Model Performance Assessment of a Predictive Controller for Propylene/Propane Separation

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Abstract: This paper presents the results of the model assessment performed on an industrial predictive controller applied to a propylene/propane separation system at Braskem, in Brazil, using the methodology proposed by Botelho et al. (2015a, b, c). Besides identifying the controlled variables with modelling uncertainties that were degrading the controller performance, the methodology diagnosed the main cause of the problem, which was related to model-plant mismatch for seven controlled variables, and due to the effect of unmeasured disturbances for other three controlled variables. This diagnosis enabled a more focused approach to the identification work, increasing the productivity of the controller revamp.

Keywords: Control applications, Model Based Control, Modelling and System Identification.

1. INTRODUCTION

Model Predictive Control (MPC) is a mature technology and it has become the standard approach for implementing constrained multivariable control applications in the industry (Darby and Nikolaou, 2012). However, the success of each application is strongly related to sustaining the controller performance through the application lifecycle (Huang et al., 2000).

Obtaining good input-output and disturbance models is the core of an MPC project. Nevertheless, due to the lack of model assessment tools, model maintenance of a controller with degraded performance generally involves identifying the whole plant, leading to high maintenance costs (Sun et al., 2013).

This work presents the case study on the performance assessment of the model of a linear dynamic matrix controller (DMC) applied to a propylene/propane fractionation system of a Braskem’s naphtha steam cracker site in Brazil, employing the methodology proposed by Botelho et al. (2015a, b, c). The method complements the current controller revision workflow used by Braskem during the quality evaluation of the current model, as well as in the problem diagnosis, guiding the actions towards the application enhancement.

The main contribution of the present work is the description of the successful model performance assessment of an industrial MPC controller of considerable size applied to a non-square plant. For such controller, most of the dependent variables are controlled within ranges.

According to Botelho et al. (2015a), the proposed methodology showed improved results when compared with the methods developed by Sun et al. (2013) and Yu and Qin (2008a, b) for a control strategy containing variables controlled within ranges. Also, the application of the methodology to another industrial controlled is discussed at Botelho et al. (2015d).

This work is organised as follows. The performance assessment methodology is presented in Section 2. Section 3 describes the industrial plant. The performance assessment results and controller improvements are presented in Section 4. Finally, the conclusions and suggestions for future work are summarized in Section 5.

2. METHODOLOGY

This section presents the methodology employed for the model performance assessment of the controller, which is fully described in Botelho et al. (2015a, b, c).

2.1 Model Quality Evaluation

The first stage of the performance assessment method employs the nominal output sensitivity function of the system (S0) to identify the controlled variables (CVs) with modelling problems that are effectively impacting the closed loop performance.
Figure 1 shows a general process under MPC control, where \( C(s) \) is the controller, \( G_0(s) \) is the identified process model (nominal model), \( y_{set} \) corresponds to the controlled variables' setpoints, \( T_0 \) is the nominal closed-loop model, and \( y_0 \) is the vector of nominal controller outputs.

![Schematic diagram of a closed-loop nominal system](image)

**Fig. 1. Schematic diagram of a closed-loop nominal system (Adapted from Botelho et al. (2015a)).**

For the system at Figure 1:

\[
\begin{align*}
  y_0 &= T_0 \cdot y_{set} \\
  T_0 &= (1 + G_0 C)^{-1} G_0 C \\
  S_0 &= (1 + G_0 C)^{-1} \\
  S_0 + T_0 &= I 
\end{align*}
\]

Botelho et al. (2015b) demonstrated that the nominal closed loop output of the system, \( y_0(s) \), can be calculated through the nominal sensitivity function, \( S_0(s) \):

\[
y_0 = S_0 \cdot \left( y_{sim} - y \right) + y 
\]

In equation (5), \( y_{sim} \) corresponds to the simulated output of the nominal model perturbed by the matrix of control actions, \( u \), and \( y \) is the vector of the measured controller outputs. \( S_0 \) works as a filter for the simulation residuals (\( y - y_{sim} \)), retaining the simulation error that is not compensated by the controller feedback action. It is usually computed by using \( T_0 \), which can be identified with a step test of the controller on a simulation environment, and equation (4).

