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Development and Application of an Integrated MPC Technology

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Abstract: This work introduces an integrated MPC controller. The integrated MPC consists of three modules: an *MPC control module*, an *online identification module* and a *control monitor module*. The three modules work together coherently in real-time; it can perform automatic controller commissioning and automatic controller maintenance. In MPC commissioning, the online identification module and the MPC control module work together and perform various steps in MPC implementation automatically. When the MPC controller is online, the control monitor module continuously monitors the MPC performance and model quality. When control performance degradation and considerable model error are detected, monitor module will start the maintenance by activating the online identification module. The identification module will re-identify the model and replace the old model. A prototype of the integrated MPC controller has applied successfully to two PTA units and the result will be reported.

1. INTRODUCTION

In the last two decades, model predictive control (MPC) technology has been widely applied in the refining and petrochemical industry (Cutler and Hawkins, 1988 and Qin and Badgwell, 2003) and is beginning to attract interest from other process industries. 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 modelling 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 very limited. In the last 10 years, work has been done in the MPC industry to improve the efficiency and accuracy in model identification. See Zhu (1998), 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 cost of manpower.

"Get the design right, the rest is automatic". In this work, we will develop an integrated MPC controller that, for a given MPC design, can perform controller commissioning and maintenance automatically. In Section 2, the architecture of the integrated MPC is introduced and motivated. In Section 3, the three modules of the integrated MPC controller are discussed and their integration is explained. In Section 4, an industrial case study, two PTA unit applications, are presented. Section 5 is the conclusion.

2. ARCHITECTURE OF THE INTEGRATED MPC

At present, a common MPC project approach has following steps:

1) MPC controller design and benefit analysis. In this step, MVs (manipulated variables), DVs (disturbance variables) and CVs (controlled variables) are selected and their control requirements specified.
2) Pre-test. In this step, short step tests are performed to obtain rough estimated of process settling time and some model gains.
3) Identification test and model identification. The test is often done manually, in single variable and in open loop although some automated test methods are emerging recently.
4) MPC controller tuning and simulation.
5) MPC controller commissioning. In this step, the MPC controller is commissioned by gradually turning on each MVs and CVs.
6) MPC controller maintenance. After some time of operation, the control performance degrades due to process changes. The main task of maintenance is to re-identify the process model and to re-commission the MPC controller.

The biggest problem of the conventional MPC technology that follows this approach is its high costs. Highly skilled control engineers with many years of experience are needed to perform the steps and each step cost considerable time and effort. Different software packages are used in different steps, which is not convenient for the user.

The integrated MPC controller introduced here can automatically and efficiently perform MPC implementation and maintenance, that is, steps 2) to 6) mentioned above. The integrated MPC controller consists of three modules: 1) an MPC control module (will be referred as **control module**), 2) an online identification module (will be referred as **identification module**) and 3) a control performance monitoring module (will be referred as **monitor module**). Figure 1 shows the block diagram of the integrated MPC controller.

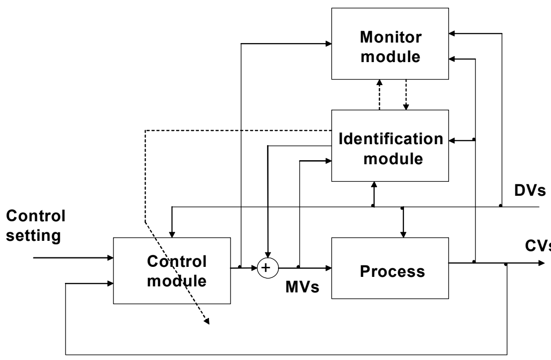

Figure 1. Block diagram of the integrated MPC

Integrated MPC control means automatic MPC implementation and automatic maintenance. Assume that an MPC controller design is given. During the MPC implementation, the online identification module performs automated plant test and automatic model identification. During the plant test, when some identified models have good quality for control according to model validation, they will be used in the MPC controller and the corresponding manipulated variables (MV) and controlled variables (CV) will be turned on. As the test continues, more and more models will be loaded in the MPC controller and MVs and CVs turned on. When all expected models become good and used in the MPC controller, the identification module will stop and the MPC commissioning is finished. For an online MPC controller, the monitoring module continuously monitors its performance. When the MPC monitor detects considerable control performance and model quality degradation, it will activate the online 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 integrated MPC performs plant test, model identification, control simulation and control commissioning in a parallel manner and, therefore, it considerably reduce the cost MPC deployment. Most of the time, plant tests are in closed-loop; open loop test time can be kept minimal. Hence disturbance to process operation is reduced. Almost all steps in MPC commissioning and maintenance are done automatically and it can be used by non control experts such as operators. Hence the cost of manpower is reduced.

