Model maintenance for Industrial Process Control

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Model-based control is widely used in chemical processes. Model fidelity is the key factor influencing the performance of these controllers. Usually, these process models are identified using open-loop step tests during the initial, commisioning phase of the control system. However, with the passage of time, mismatches develop between the process and its model. These could be caused, for example, by physical changes in the process and changes in the operating conditions. In general, this model-plant mismatch increases with time and leads to a degradation in the closed loop performance. In order to restore satisfactory performance, it might be necessary to repeat the identification exercise and retune the controller using the new model.

The disadvantage of using traditional open-loop step tests for this purpose is that they are time-consuming, affect the productivity and are prohibitively expensive. Closed loop identification provides an attractive alternative for re-identifying the models. It uses data collected when the process is under closed-loop control, i.e., the controller is regulating the process. One of the main advantages of using closed-loop identification is that the controller attempts to preserve the system performance to some extent, while ensuring that constraints are not violated. Additional advantages include disturbance reduction, safe operation and better control-relevant models. The price to pay is in terms of the inherent reduction in the excitation, which could lead to poor signal-to-noise ratios. In addition, there can be a significant correlation between the manipulated variables and disturbances affecting the system, and this could introduce a bias in the estimates. Nevertheless, in view of its advantages, closed-loop identification is receiving more attention from process engineers and is being considered as an alternative which can be used for restoring controller performance when significant model-plant mismatch occurs.

Among recent developments related to industrial applications, Zhu (1999) extended the asymptotic theory of Forssell and Ljung (1998) and developed practical guidelines for input signal design. In this approach, a high order ARX model was identified to capture the deterministic and stochastic effects. This was followed by a filtering-based, model reduction technique to obtain a low order, high fidelity approximation of the deterministic dynamics. Vuthandam and Nikoloau (1997) proposed an MPC relevant identification methodology, which explicitly incorporated the input excitation requirements in the objective function of the MPC. However, the bias introduced due to the correlation between disturbances and manipulated inputs has not been completely addressed in these papers.

In this paper, we study the direct identification method and the indirect, two-step method, for closed-loop identification, focussing on the issues of signal-to-noise ratio (SNR), disturbance-input correlation, and order reduction in the presence of noise. We propose a modification of the conventional SNR definition so that it reflects both input as well as output variability, and seek to maximize this index. We study the issue of input signal design with the objective of introducing variability in the closed loop data. We approach this problem as a trade-off, between balancing operating goals and introducing enough excitation to facilitate model identification. To minimize bias in the identified model which is caused by noise-input correlation, we analyze the applicability of the projection method (Forsell and Ljung, 1999) in the MPC scenario. Forsell and Ljung (1999) proposed a modified, two-step method for closed loop identification, wherein a non-causal structure for the sensitivity is used. We show that such a non-causal structure can be theoretically realized in an MPC framework, and can provide the benefit of minimizing the bias. In addition, we propose and discuss an alternate method of breaking the noise-input correlation by exploiting the nature of the MPC regulator. A few MPC regulators classify outputs to be restrained within zones/ ranges instead of trying to regulate them at desired values. We propose the use of a dynamic, active constraint set based strategy in the MPC optimization problem, which can be coupled with the above range-control formulation. This yields a time-varying controller, which minimizes the input-noise correlation while accommodating some of the closed loop objectives, and results in better quality models.

We analyze these algorithms by applying them on a simulation case-study, the benchmark Shell Control Problem (Prett and Morari, 1987). We will present results from the case-study which demonstrate the practicality of closed-loop identification techniques for model maintenance in advanced process control.

Case study

In the proposed case study, the Shell Control problem is used as a test bed for verifying these ideas. The Shell standard control problem was first published by the company in 1986 in the 1st Shell Process Control Workshop, with the intention to provide a standard and realistic test bed for the evaluation of new control theories and technologies. It captures most of the relevant control issues while staying as realistic as possible. The full model of the process is as follows. The model of the heavy oil fractionator process is a transfer function matrix whose (i, j) element relates the ith process output with the jth process input and has the standard first-order dead time form. The model gains, time constants and time delays are shown in the following table:

$$G_{ij}(s) = \frac{K_{ij} e^{-\theta_{ij} s}}{\tau_{ij} s + 1}$$

Process Model Parameters	Top Draw (u1)			Side Draw (u2)			Bott. Reflux Duty (u3)			Inter. Reflux Duty (d1)			Upper Reflux Duty (d2)		
τ, θ in min	K	τ	θ	K	τ	θ	K	τ	θ	K	τ	θ	K	τ	θ
Top End Point (y1)	4.05	50	27	1.77	60	28	5.88	50	27	1.20	45	27	1.44	40	27
Side End Point (y2)	5.39	50	18	5.72	60	14	6.90	40	15	1.52	25	15	1.83	20	15
Top Temp (y3)	3.66	9	2	1.65	30	20	5.53	40	2	1.16	11	0	1.27	6	0
Upper Reflux Temp (y4)	5.92	12	11	2.54	27	12	8.10	20	2	1.73	5	0	1.79	19	0
Side Draw Temp (y5)	4.13	8	5	2.38	19	7	6.23	10	2	1.31	2	0	1.26	22	0
Inter. Reflux Temp (y6)	4.06	13	8	4.18	33	4	6.53	9	1	1.19	19	0	1.17	24	0
Bottoms Reflux Temp (y7)	4.38	33	20	4.42	44	22	7.20	19	0	1.14	27	0	1.26	32	0

Table 1. Model parameters of the Shell Control Problem

The process is a multivariable heavy oil fractionator (5 inputs and 7 outputs) which is highly constrained, with very strong interactions and large dead times. The key elements of the Shell standard control problem are shown in Figure 1 & 2 below.

