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Performance Assessment and Model Validation of Two Industrial MPC Controllers

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Abstract: This paper presents two case studies on the performance evaluation and model validation of two industrial multivariate model predictive control (MPC) based controllers at Suncor Energy Inc., Fort McMurray, Canada: (1) a 7 controlled variable (CV), 3 manipulated variables (MV) kerosene hydrotreating unit (KHU) with three measured disturbance variables that are used for feedforward control; and (2) an 8 CV, 4 MV naphtha hydrotreating unit (NHU) with 5 measured disturbances. The NHU and KHU controllers are implemented on the product stripping distillation towers. The first case study focuses on potential limits to control performance due to constraints and limits set at the time of controller commissioning. The root causes of sub-optimal performance of KHU are successfully isolated. Data from the NHU unit with MPC on and with MPC off are analyzed to obtain and compare several different measures of multivariate controller performance. Model quality assessment for the two MPCs are performed. A new model index is proposed to have a measure of simulation ability and prediction ability of a model. Open-loop identification of KHU and closed-loop identification of NHU are conducted using the asymptotic method (ASYM).

Keywords: Model predictive control, Control Loop Performance Assessment, Constraints,

1. INTRODUCTION

Multivariate model predictive control (MPC) has been widely applied in industry to control increasingly complex processes. At each control interval, an MPC controller attempts to optimize future plant behavior by computing a sequence of future moves of manipulated variables (MVs). Only the first moves of the MVs are sent into the plant and the entire calculation is repeated at the next control interval. This is also known as receding horizon control. There is a large volume of publications concerning the theoretical and practical issues associated with MPC technology. Rawlings (2000) has provided an excellent introduction to MPC technology; Qin and Badgwell (2003) have given a good survey of industrial MPC. Several books on MPC have also been published recently (Kouvaritakis and Cannon, 2001; Maciejowski, 2002).

Although there are many publications discussing the design of MPCs and the properties of MPCs, relatively few of them talk about the performance monitoring of MPC controllers which is also an important issue. MPC control systems usually work well and deliver profit near the time when they are commissioned, however their performance deteriorates with time and the MPC controllers are often eventually turned off without proper maintenance. There are many reasons for sub-optimal MPC performance: process changes, unmeasured disturbances, inappropriate limit settings and poor tuning of lower level PID loops. How to effectively evaluate the performance of the MPC is still an open question.

The kerosene hydrotreating unit (KHU) and the naphtha hydrotreating unit (NHU) at Suncor Energy Inc., Fort McMurray, Canada are controlled by commercial MPC controllers. These two MPC controllers were commissioned in May 2005 and have performed well until late 2006. Both units have been able to deliver significant monetary benefits each year. However, since late 2006, these' MPC controllers have not performed as well as possible. Sometimes, the MPC controller could not control the CVs within their limits and therefore could not achieve optimal performance.

In this paper, we discuss the performance issues of the generic MPC controllers and then apply the developed techniques for studying sub-optimal performance when applied to the KHU and NHU MPC controllers. The objectives of our work are: (1) to assess the performance of the two MPC controllers; (2) to diagnose the root cause of the deteriorated control performance; (3) to provide remedial suggestions; (4) to validate the models in the

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MPC controllers; and (5) to re-identify the model using routine operating data.

2. PERFORMANCE ANALYSIS OF THE KHU MPC

The kerosene hydrotreating unit (KHU) at Suncor Energy Inc. is a standard hydrofining unit that desulphurizes the coker intermediate kerosene streams through a catalytic reaction with hydrogen. The KHU is controlled by an MPC controller which has 3 manipulated variables (MVs), 7 controlled variables (CVs) and 3 feedforward variables (FFs). The MPC controller recalculates and executes MV moves every 1 minute. Our analysis is based on 2 days of 1 minute data when KHU MPC was turned on.

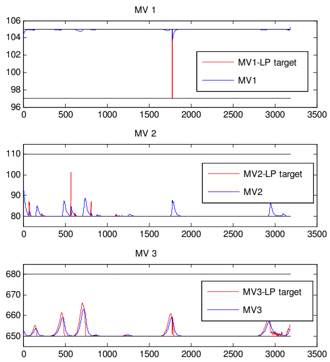


Fig. 1. MVs moves when the MPC was on. The black lines are the limits.