3. THE THREE MODULES

The three modules will be described briefly and more details can be found in cited literature.

3.1 Identification Module

The identification module uses the so-called asymptotic method (ASYM); see Zhu (1998). The approach is based on the asymptotic theory of identification; see Ljung (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 spectra of the test signals is realised by modified GBN (generalised binary noise) signals. The character of a GBN signal can be determined by its average switch time and its amplitude. The amplitudes of GBN signals are determined by *a priori* knowledge of the process. A test program carries out plant test automatically by writing out the test signals. In general, all MVs will be excited (tested) simultaneously. During the plant test, an MV can be switched from open loop to closed-loop test.

2) Parameter estimation and order selection

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. The best order of the reduced model is determined using a frequency domain criterion. The basic idea of this criterion is to equalise the bias error and variance error of each transfer function in the frequency range that is important for control.

3) Model validation

Based on the asymptotic theory, a 3σ error bound can be derived for each transfer function of the identified model.

Grading the models. This is done by comparing the relative size of the bound with the model over the low and middle frequencies. More specifically, identified transfer functions are graded in A (very good), B (good), C (marginal), and D (poor, or, no model exists). 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, modify the ongoing test in order to improve the accuracy of these models.

There are several ways to modify the ongoing test for improving model quality: 1) Increase the amplitudes of test signals will in general decrease model errors; 2) increase the test time will reduce model errors; 3) change the average switch time of GBN signals will influence the error distribution in the frequency domain.

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 method outlined here has been applied many times in the industry; see, e.g., Celaya *et. al.* (2004, 2005) and Kautzman *et. al.* (2006).

3.2 Control Module

The MPC control module performs MPC auto-tuning, 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 LP (linear programming) and QP (quadratic programming) can be used and IRV (ideal resting value) can be assigned to each MVs and CVs.
At each control sampling interval, the MPC control algorithm consists of three steps: prediction, steady state optimization and dynamic control.

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

$$\begin{aligned} &\min_{u} \left(\left\| u - IRV_u \right\|^2_{w_u} + \left\| y - IRV_y \right\|^2_{w_y} + b_1^T u + b_2^T y\right) \\ &s.t. \quad y = Gu + d(t) \\ &\qquad y_{\min} \le y \le y_{\max} \\ &\qquad u_{\min} \le u \le u_{\max} \end{aligned} \tag{1}$$

where u is the vector of MVs, y is the vector of CVs, IRV_u is the vector of MV IRVs, IRV_y is the vector of CV IRVs, w_u is the diagonal matrix of MV QP weightings, w_y is the diagonal matrix of CV QP weightings, b_1 is the vector of MV LP weightings, b_2 is the vector of CV LP weightings, G is the model gain matrix, $d(t)$ is the bias at sample time t, $y_{\min}$ and $y_{\max}$ are the vectors of CV low limits and high limits respectively, and $u_{\min}$ and $u_{\max}$ are the vectors of MV low limits and high limits respectively.

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 denoted as vectors y^* and u^*.

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:

$$\begin{aligned} &\min_{u} \Big[\sum_{j=1}^{P} \left\| y(t+j|t) - y^{\text{ref}}(t+j) \right\|^2_Q + \sum_{j=0}^{M-1} \left\| u(t+j) - u^* \right\|^2_R + \sum_{j=0}^{M-1} \left\| \Delta u(t+j) \right\|^2_S \Big] \\ &s.t. \quad y^{\text{ref}}(t+j) = y(t) + \left(y^* - y(t)\right)\left(1 - e^{-jT/T_{resp}}\right) \\ &\qquad u_{\min} \le u(t+j) \le u_{\max} \\ &\qquad \Delta u_{\min} \le \Delta u(t+j) \le \Delta u_{\max} \end{aligned} \tag{2}$$

where vector $y^{\text{ref}}(t)$ is the vector of desired CV closed-loop response trajectories, vectors y^* and u^* are the steady state values of CVs and MVs respectively obtained by steady state optimization, P is the prediction horizon, M is the control horizon, Q is the diagonal matrix of CV weightings, R is the diagonal matrix of MV weightings, and S is the diagonal matrix of MV increments weightings.