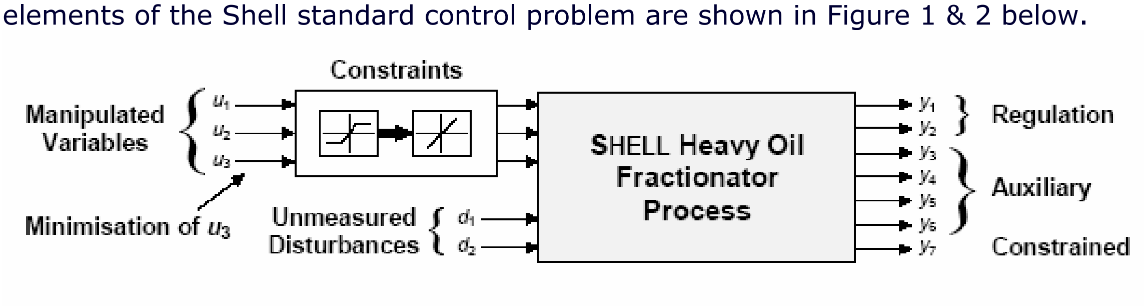


Figure 1. Shell standard control problem

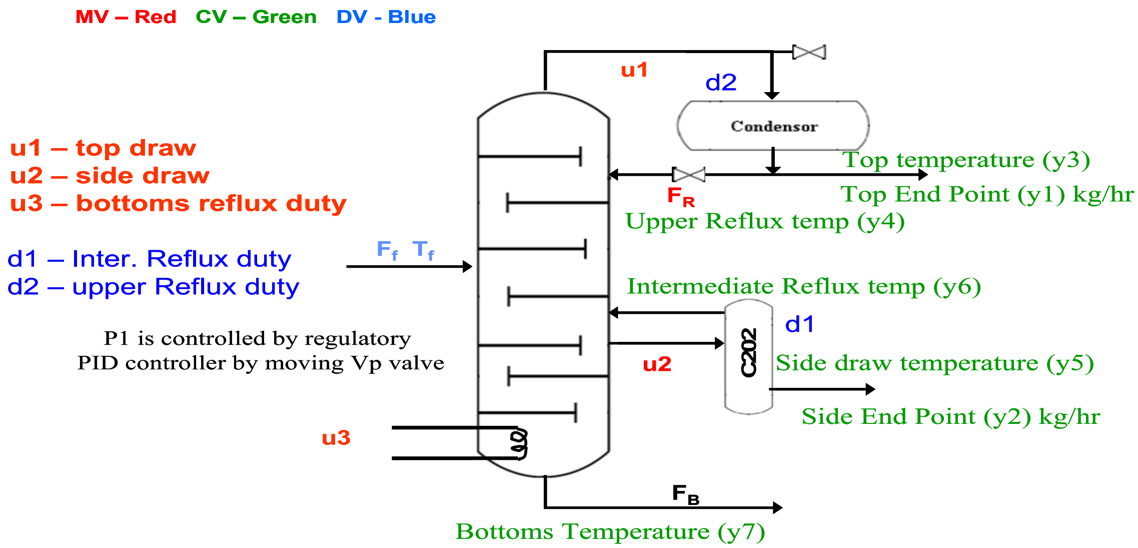


Figure 2. Shell Heavy Oil Fractionator Column

The problem is stated such that an infinite number of scenarios can occur in controlling the unit. The process input/output relations are linearly modeled using a transfer function matrix of first-order dead time transfer functions. Inputs u1, u2, and u3 can be used as manipulated variables to control the process, but are subject to saturation (±0.5) and rate limit (±0.05 per minute) hard constraints, thus making the process non-linear. Inputs d1 and d2 are unmeasured disturbances, with $| d1 | \le 0.5$ and $| d2 | \le 0.5$, entering the process. Furthermore, the process is subject to large uncertainties in the gains of the model transfer functions. The main objective is to maintain outputs y1 and y2 at specification (0.0 ±0.005 in the steady state) while at the same time, input u3 has to be minimized, and output y7 has to be kept to values of at least −0.5. Unmeasured disturbances d1 and d2 have to be rejected even when the sensors of y1 and y2 fail. The closed-loop speed of response must be kept between 0.8 and 1.25 of the open-loop process bandwidth and the fastest sampling time that can be used is 1 minute. The problem features are summarized below.

- Actuator and output constraints are present.
- Simultaneous regulation and optimization are required.
- Strong interactions and large dead times are present.
- Unmeasured disturbances are present.
- Large uncertainties in the gains of the plant are present.

Open loop identification

In the initial phase of MPC installation, the plant models are identified using following steps

Pre tests for getting initial information about the process gains, time constants and order of non-linearity of the process

Design of the 'RBS' signal based on the settling time and the SNR (signal to noise ratio) consideration. The RBS signals can be applied to either one MV at a time or simultaneously to all MVs.

The step data for the process is shown in Figures 3 and the RBS responses of input, output are shown in Figure 4(a), 4(b) respectively.

The actual and identified process models are compared in Figure 5.