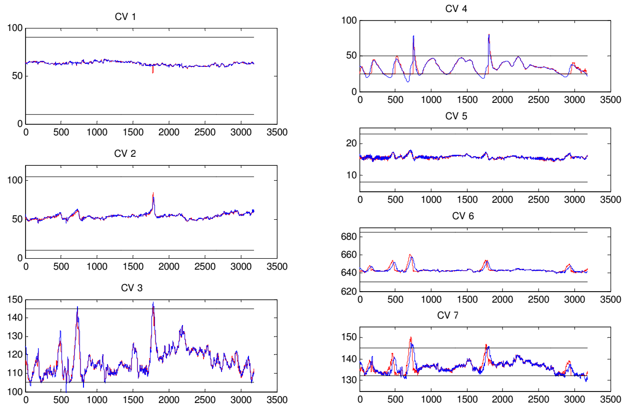
The MV moves of these 2 days that the MPC was on are shown in Figure 1. The corresponding CV trajectories are shown in Figure 2. In both figures, the blue lines are the real measurement, the red lines are the LP-targets and the black lines are the limits. The 'LP-target' is short for 'linear programming target' which is calculated by the MPC every minutes as the steady state target for the MVs and CVs. Looking at the MVs and CVs, we can notice that:

- The MVs are at their limits most of the time.
- There is limit violation in CV3(low rank), CV4(medium rank) and CV7(low rank). Especially CV4, which has median rank, has large excursions from its limits.
- There are some wave pattern fluctuations in MV2 and MV3. Very similar patterns of fluctuation also exist in CVs, such as CV2-CV7.
- The MVs and CVs follow their LP-targets very well.

To understand and diagnose these observations, we perform limits and constraints analysis, PID loop diagnosis and cause & effect analysis in the following sub-sections.

2.1 Analysis of Limits and Constraints

An important feature of the MPC method is its ability to handle multiple constraints and limits. During each control execution, the MPC controller will carry out LP or QP optimization to find the feasible solution for CV and MV moves. If there is no feasible solution that satisfies all of the limits and constraints, the MPC controller will choose to violate some of the constraints and limits according to the weights of different CVs and MVs. MV limits are 'hard constraints' which means that they should be respected all the time and not violated. CV limits are "soft constraint" meaning they can be violated to some extent if there is no feasible solution to satisfy all the limits and constraints. For a well designed MPC application, one expects the CVs to be at their designed limits to achieve maximum profit and MVs to be between their limits to have enough freedom for control. Consequently the analysis of limits and constraints of a MPC controller can provide valuable information about control performance.



(a) CV1 - CV3 (b) CV4 - CV7

Fig. 2. CVs trajectories when the MPC was on. The blue lines are the real measurement, the red lines are the LP-targets and the black lines are the limits.

Table 1. Constraints analysis of the MVs LP-targets

Tags	Cost Action	High limit activation	Low limits activation
MV1	Maximize	99.76%	0.14%
MV2	Minimize	0%	98.16%
MV3	Minimize	0%	74.95%

Table 2. Limits activation analysis of the CVs LP-targets

Tags	Control objective	High limit activation	Low limit activation
CV1	Between limits	0%	0%
CV2	Between limits	0%	0%
CV3	Between limits	0.07%	2.85%
CV4	Low limit	0.31%	30.08 %
CV5	Between limits	0%	0%
CV6	Between limits	0%	0%
CV7	Low limit	0.28%	1.11%

Limits and constraints analysis of 2 days of data from the KHU MPC controller was performed using the Control Performance Monitor (CPM) software from Matrikon Inc. Table 1 shows the limit activation of the MVs. Here 'limit activation' measures the percentage of time one MV LP-target is at its high or low limit. The '*cost action*' of a MV indicates the desired move direction of that MV in order to achieve the control objectives of the CVs. This information can be easily obtained through the gain matrix of the process model. An ideal scenario is that the MVs move in the desired move directions until the

CVs achieve their control objective and some of the CVs stay at their desired limits. We can see in Table 1 that the MVs do move in the desired directions, but they hit their constraints most of the time and are therefore unable to move anymore. At the same time, we can see from Table 2 that the CVs actually have not achieved their control objectives, especially CV4 and CV7 whose control objective is to operate at the low limit settings. Therefore, we can say that the MVs are moving in the right direction to achieve the control objectives; but they hit their constraints before they can fully achieve the control objectives. Consulting with Suncor engineers, we know that the limits may be overly restrictive, however they may be set for safety or other considerations and cannot be extended. This situation is not rare in practice where people try to maximize production and always tend to hit the process or equipment related MV limits.

Another obvious problem with the current system is that the MVs stay at their limits for long periods and therefore do not have enough freedom for control. In this situation, any unmeasured disturbance can easily affect the system and the MPC controller may not be able to do much about such disturbances. This could explain why the operators sometimes see unsatisfactory control performance and decide to turn the MPC off.