In order to achieve integrated 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
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
Based on many simulation studies and industrial experience, the following auto-tuning rules are suitable for MPC control in the refining/ petrochemical industry.
- Control horizon: M = 0.5* Model time to steady state
- Prediction horizon: P = 1.5*Model time to steady state
- CV closed-loop settling time: $T_{\text{resp}}(i)$ =Desired closed-loop settle time of CV_i
- Weighting for CV_i: 1/(CV_i high limit - CV_i low limit)
- Weighting for MV_i: (1~3)/(MV_i high limit - MV_i low limit)
- Weighting for ΔMV_i: (1~3)/(MV_i high limit - MV_i low limit)

3.3 Monitor Module

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.
2) Oscillations of MVs and CVs.
3) CV standard deviations. Immediately after the MPC controller is commissioned or maintained, the monitor module will calculate standard deviations of all CVs and use them as benchmarks for CV variations. The CV standard deviations will be calculated repeatedly and compared to their benchmarks. If the standard deviation of a CV is much greater than its benchmark, it will indicate that control performance for the CV can be poor.
4) Model quality. The model quality for a CV is measured by the standard deviation of its simulation error. Immediately after the MPC controller is commissioned or maintained, the monitor module will calculate standard deviation of simulation errors of all CVs and use them as benchmarks for model quality. After that, standard deviations of CV simulation errors will be calculated repeatedly and compared to their benchmarks. If the standard deviation of a CV simulation error is much greater than its benchmark,, it will indicate that model quality for the CV can be poor.

3.4 A Prototype of the Integrated MPC Software

So far, two modules of the proposed integrated MPC controller have been implemented in an MPC software package: the control module and the identification module.

The software consists of three parts: Configuration Section, Identification Section and Control Section. The Configuration Section is for user to enter the MPC design information, namely, the MV/DV/CV lists and MV/CV high/low limits, sampling time, estimate of process time to steady state, MV amplitudes (step sizes) for identification test, expectation matrix of the process. Also the communication between the PC and the DCS is handled here and the user needs to specify the name of the OPC server and the name of the host computer.

The MPC software can run plant test, model identification and MPC control simultaneously, which makes integrated control possible. Considering the fact that process industries are not yet familiar with totally automated integrated controllers, the MPC software can be configured that the user starts certain functionalities by press a button. These functions include starting plant test, starting model identification, turning on MPC controller and turning on/off certain MVs and CVs. Also the user can manually select models for MPC control.

4. MPC CONTROL OF TWO PTA UNITS

This section will present an industrial application of the integrated MPC. The processes are two PTA (pure terephthalic acid) units located at the Chemical Plant of Sinopec Yangtze Petrochemical Company in Nanjing, China. PTA is an important raw material that synthesizes polyesters. It is produced under certain temperature and pressure with para-xylene (PX) as raw material and acetic acid as solvent. The two PTA units are very similar and they are AMOCO design.

Two MPC controllers were designed and commissioned for the PTA unit 1: solvent dehydration tower MPC controller and oxidation section MPC controller. In fact both parts can be easily controlled using one controller. The reason that we used a separate MPC controller for the dehydration tower is that we wish to test the functionality of the MPC package for the first time on a relatively simple process.

MPC Control of the Solvent Dehydration Tower, Unit 1
The main role of the solvent dehydration tower is to purify acetic acid solvent used in oxidation section, which can obtain stated purity acetic acid solvent to return to system usage through removing the water produced in the oxidation reaction or added in the catalyst allocation. The tower operation requirements are: 1) to keep the bottom water content as constant as possible and 2) to keep the tower top acid content below 0.8% in order to reduce the acid loss. There are online analysers for measuring top acid content and bottom water content.

Because of the large tower volume capacity, both top quality and bottoms quality have slow responses to changes in reflux flow and reboiler steam flow. Also top and bottoms qualities have strong interactions. These problems make it difficult to control both top and bottoms qualities using two PID controllers and it is a good candidate to use an MPC controller. The main goal of the dehydration tower MPC is to reduce the product quality variation and to reduce the acid loss. The MPC variables are

Manipulated Variables (MV)

	Tag name	Description
MV1	1TC1701.SP	Bottoms temperature setpoint
MV2	1FC1702.SP	Reflux flow rate setpoint
MV3	1FC1411.SP	2nd oxidation react. air flow 1
MV4	1FC1412.SP	2nd oxidation react. air flow 2

Disturbance (Feedforward) Variables (DV)

	Tag name	Description
DV1	1FI1614.PV	Tower feed 1
DV2	1FI1615.PV	Tower feed 2
DV3	1FI1703.PV	Tower feed 3
DV4	1FI1704.PV	Tower feed 4
DV5	1LS1301.PV	2nd oxidation reactor feed valve