The nominal sensitivity function provides a complete diagnosis of the model, highlighting not only the effect of the model uncertainties in the corresponding output systems (through \( S_0 \) diagonal elements), but also how one output impacts the other variables (through the off-diagonal elements).

Badwe et al. (2010) proposed the variability ratio index to compare the observed variability with the variability that would have been observed in the perfect model case under the same conditions. Similarly, Botelho et al. (2015a) proposes the identification of controlled variables with relevant modeling problems by calculating the \( I_{var} \) indicator:

\[
I_{var} = \frac{\text{var}(y - \bar{y})}{\text{var}(y_0 - \bar{y}_0)} .
\]

This indicator employs the ratio of variances between the measured output \( y \) and the nominal closed output \( y_0 \), both with respect to the average value of the period, to quantify the discrepancy between the current plant dynamics and the controller nominal model. According to Botelho et al. (2015a), an acceptable model should have \( I_{var} \) varying between 0.8 and 1.2.

### 2.2 Diagnosing the main source of modelling problem

Model uncertainties can be caused by a difference between the current process dynamics and the identified model (Figure 2a), as well as by unmeasured disturbances, as represented by \( y_d \) in Figure 2b. The second part of the assessment methodology consists of diagnosing the dominant source of model uncertainties, through the comparison of the nominal error, \( e_0 \), with the nominal controller output, \( y_0 \).

The nominal error, \( e_0 \), represents the effect of modeling problems in the closed loop, and it is defined by:

\[
e_0 = y_0 - y .
\]

**Fig. 2. Schematic diagram of a closed-loop system. (a) With model-plant mismatch (AG(s)) and (b) with unmeasured disturbances (y_d). Source: Botelho et al. (2015c).**

Botelho et al. (2015c) demonstrated that \( e_0 \) can be expressed by (8) when the dominant source of problem is related to model-plant mismatch (MPM). In this case, both \( e_0 \) and \( y_0 \) will be dependent on \( y_{set} \), and their frequency of variation will be correlated. On the other hand, when the process is affected by UD, \( e_0 \) can be expressed by (9), showing that it is not correlated to \( y_0 \).

\[
e_0 = (T_0 - T)y_{set} \\
e_0 = -S_0 y_d
\]

Considering that the objective of the diagnosis of this stage of the assessment is to distinguish the effect of MPMs from UDts, the method proposes computing \( y_0 \) using only the diagonal elements of \( S_0 \). The indicator proposed to quantify the correlation between \( e_0 \) and \( y_0 \), called \( CO_{dZ} \) is defined as the average of the absolute value of the correlation between the statistical distributions of interest for different sizes of moving windows (MW). These sizes vary from half to twice the length of the prediction horizon (\( ph \)):

\[
CO_{dZ} = \frac{\sum_{MW=0.5ph}^{2ph} \text{var}(y_d^{MW})}{n_{MW}} .
\]

In equation (10), the correlation calculated for each size of moving window, \( CO_{dZ}^{MW} \), corresponds to the coefficient of Pearson (\( p \)) of the derivative of the statistical indicators selected for reference, \( Z \):
The statistical distributions proposed as reference ($Z$) are the skewness ($skn$) and kurtosis ($kts$) coefficients, expressed by:

\[
skn_{Xi}^{MW} = m_3 / \left( \sqrt{m_3^3} \right), \quad (13)
\]

\[
kts_{Xi}^{MW} = m_4 / \left( \sqrt{m_2^4} \right), \quad (14)
\]

where the variables $m_2$, $m_3$, and $m_4$ correspond, respectively, to the second, the third, and the fourth order central moments, defined by (15).

\[
m_l = \frac{\sum_{i=1}^{MW} (X_i - \bar{X})^l}{MW}, \quad l = 2, 3, 4, \quad (15)
\]

where $X_i$ is the distribution of interest ($y_0$ or $e_0$) and $\bar{X}$ is the distribution’s mean along the moving window. According to the methodology, the main source of model uncertainties will be considered unmeasured disturbances only if both indicators based on skewness and kurtosis are below 0.1.

### 3. INDUSTRIAL PLANT DESCRIPTION

Figure 3 shows a simplified diagram of the propylene/propane separation system and its respective MPC structure. It comprehends three distillation columns, and its main feed, known as hydrogenated C3 cut, consists basically of propylene and propane. The main purpose of T01 is to specify the chemical grade propylene, a stream containing 92% to 96% of propylene on volume basis, by removing heavier components with the bottoms flow and recycling lighter components to the compression section of the plant.