2.2 Diagnosis of the Limit Violation

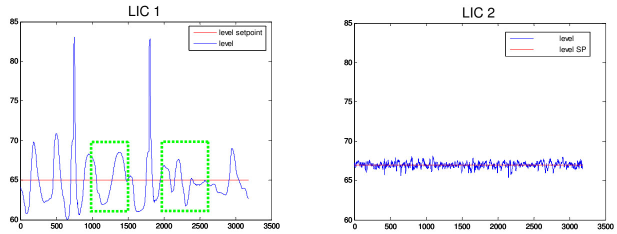
As we have seen in Figure 2, CV3, CV4 and CV7 encounter limit violations. Table 3 shows the average violation and peak violation of each CV. Peak violation of a CV is a ratio between the maximum violation and the CV's operation range. Average violation of a CV is a ratio between its averaged violation magnitude and the CV's operation range. It is clear that CV4 has significant amount of limit violations. A detailed diagnosis of CV4 is apparently needed.

Table 3. Constraints violation analysis of the CVs

Tags	Average violation	Peak violation
CV1	0%	0%
CV2	0%	0%
CV3	4.6%	14.53%
CV4	20.88%	116.64%
CV5	0%	0%
CV6	0%	0%
CV7	5.08%	12.92%

CV4 is the position of an accumulator level valve which is directly controlled by a PID level controller (denoted as LIC1). This level controller regulates the level in the accumulator by manipulating the valve opening. Therefore the performance of this PID loop has great effect on CV4. A plot of SP and PV of the level is shown in Figure 3(a). Before we judge whether this PID controller is performing well or not, two important issues should be taken into account:

(1) This is a level controller for an accumulator. It is quite often that a level controller is tuned loosely to have buffer effect to absorb or filter upstream disturbances in the process.
(2) The level is not only affected by the valve opening. The MVs of the MPC controller also have an effect on the level.



(a) SP and PV of PID loop LIC1 (b) SP and PV of PID loop LIC2

Fig. 3. PID loop LIC1 and LIC2

To clarify whether LIC1 actually is tuned to be sluggish as shown in Figure 3(a), we compare it with another PID level controller LIC2. PID LIC2 controls the level of the feed flash drum and the valve opening (LIC2.OP) is also a CV in KHU MPC controller. Consulting with the Suncor engineers, we know that PID LIC1 and LIC2 have very similar control strategy and control objectives. Figure 3(b) shows the SP and PV of PID controller LIC2 which is very different from Figure 3(a). Apparently, LIC2 is performing very well but LIC1 is not.

An additional point to clarify is how can we be sure the sub-optimal performance was not because of the effect of the MV moves of the MPC controller? To answer this question, examine the two highlighted areas with red dashed box in Figure 3(a). During these two highlighted periods (1000th-1500th & 2000th-2700th data points), there are almost no MV moves as can be seen in Figure 1. Therefore, during these two periods, only the PID controller LIC1 controlled the level and the performance is not good.

From the above analysis and experience from Suncor engineers, we have confirmed that this level PID loop was not performing well. There is a severe known nonlinearity/backlash in the LIC1 control valve that causes the sub-optimal level control (Suncor engineers try to control this valve output at a very low opening). Then some obvious questions arise: how does the limit violation occur? Why are there similar wave pattern fluctuations in MV2-MV3 and CV2-CV7? What is the root cause?

A simple way to answer these questions is to plot all the MV and CV Lp-targets in one figure and to see which LP-target changes first just before a limit violation occurs. Our cause & effect analysis has shown that

- The sub-optimal performance of the PID controller LIC1 is the root cause of limit violation.
- Every time, when CV4 (LIC1.OP) hits its lower limit, the MPC makes MVs move and tries to bring CV4 back to its limits. These MV moves make the other CVs move, such as CV2, CV3, CV6, CV7 and CV8 (see Figure 2).
- The limit violation of CV3 and CV7 is due to the MV moves which are used to bring CV4 back to its limits. This is because CV3 and CV7 have lower rank than CV4 and the MPC will try to bring CV4 back

to limits even at the cost of sacrificing performance of CV3 and CV7.

- Once CV4 goes back to its limits, MVs will be optimized to move in their desired directions which is towards their limits in this MPC. The MVs will not move until CV4 reaches its limit again next time.
- The above procedure explains why we see the wave pattern in MV2-MV3 and CV2-CV7.

2.3 Summary of KHU MPC Performance

As we can see in Figures 1 and 2, MVs and CVs follow their LP-targets very well. This is an indication of good performance of the lower layer of the MPC system, such as sensors, valves and actuators. Valve stiction analysis did not show any valve problem in the KHU.

Limits and constraints analysis in Section 2.1 reveals that the limit settings for some CVs and MVs have limited the optimal performance of the MPC controller. The MPC controller did try to move the MVs to achieve the control objectives for CVs. However, the MVs hit their limits before they can achieve the optimal performance. This makes the MVs stay at their limits and lose certain degree of freedom of control.

