of free lunch in control (high performance and high robustness).
- Given a large process, how to determine key models that have strong influences on control performance and how accurate these models should be?
- Often there is no theoretical proof of stability for industrial MPC controllers. Simulations are used to check stability and performance. What is the relation between MPC simulated stability and theoretical stability, or, how to verify theoretical stability using simulations?
- Can we further reduce the identification test time, or, can we go beyond the accuracy of prediction error model?
- Should nonlinear weightings be used for nonlinear MPCs and how?
- Analyze the two layer multi-objective MPC algorithms (consist of steady-state economic optimization layer and dynamic control layer) used in industrial MPC packages instead of one layer single objective MPC algorithms.

It is our hope that the new generation MPC technology considerably reduces the cost of MPC deployment and maintenance so that there is an MPC for every industrial process, just like that there is a desktop computer on every desk.

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