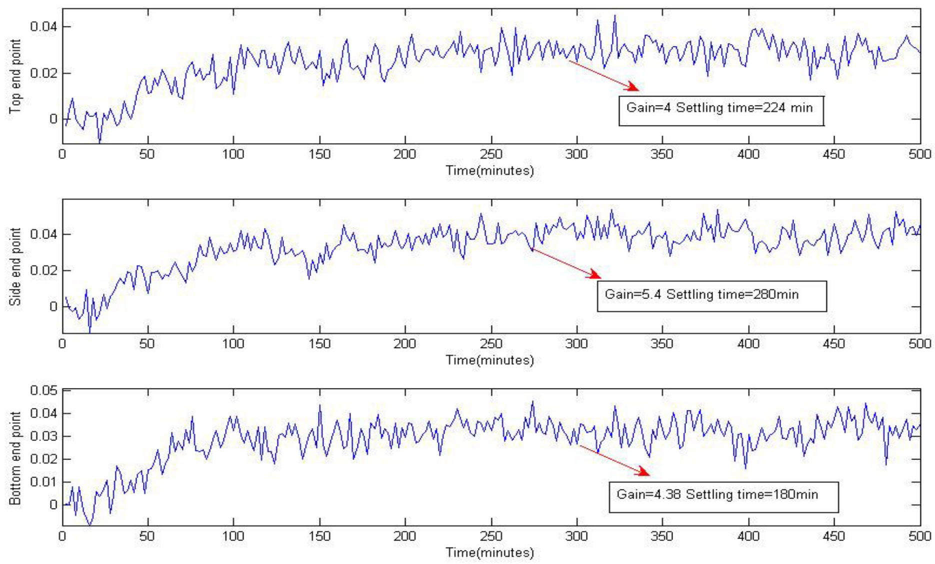


Figure 3 : Step data for top draw perturbation

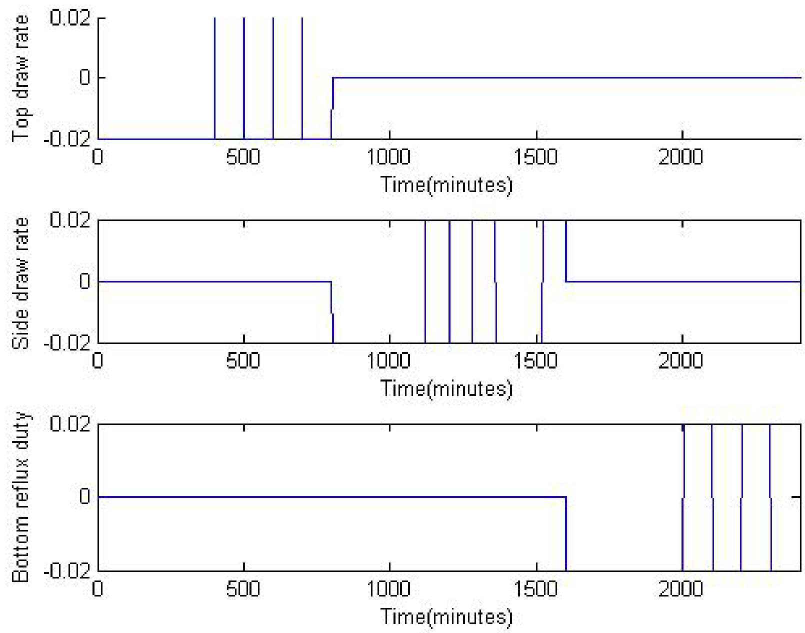


Figure 4 (a): Input Perturbations

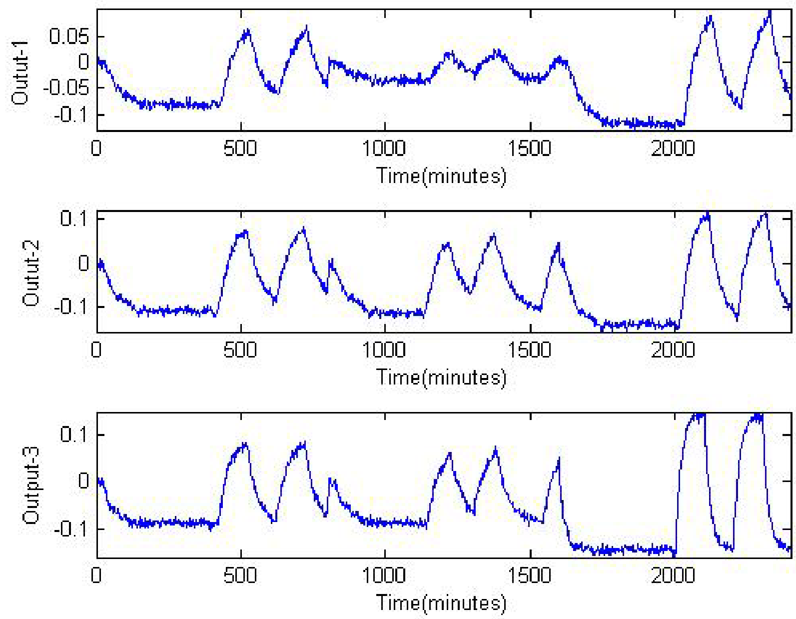


Figure 4 (b): Output Perturbations

	Top Draw Rate	Side Draw Rate	Bottoms Reflux Duty
Top End Point	4.18	4.3	4.18
Side End Point	3.19	3.3	3.19
Bottoms Temperature	4.15	4.29	4.15