The limits violation analysis in Section 2.2 shows that the PID loop LIC1 is the root cause of limit violation. The PID controller could not control the accumulator level well and made CV4 (LIC1.OP) out of its limit from time to time. In order to bring CV4 back to its limits, the MPC controller moved the MVs and even sacrificed the performance of two lower rank CVs (CV3 and CV7). The main reason for the sub-optimal performance of PID controller LIC1 is because of the valve nonlinearity that has developed over two years of operation since commissioning. The problem is the backlash nonlinearity in the control valve and the valve is likely oversized but can not be replaced until turnaround.

3. PERFORMANCE ANALYSIS OF THE NHU MPC

The naphtha hydrotreating unit (NHU) at Suncor Energy Inc. is a standard hydrofining unit that desulphurizes the coker intermediate naphtha streams through a catalytic reaction with hydrogen. The NHU is controlled by a MPC controller which has 4 manipulated variables (MVs), 8 controlled variables (CVs) and 5 feedforward variables (FFs). The MPC controller recalculates and executes MV moves every 1 minute.

The analysis is based on 8 days when the controller was off, followed by 7 days when the controller was on. Our purpose is to assess the performance of MPC controller and compare the plant performance when MPC was on and off. Figures 4 and 5 show the MV and CV activities during the selected 15 days period. The portion that is highlighted by dashed line box in each figure corresponds to the period that the MPC was on.

In Figure 5, it is quite clear that most of the CVs are better regulated with reduced variance after the MPC was turned on. Variances of each CV when MPC was on and when MPC was off are calculated and compared. For each CV, the percentage of variance reduced after MPC

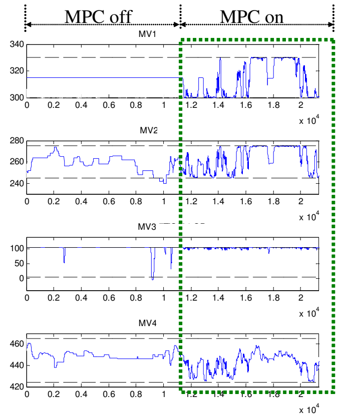
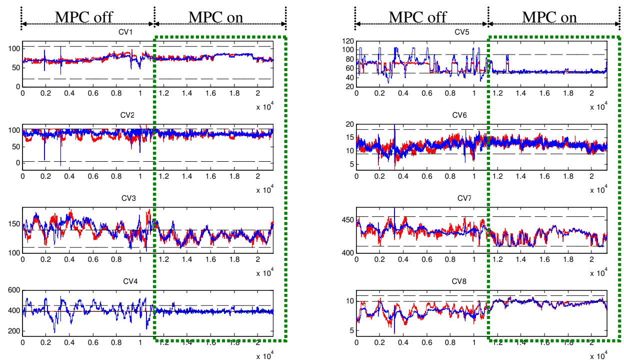


Fig. 4. MVs moves for the selected 15 days. The black lines are the limits.

turned on is shown in Table 4. It is obvious that most of the CVs have reduced variance after the MPC was turned on. The only variable with increased variance is CV7 (TI25.PV). This CV is the bottom temperature of the naphtha depropanizer which has a low rank (weight) in the MPC. The MPC controller transferred the variability of other CVs to CV7 where the process can afford to have increased variance. This is an indication of good performance of the NHU MPC.



(a) CV1 - CV4 (b) CV5 - CV8

Fig. 5. CVs moves when the MPC was on. The blue lines are the real measurement, the red lines are the LP-targets and the black lines are the limits.

Table 4. Percentage of variance reduced after MPC turned on

Tags	CV1	CV2	CV3	CV4
Variance reduced	6.12%	61.11%	47.88%	94.11%
Tags	CV5	CV6	CV7	CV8
Variance reduced	90.55%	64.40%	-199.89%	59.20%

3.1 Analysis of Limits and Constraints

Within the selected 15 day period, the NHU MPC was on over the last 7 days. Limits and constraints analysis of the last 7 days data was performed using the CPM software from Matrikon Inc. Table 5 shows the limit activation of the MVs. Among 4 MVs, only MV3 stays at its limit most of the time. This means that the MPC controller has at least the remaining 3 MVs with room to move most of the time. At the same time, we can see in Figure 5 that CV4, CV5 and CV8 are very close to their limit while other CVs are within their limits. Such CV activities indicate that the MPC controller was performing well to push some CVs to their limits and control other CVs to remain within their limits.