Controlled Variables (CV)

	Tag name	Description
CV1	1DI1701.PV	Top acid aontent
CV2	1DI1702.PV	Bottoms water content
CV3	1PD1701.PV	Tower delta pressure
CV4	1FV1701.OP	Steam control valve
CV5	1FV1702.OP	Reflux flow control value

CV6	1QI1401.PV	Secondary oxidation reactor tail O_2 analyzer 1
CV7	1QI1402.PV	Secondary oxidation reactor tail O_2 analyzer 2
CV8	1TI1731.PV	Reflux temperature

All CVs are controlled in ranges. Note that MV3, MV4, CV6 and CV7 are the variable in the secondary oxidation reactor. The sampling time for the identification and for MPC control was set to 0.5 minute, the estimated process time to steady state was 90 minutes. The plant test started at 10:00. After 5 hours of plant test, models were identified. This is repeated each 1 or 2 hours. After 11 hours of test, most expected models from MVs to CVs show A, B or C grades and the plant test was stopped. Figure 2 shows MV plots during the plant test. The dehydration tower MPC controller was turned on the next day after lunch. Figure 3 shows the CV plots during the first hours after the MPC was turned on. Its performance has been good and CV variations have been reduced. However, most models from DVs to CVs are very poor with grade D because the very short test. Therefore, DVs was not turned on. DV models can be improved when more data are collected.

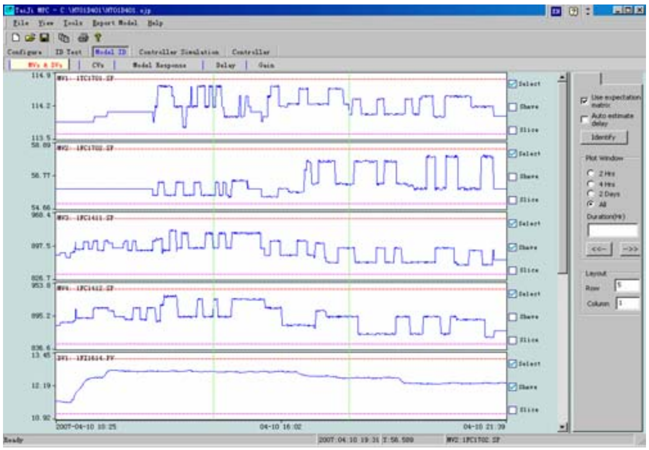

Figure 2. MV/DVplots during the plant test.

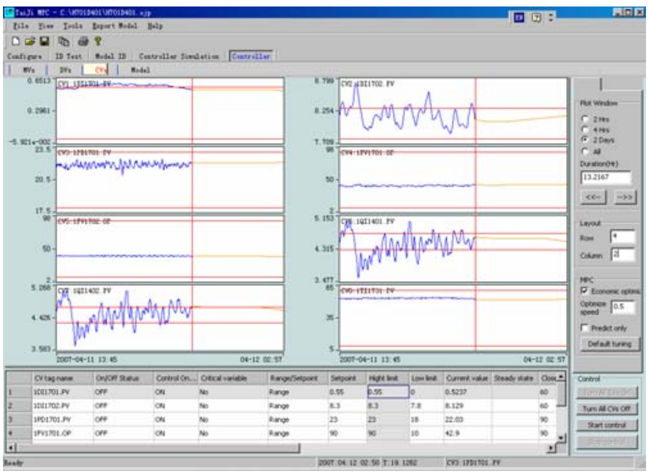

Figure 3. CV plots in the first hours after the MPC was turned on

MPC Control of the Oxidation Reaction Section, Unit 1

The MPC control requirements are to reduce the variations of temperature and tail oxygen content in the reactor and to control the 4-CBA content in TA product within ±100 ppm while respecting all production constraints. The MPC controller has 17 MVs, 3 DVs and 17 CVs. MVs include Feed flows and air flows of the A, B, C reactors, condenser extraction valves of the reactors, reactor levels, fresh catalyst flow and fresh accelerant flow. DVs are the reactor pressures. CVs are reactor middle temperatures, reactor tail O_2 concentrations, reactor O_x concentrations, 4CBA prediction, and some valve positions. All CVs are controlled in ranges.