Table 2: SNR with respect to the inputs

	SNR
Top End Point	86
Side End Point	121
Bottoms Temperature	198

Table 3: SNR with respect to the outputs

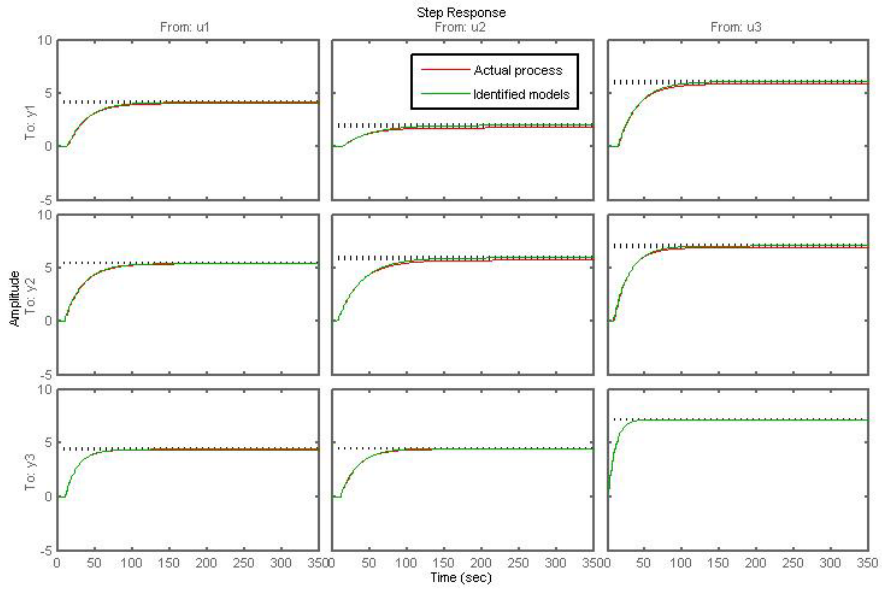


Figure 5: Identified models and the actual process models

Tuning and performance of MPC and RMPCT

MPC and RMPCT algorithms are developed based on these identified models. Performance ratio for each output is a tuning parameter in RMPCT. Performance ratio (PR) is the ratio of closed loop settling time to open loop settling time. Lower the PR, faster the control action and higher the PR, slower the control action.

The tuning parameters are typically chosen based on the settling time of the process, the disturbance characteristics, the model fidelity etc. These parameters are chosen by thumb rules and are tabulated in Table 4.

Performance of MPC and RMPCT

The performance of MPC and RMPCT for set point tracking and disturbance rejection is done in terms of various metrics. The important metrics considered in this report are the settling times, the input energies, the output variability across the set point, IAE (Integrated absolute error), and ISE (Integrated square error), number of constraint hits.

The settling time is related to the speed of control and ideally it should be as minimum as possible. The settling time of the response depends on the process settling time and the dead times. The IAE and ISE are given by following formulae 1 and 2 respectively and decide the variability of the outputs across the set points. Smaller IAE and ISE indicate better performance.

$$IAE = \int_0^t |e(t)|dt \qquad (1)$$

$$IAE = \int_0^t (e(t))^2 dt \qquad (2)$$

Parameters \ Controller		MPC	RMPCT (PR=1)
Model Horizon		60	60
Prediction Horizon	CV1	50	50
	CV2	50	40
	CV3	50	25
Control Horizon	MV1	8	8
	MV2	8	8
	MV3	8	8
CV weights	CV1	1	1
	CV2	1	1
	CV3	1	1
MV weigths	MV1	0.1	0
	MV2	0.1	0
	MV3	0.1	0
Set points	CV1	0.5	-
	CV2	0.5	-
	CV3	0.5	-
Ranges (maximum)	CV1	-	0.55
	CV2	-	0.55
	CV3	-	0.55
Ranges (minimum)	CV1	-	0.45
	CV2	-	0.45
	CV3	-	0.45
Absolute MV constraints	MV1	±0.5	±0.5
	MV2	±0.5	±0.5
	MV3	±0.5	±0.5
MV rate constraints (maximum)	MV1	±0.05	±0.05
	MV2	±0.05	±0.05
	MV3	±0.05	±0.05
Set point Blocking	CV1	[10 10 10 10 10]	[10 10 10 10 10]
	CV2	[10 10 10 10 10]	[10 10 10 5 5]
	CV3	[10 10 10 10 10]	[5 5 5 5 5]
MV Blocking	MV1	[2 2 2 2]	[2 2 2 2]
	MV2	[2 2 2 2]	[2 2 2 2]
	MV3	[2 2 2 2]	[2 2 2 2]
Performance Ratio (PR)	CV1	-	1
	CV2	-	1
	CV3	-	1

Table 4: The parameter values used in MPC, RMPCT

The input energies indicate the control efforts for achieving the control objective and are measured in terms of variance of the MVs. Ideally, these should also be as small as possible.

The frequency of the input and input rate constraints hits is also considered as an important metric for performance monitoring. If the controller remains constrained for large time, then the optimal controller performance can not be ensured. The ideal situation would be no constraints hits throughout the online time.

An important focus of this case study is to compare the performance of MPC, RMPCT when there is no mismatch. Later performance of RMPCT without mismatch and with mismatch is studied. This model plant mismatch arise from the shift in operating point, scaling of heat exchangers, replacement of equipments etc. To simulate the model plant mismatch, the models (used for prediction) are chosen 50% off gain from the plant dynamics. The controller performance is compared with the earlier case. The clear cut degradation in performance is indicated through higher IAE, ISE, and higher settling times.