Table 5. Constraints analysis of the MVs LP-targets

Tags	Cost Action	High limit activation	Low limits activation
MV1	Minimize	39.05%	41.05%
MV2	Maximize	55.75%	20.23%
MV3	Maximize	99.21%	0%
MV4	Minimize	3.08%	0%

Table 6. Limits activation analysis of the CVs LP-targets

Tags	Control objective	High limit activation	Low limit activation
CV1	High limit	0%	0%
CV2	High limit	5.25%	0%
CV3	Between limits	8.5%	1.11%
CV4	Between limits	0%	98.99 %
CV5	Between limits	0%	0%
CV6	High limit	0%	0.2%
CV7	Between limits	0%	4.18%
CV8	Between limits	0%	25.49%

3.2 Summary of NHU MPC Performance

Considering the variance reduction and the limit tracking of some CVs, we would consider the NHU MPC controller performance was acceptable during the 7 day period. However, it is not the most optimal performance that the MPC controller can achieve and there still appears to be some room for improvement, such as

- Ideally, we want MVs to stay within their limits and not activate any limits. This could provide maximum degree of freedom for the MPC controller to handle disturbances and operating condition changes. However, this is not the case for NHU. One of the MVs stayed at its limit most of the time. Therefore the MPC controller lost one degree of freedom for control.
- Limit violations existed in CV8(see Figure 5(b)). Calculations show that 56.01% of the time, its LP-target is out of limit. This indicates that the MPC controller has to sacrifice this low rank CV to ensure performance of other CVs.
- Table 6 shows the control objective of each CV. Actually the plant is designed to operate CV1, CV2 and CV6 at their upper limits. But in reality, these three CVs are not at limits while some other CVs are at limits.
- The MPC controller could not perform as well as possible.

There are many reasons that can cause the problems mentioned above, such as a deficient model, lower layer PID tuning, operating condition changes and so on. This MPC has been running over 2 years, but the service factor could be improved.

4. MODEL QUALITY ANALYSIS

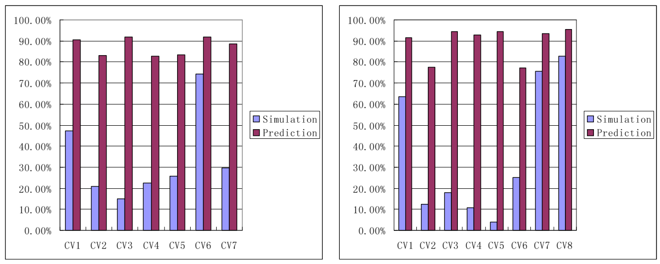
4.1 Initial Model Quality Assessment

The initial step test data of the KHU and NHU was provided by the process engineers at Suncor Energy Inc. The step tests were completed in 2005. In order to evaluate the initial model quality, we first evaluate the simulation and 1-step ahead prediction (Ljung, 1998) performance using the model and the step test data. In order to quantify the model fit, we used the equation (which is also used in MATLAB function 'compare')

$$model\ fit = 1 - \sqrt{\frac{\sum_{t=1}^{n}[y(t+k) - \hat{y}(t+k|t)]^2}{\sum_{t=1}^{n}[y(t) - \bar{y}]^2}} \qquad (1)$$

where $y(t)$ is the measured output, $\hat{y}(t+k|t)$ is k-step-ahead prediction and $\bar{y}(t)$ is the mean value of the measured output. This model fit measures the percentage of variation that is explained by the model in terms of k-step-ahead prediction. If we choose $k = 1$ and substitute $\hat{y}(t+1|t)$ into the equation, then we have a 1-step-ahead prediction fit which evaluates the 1-step-ahead prediction ability of a model. If we choose $k = \infty$ and substitute $\hat{y}(t)$ into the equation, then we have a simulation fit which evaluates the simulation ability of a model.

Figure 6(a) shows a comparison of the 1-step-ahead prediction fit and simulation fit of KHU and NHU models.



(a) KHU (b) NHU

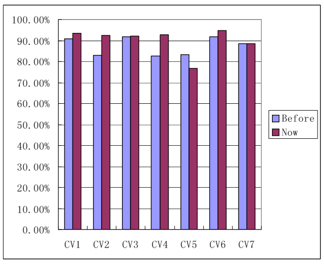
Fig. 6. Initial model fit

The 1-step-ahead prediction fits of the CVs are around 80% to 90% and the difference is not significant; however the simulation fits of the CVs are relatively low and are quite different from each other. For example, the average 1-step-ahead prediction fit of the 7 CVs of KHU is 87.4% while the average simulation fit of the 7 CVs is 33.64%. It is clear that the simulation fit is much lower than the 1-step-ahead prediction fit.

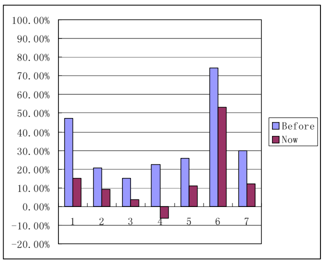
4.2 Recent Model Quality Assessment

In 2007, 5 weeks data of KHU and NHU were collected. We calculated the 1-step-ahead prediction and simulation fit based on this recent data. The results are shown in Figure 7 along with initial model fits.