It was planed to run an open loop test for 50 hours with all MVs excited simultaneously. However, the PTA unit is operating 30% above its design capacity and many constraints were hit, which makes the plant test difficult. The operators were very concerned about the test. Not all MVs were allowed to be tested together, and the test was interrupted several times due to operation problems. Finally, three 10 hour tests were carried out and only part of MVs were moved during each test. Because of short test, model obtained are not with high quality and most identified models are with grade D. If we would have tested 50 hours as planed, the model quality would be much better.

Identified models were selected manually in the Control Section of the MPC software (D models cannot be selected automatically) when model responses agrees with the process knowledge. When a model is expected and the identified model is too poor according to model validation, the existing model identified many years ago using a traditional identification method, was used. Although the model quality is believed not high, it was decided to implement the controller first and, if necessary, re-identify the process model in a closed-loop operation. Figure 4 shows two CV plots before and after the MPC commissioning. One can see that there is some variation reduction in the CVs. It is still planed to perform a closed-loop test of about 50 hours in the future. The closed-loop test should be much less disturbing than the open loop test.

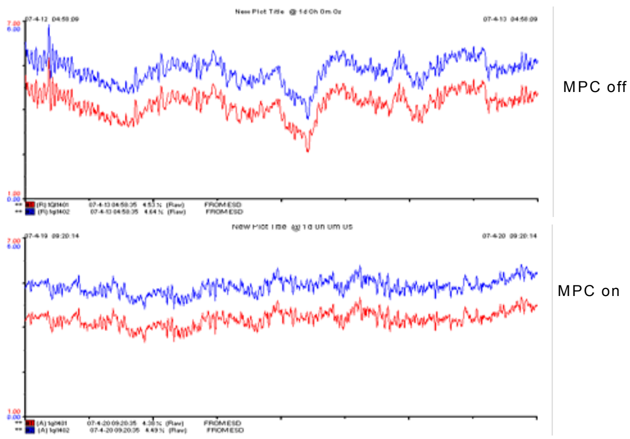

Figure 4. Plots of CVs 1QI1401 and 1QI1402 when MPC was off and on

Migration of MPC Control for PTA Unit 2

There exist two MPC controllers for the PTA unit 2, one for the dehydration tower and one for the oxidation reaction section. The two MPC controllers were down due to communication problems. The communication problems can be avoided using the new MPC software because of its simpler software structure. It was, therefore, decided to migrate the two MPC controllers of PTA unit 2 to the new MPC software. The existing process models of the two MPC controllers were identified three years ago using the same identification approach as that of the new MPC software and most models obtained had A, B or C grades. Because there are no big process changes in the period, it is believed that the models are still valid. Hence the models are loaded into the new controllers and no identification test was performed. The two controllers have almost the same designs as that of PTA Unit 1. After turning on the new MPC controllers, good performances have been observed. Figure 5 shows the plots of three CVs before and after MPC controllers were turned on. It can be seen that good variance reduction has been achieved. The migration took only few days and the main work was building the DCS user interface.

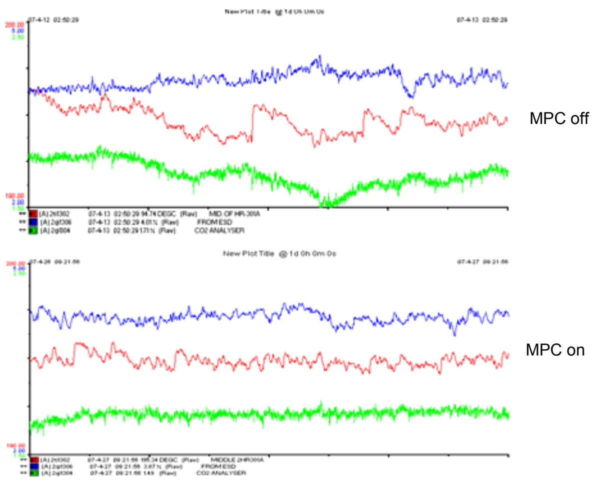

Figure 5. Plots of CVs 2TI1302, 2QI1306 and 2QI1304, oxidation section of PTA Unit 2

5. CONCLUSION AND DISCUSSION

An integrated MPC technology is introduced. It consists of three modules, a control module, an identification model and a monitor module. It can perform various steps of an MPC project automatically and in a parallel manner. Thus, the efficiency of MPC commissioning and maintenance can be increased by a factor of 3 or higher when compared with the conventional MPC technology. The application of the prototype integrated MPC to the two PTA units has shown the feasibility of the technology. This technology may change the way MPC is applied and can make MPC feasible for all process industries, not just the refining/petrochemical industry.

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