In figure 6, the performance of RMPCT (left) and MPC (right) in tracking the set point, and rejecting the disturbance is depicted. The quantitative performance measures such as IAE, ISE, settling times for set point tracking and disturbance rejections are tabulated in Table 5. In addition the input, output variances are tabulated in Table 6. From this figure it is evident that the input movements in RMPCT are minimal to that of MPC. The error propagation in RMPCT is less compared to that of MPC as the input movement is minimal in RMPCT. Thus RMPCT is more robust than MPC.

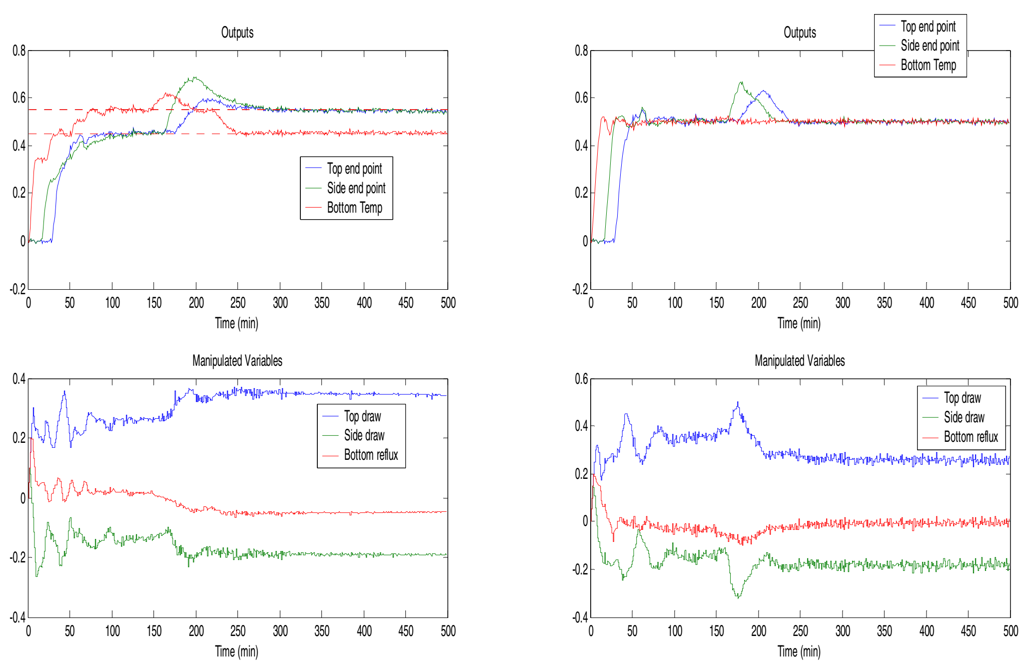


Figure 6: Comparison of performance for RMPCT and MPC controller

Note: Disturbance is introduced at time t = 150 min.

	Settling time for CVs with set point change (min)			Settling time for CVs after disturbances (min)			IAE			ISE		
	CV1	CV2	CV3	CV1	CV2	CV3	CV1	CV2	CV3	CV1	CV2	CV3
MPC	70	70	64	240	222	170	25.0	18.7	6.2	8.82	5.70	1.26
RMPCT	120	120	36	280	280	196	20.0	23.3	6.9	7.04	5.62	1.20

Table 5: Comparison of MPC and RMPCT (PR=1) performances in set point tracking and disturbance rejection

	Variance					
	Output			Input		
	CV1	CV2	CV3	MV1	MV2	MV3
MPC	0.0172	0.0115	0.0027	0.0037	0.0025	0.0013
RMPCT	0.02	0.184	0.0056	0.0030	0.0015	0.0016

Table 6: Variances in outputs and inputs with MPC, RMPCT during set point tracking and disturbance rejection

From the earlier discussion it is understood that RMPCT is more robust and sluggish than MPC. If the operator has confidence in the models used in controller, the performance ratios for each of output can be reduced to make the controller aggressive

In figure 7, the performance of RMPCT with mismatch and no mismatch are shown. In these simulations 50% mismatch in the gains for each input and output model are considered. The transient response of RMPCT is very sluggish in the presence of mismatch. The quantitative performance measures such as IAE, ISE, settling times for set point tracking and disturbance rejections are tabulated in Table 7. The input, output variances are tabulated in Table 8. So the step disturbance is introduced at t=350 min in mismatch case, rather than at t=150 min. From the figure and Table 7 & 8, there is significant degradation in the performance of RMPCT.

As discussed, the model plant mismatch degrades the controller performance. This degradation in controller performance motivates to go for re-identifying the models to sustain the benefits of using advanced process control. As mentioned in the introduction closed loop identification is preferred.

Closed loop re-identification

The important steps in closed loop identification are

1)Signal design
2)Model structure selection
3)Identification algorithm
4)Model validation