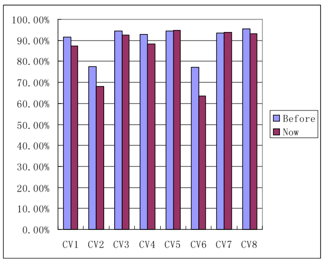
Figures 7(a) and 7(c) show that the 1-step prediction ability of the models is still very good. Some of the CVs even have better 1-step prediction ability than before (e.g. CV1, CV2, CV4 and CV6 in Figure 7(a)). Figures 7(b) and 7(d) show significant degradation of simulation fit for



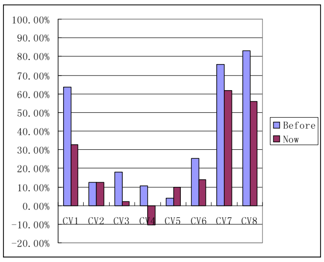
(a) 1-step-ahead prediction fit of KHU



(b) Simulation fit of KHU



(c) 1-step-ahead prediction fit of NHU



(d) Simulation fit of NHU

Fig. 7. Model fit comparison of KHU and NHU

most of the CVs. Especially CV4 of both KHU and NHU show negative simulation fit.

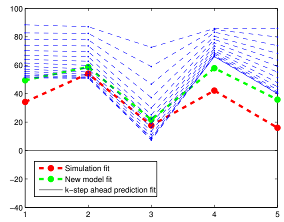
Our experience with 1-step-ahead prediction fit and simulation fit of industrial data leads us to the following remarks:

- 1-step-ahead prediction is not sensitive to either model changes or disturbances. It is actually one step extrapolation which is very easy to achieve even with a bad model.
- Simulation on the other hand, is sensitive to both model changes and disturbance. Good simulation fit is only achieved by a good model. However, even a good simulation model will give poor fit in the presence of disturbances.
- Even when MPC performance is satisfactory, simulation fits are often relatively poor in multivariate industrial data sets because of the presence of disturbances.
- Simulation fit is sensitive to disturbances and therefore it can give false alarm about model quality. For example, CV4 of NHU also has a negative simulation; however our other analysis does not indicate any significant problem with this CV at all. In next sub-section and also in Section 5, we will present that the low simulation fit of CV4 of NHU is mainly because of the effect of disturbances and it is a false alarm.

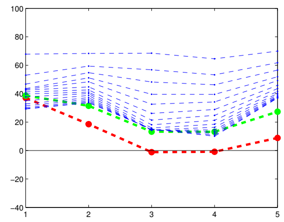
4.3 A New Model Index for Assessment of Model Quality

As discussed in the previous sub-section, the use of prediction or simulation fit alone to evaluate model quality has its pros and cons. In this sub-section, we will explore issues of k-step-ahead predictions and propose a new model index which considers both prediction and simulation ability of a model at the same time.

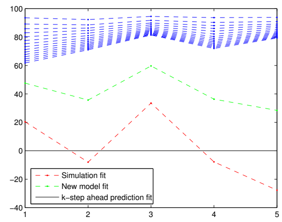
An important concept in MPC control is the *prediction horizon* which defines how far in the future the algorithm has to predict at each control execution. The prediction horizon is an integer number of sampling intervals and the MPC controller will predict the future CV trajectory within the prediction horizon. For example, if the sampling interval is 1 minute and the prediction horizon is 15 minutes, then at each control execution, the MPC controller needs to predict the CV trajectory over the next 15 minutes. Therefore for this example, the MPC controller has to do k-step-ahead prediction with $k = 1, 2, 3, ..., 15$ that is from 1 upto the prediction horizon. The accuracy of the future CV trajectory not only depends on 1-step-ahead prediction fit, but also depends on the k-step-ahead prediction fit. Therefore it is meaningful to compute k-step-ahead prediction fit and compare it with the 1-step ahead prediction fit and the (infinite-horizon) simulation fit.



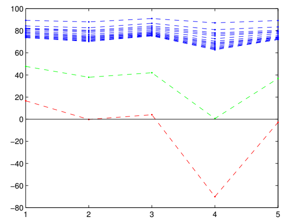
(a) Weekly model fit of CV1



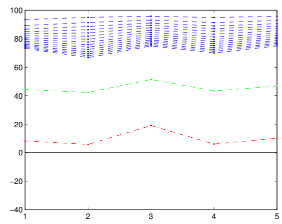
(b) Weekly model fit of CV2



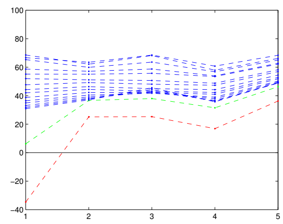
(c) Weekly model fit of CV3



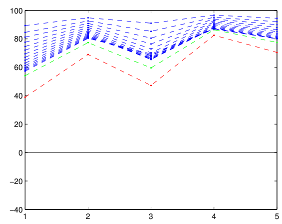
(d) Weekly model fit of CV4



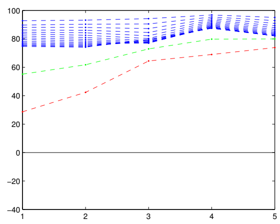
(e) Weekly model fit of CV5



(f) Weekly model fit of CV6



(g) Weekly model fit of CV7



(h) Weekly model fit of CV8

Fig. 8. Recent model fit of NHU model (the y-axis is in unit of %)