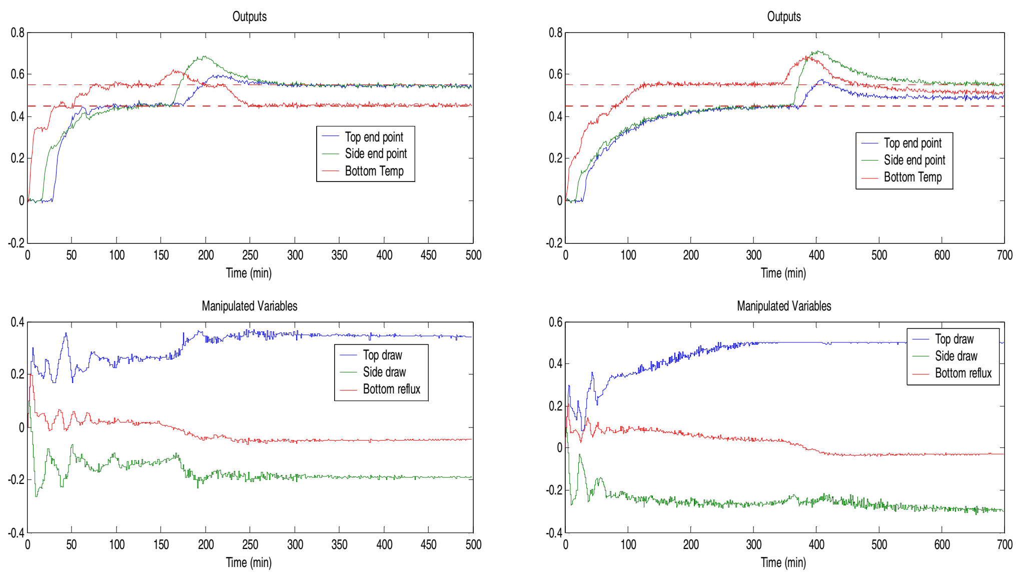


Figure 7: Comparison of performance for RMPCT controller without and with gain mismatch

Note: Disturbance is introduced at time t = 150 min for first row (no mismatch) and at time t = 350 min for RMPCT with 50% gain mismatch (Bold). The time at which the disturbances are entered is shown in the brackets in the 3rd column.

	Settling time for CVs with set point change (min)			Settling time for CVs after disturbances (min)			IAE			ISE		
	CV1	CV2	CV3	CV1	CV2	CV3	CV1	CV2	CV3	CV1	CV2	CV3
RMPCT	120	120	36	280 (150)	280 (150)	196 (150)	20.0	23.3	6.9	7.04	5.62	1.20
RMPCT with 50% gain mismatch	300	300	82	421 (350)	620 (350)	458 (350)	37.8	47.1	19.6	10.4	9.71	3.3

Table 7. Comparison of RMPCT performance without mismatch and with mismatch, while tracking set point and rejecting disturbance

	Variance					
	Output			Input		
	CV1	CV2	CV3	MV1	MV2	MV3
RMPCT (PR=1)	0.0152	0.0136	0.0041	0.0023	0.0011	0.0012
RMPCT with 50% gain mismatch	0.0167	0.0214	0.0079	0.0088	0.0028	0.0023

Table 8. Variances in outputs and inputs with RMPCT (PR = 1), RMPCT with 50 % gain mismatch in models during set point tracking and disturbance rejection.

Signal Design

The external test signals can be added either at set points or at MVs. The amplitude and frequency spectrum of the signals can be computed based on the already existing models in APC. In this case study the set point excitations are used as they are easy to integrate with RMPCT product.

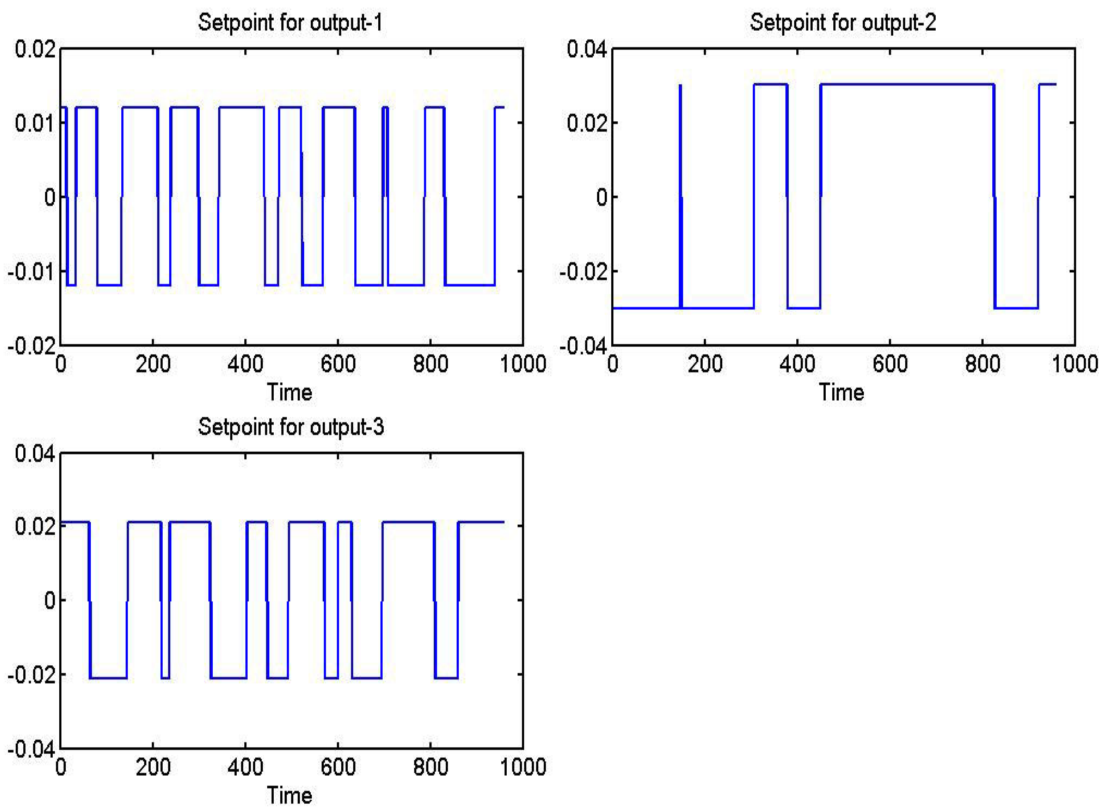


Figure 11: Set-point excitations

	Top Draw Rate	Side Draw Rate	Bottoms Reflux Duty
Top End Point	62	21	24
Side End Point	47	16	19
Bottoms Temperature	67	23	26

Table 7: SNR with respect to the inputs

	SNR
Top End Point	8.6
Side End Point	14.2
Bottoms Temperature	184

Table 8: SNR with respect to the outputs

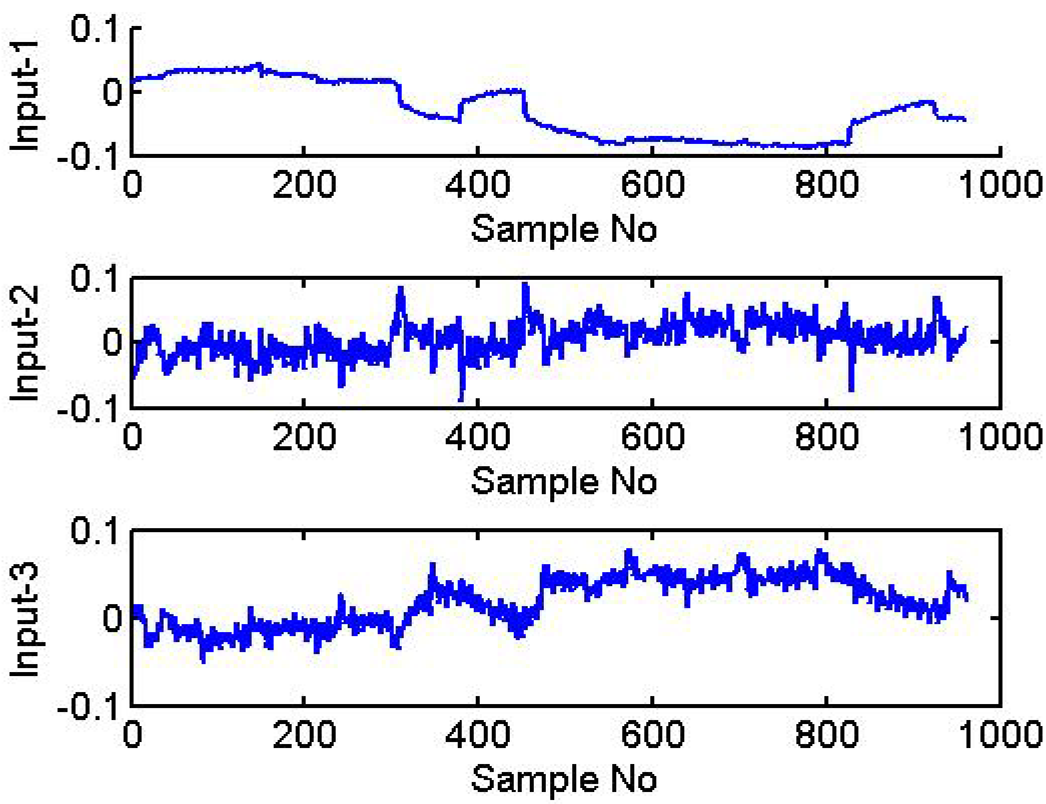


Figure 12: Input excitations

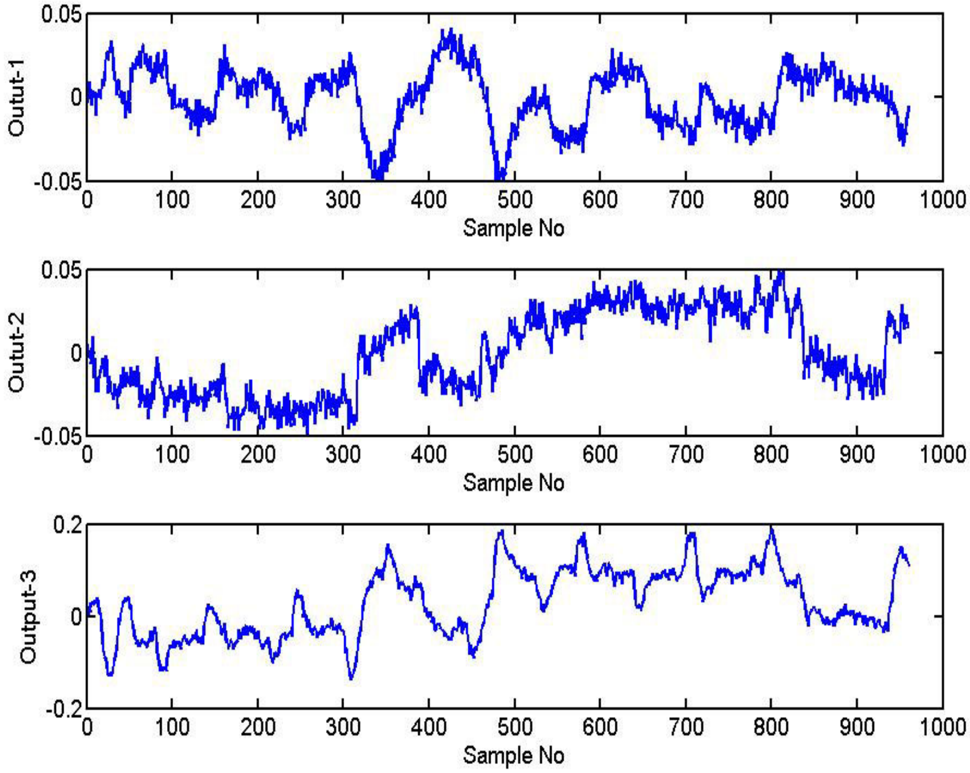


Figure 13: Output excitations

Model structure selection

The RMPCT already have an identifier which uses FIR models. OE models (which are parametric form of FIR models) can easily be integrated with the RMPCT. Hence, in the proposed case study, OE kind of models is used.