Five weeks data of NHU was collected between May to June 2007. We calculated the prediction and simulation fit based on weekly data. The model fits of the CVs are shown in the plots in Figure 8 where the blue lines represent k-step-ahead prediction fits and the red lines represent simulation fits. Here $k = 1, 2, ..., 15$ because the prediction horizon of the NHU MPC is 15 minutes.

One interesting observation from Figure 8(a) and Figure 8(b) is that the k-step-ahead prediction fits of some weeks are even lower than the simulation fit. The k-step ahead prediction fit of CV1 in week 3 (Figure 8(a)) is as low as 7.3% while its 1-step-ahead prediction fit is 72.58% and the simulation fit is 17.62%. This observation once again supports our claim that the prediction ability of a model should not be measured only by 1-step-ahead prediction fit.

From the plots of model fit, we arrive at the following observations based on the NHU process data:

- A good model will have good 1-step-ahead prediction and its k-step-ahead prediction will degrade slowly, such as the case in Figures 8(g) and 8(h). But a bad model with good 1-step-ahead prediction will not have good k-step-ahead prediction. The fit will drop quickly as k increases, such as the case in Figure 8(b).
- If the k-step-ahead fits of a model drop quickly and its simulation is also low, then it is a signature of bad model.
- If the k-step-ahead fits of a model are good, but the simulation is low, we probably still do not need to worry about it because it is quite possible that the low simulation fit is due to the effect of disturbances.
- The simulation fit of CV4 in Figure 7(d) indicates a bad model. However, our experience with simulation fit and prediction fit does not indicate a bad model for CV4. This is because the k-step-ahead predictions of CV4 are consistently good over the weeks and are the best among all 8 CVs. While its simulation fits fluctuate from close to 20% to close to -60%. It is quite possible that the low simulation fit is because of the effect of disturbances. If CV4 had a bad model, we would expect its k-step-ahead predictions to deteriorates quickly as k increases which is not the case here.

Therefore, we can see that the prediction ability of a model may not be as good as the 1-step-ahead prediction fit shows. We should also take the k-step-ahead prediction fit into account to have a complete evaluation of the prediction ability. Our new idea of model index is to include information of 1-step-ahead prediction fit, k-step-ahead prediction fit and simulation fit. The new model index we propose is defined as

$$model\ index = \frac{averaged\ prediction\ fit\ +\ simulation\ fit}{2}$$

where the 'averaged prediction fit' means the average value of k-step-ahead prediction fits ($k = 1, 2, ..., p, where\ p\ is\ the\ prediction\ horizon\ value$).

This model index serves as a measure of both prediction ability and simulation ability of a model. It not only has the advantage of the prediction fit that reduces the effect of disturbances by using the feedback of the CV measurement, but also has the advantage of simulation fit which is sensitive to model change. The green lines in plots of Figure 8 are the values of this new model index.

Our new model quality index for NHU MPC controller is calculated based on initial step test data and recent process data. The comparison between the initial model quality and recent model quality is shown in Figure 9.

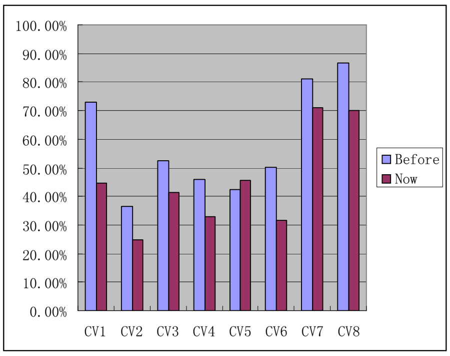


Fig. 9. New model index value of NHU model

The new model index values show that most of the models have degraded except the model for CV5. The worst model is the one for CV2. This makes sense because the model for CV2 not only has low 1-step ahead prediction fit (around 70%) and low simulation fit, its k-step-ahead prediction fits also deteriorate quickly as k increases. The new index does not indicate any problem for CV4 which matches our expectation. Overall, we did not find any particular model that has a significant problem.

Results for KHU model are omitted due to lack of space.