Identification method

In the proposed case study, the identification method employed can be stated as

1)Fit high order ARX model (model order ranging between 30-40)

2)Frequency weighted model order reduction

3)Iterative calculation of OE models of lower orders via high order ARX models

Model validation

Model validation is done based on comparison of the step responses of the actual process models with the identified models

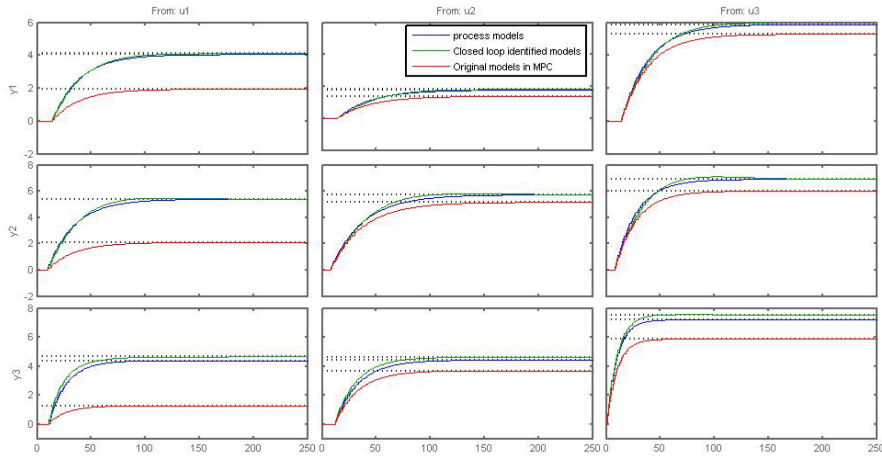
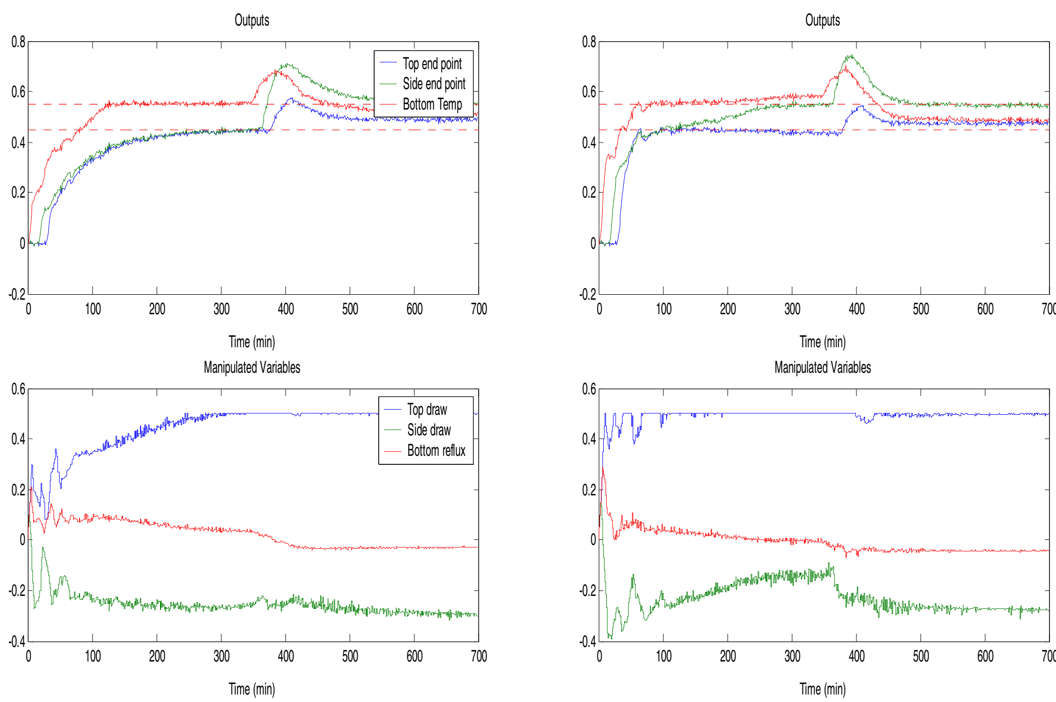


Figure 14: Comparison of the models

Performance using the identified closed loop models



Performance of RMPCT before and after re-identification

	IAE	ISE
Top end point	20.4	7.1
Side end point	23.8	5.6
Bottoms end point	7.11	1.23

Table 9: Integrated absolute and squared error

	Input energy
Top draw rate	0.0032
Side draw rate	0.0017
Bottoms reflux duty	0.0015

Table 10: Input energy

Conclusions

Effective Model maintenance is a need for sustained benefits of APC projects. The model plant mismatch that widens with time needs to be corrected by reidentifying the process models. Closed loop identification is an effective way for reidentification. In the reported case study, the clear cut improvement in performance (reduced variation in the outputs and the faster settling times) provides motivation for the model maintenance. Some future directions are: Performing the closed identification on a realistic test bed with higher dimensionality, techno-economic evaluation for closed loop identification (ROI analysis) and signal design issues.

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