5. MODEL IDENTIFICATION USING ROUTINE OPERATING DATA

Zhu (1998) has introduced the asymptotic method (ASYM) for identification of multivariable processes. The ASYM method is especially efficient in identifying models for MPC controllers. Besides identification, the ASYM method also validates models. The identified models are graded A (very good), B (good), C (marginal) and D (poor, or, no model exists). In this section, we use the ASYM method to re-identify the models of KHU and NHU using routine operating data. The software used is the Tai-Ji Module of the CPM product from Matrikon Inc. (*Matrikon Inc., Tai-Ji Multivariable Identification Package*, 2007)

The KHU MPC controller was turned off for 1 week in November 2006. During that period, operators at Suncor manually changed the MVs from time to time in order to keep the process within the safe operating range. This week of data was used to identify the model of KHU using the ASYM method. The results are shown in Figure 10. The blue lines represent the original model used in the MPC and the red lines represent the newly identified model with A or B grade. The models with C or D grade are not shown. If there is no model between a CV and a MV, we omit that plot. In Figure 10, we observe significant changes in the models for CV2 & MV3, and CV4 & MV2 where the model gain has changed from negative to positive. Gain mismatch is also observed in models for CV1 & MV1, CV3 & MV3 and CV5 & MV2. Overall, the model of KHU has changed considerably and re-identification of the process is recommended.

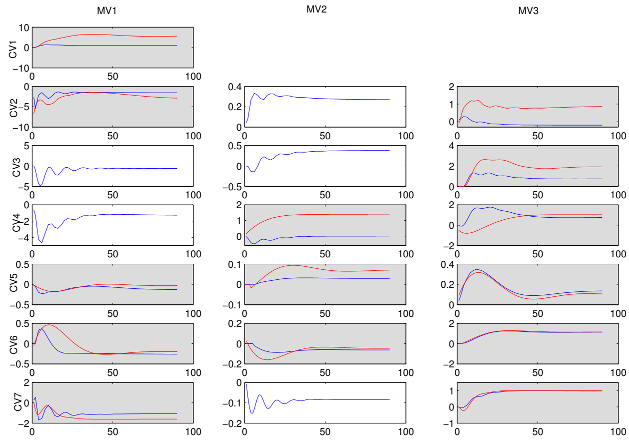


Fig. 10. KHU model

For NHU, we performed closed-loop identification using the routine operating data with MPC on. The results are shown in Figure 11. In Figure 11, we see some gain mismatches, but the overall dynamics of the models are close to their original ones. We do not see significant mismatches for the NHU models. Especially for CV4, the newly identified models are close to the original ones. This again indicate that the negative simulation fit of CV4 in Figure 7(d) is a false alarm.

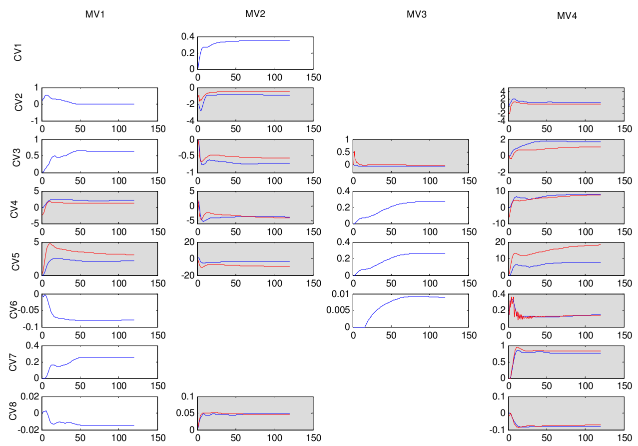


Fig. 11. NHU model

6. CONCLUDING REMARKS

This paper has assessed the performance and the model quality of two industrial MPC controllers. Analysis shows that the performance of the KHU MPC controller was less than optimal. There are two main reasons why the KHU MPC performance was less than optimal. The first reason is because the limit settings for the MVs and CVs are overly restrictive, but possibly for valid reasons. The MPC computations have the MVs reach the limits set by the designers before it can achieve the control objective for each CV. The second reason is that one of the PID controllers in the unit could not perform well. Because of this the CV related to this PID controller was out of limit from time to time.

The performance of the NHU MPC controller was acceptable. Compared to manual control, the MPC greatly reduced the variance in most of the CVs and transferred the variability to a temperature loop where the plant can afford to have it. During the period that MPC was on, the MVs and CVs were within their limits most of the time. Some of the CVs were operating at their limits and this indicates that the MPC controller was performing optimization to achieve the performance it could. There is also some room for improvement and we have suggestions for improving this level of control.

A new model index based on k-step-ahead prediction and simulation was introduced. Its advantage over 1-step-ahead prediction fit and simulation fit were also discussed. Identification of KHU and NHU using routine operation data were performed using the ASYM method.

7. ACKNOWLEDGEMENT

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