![Fig. 3. Simplified process diagram of the propylene/propane fractionation system.](image)

Table 1. Description of the MPC variables.

| Variable | Description | Engineering Units |
|----------|-------------|-------------------|
| MV1      | T01: internal reflux flow setpoint | t/h |
| MV2      | T02: feed flow setpoint | t/h |
| MV3      | T03: feed flow setpoint | t/h |
| MV4      | T02: temperature compensated reflux flow setpoint | t/h |
| MV5      | T02: bottoms flow setpoint | t/h |
| MV6      | T02: column pressure setpoint | kg/$cm^2$ |
| MV7      | T03: reflux flow setpoint | t/h |
| MV8      | T03: bottoms flow setpoint | t/h |
| DV1      | T01: feed flow setpoint | t/h |
| DV2      | T02: supplementary feed flow | t/h |
| DV3      | T01: propane content in the feed | % mol |
| DV4      | T03: supplementary feed flow | t/h |
| CV1      | T01: accumulator drum level | % |
| CV2      | T01: column ΔP | kg/$cm^2$ |
| CV3      | Difference between T02 and T03 main feed flows | t/h |
| CV4      | Total propylene in bottoms flows (T02 + T03) | t/h |
| CV5      | T02: propylene impurities content | ppm mol |
| CV6      | T02: propylene content in the bottoms flow | % mol |
| CV7      | T02: column ΔP | kg/$cm^2$ |
| CV8      | T02: pressure controller output | % |
| CV9      | T02: (overhead – reflux) ΔT | °C |
| CV10     | T03: propylene impurities content | % mol |
| CV11     | T03: propylene content in the bottoms flow | % mol |
| CV12     | T03: column ΔP | kg/$cm^2$ |
The chemical grade propylene leaves T01 through a side withdrawal and is sent to the propylene/propane separation columns, T02 and T03, which operate in parallel. Occasionally, T02 and T03 can process supplementary feeds, identified as Feed 2 and Feed 3 in Figure 3. Polymer grade propylene, with a minimum propylene content of 99.5% (on volume basis) is produced in the overhead section of columns T02 and T03. The propane rich bottoms flows from both columns are sent to storage.

The MPC application is a linear Dynamic Matrix Controller (DMC) developed on commercial software package. The controller has eight manipulated variables (MVs), four disturbance variables (DVs) used for feedforward actions, and twelve controlled variables (CVs), which are identified in Figure 3 and described at Table 1. It operates at the supervisory level, sending setpoints to PID controllers running at the digital control system (DCS).

The application is organised in three sub-controllers, one for each column. All CVs are controlled within ranges, except for CV1, which is an integrating variable and is controlled with a setpoint. The MPC controller operating limits for both MVs and CVs are updated by operators according to business policies and plant constraints.

4. RESULTS AND DISCUSSION

Figure 4 shows a block diagram of the workflow used for the controller performance assessment, identification work and evaluation of the new models before commissioning the updated controller.

The $S_0$ determination and the historical data collection for the assessment are the key steps to obtaining reliable results in the assessment, as they will be used to generate the nominal controller output ($y_0$). $T_0$ was identified using the MPC controller simulation software, which is normally used simulate the control strategy and tune the controller.

The case studies consisted of simulating the controller response to changes in the upper and lower limits of all CVs, while avoiding the MVs saturation. This strategy allowed generation of the data needed to identify $T_0$.

Next, the historical data collection for the performance assessment consisted of using a process trending tool to select periods of data for which the plant had stable performance (without significant process disturbances) for a period of at least sixty hours, which corresponds to three times the length of time to reach the steady state.

Figure 5 displays the plot of the measured ($y$), nominal ($y_0$) and simulated ($y_{sim}$) controller outputs for the controlled variable number eight (CV8), using the dataset for the second period of the assessment. DMC controllers have a certain degree of robustness to modelling errors, due to the smooth response that results from the plan of small movements for the manipulated variables (Qin et al., 2003). This figure confirms this information by showing that the nominal error ($y_0-y$) is usually smaller than the simulation error ($y_{sim}-y$).

As $y_0$ can filter the modelling problems attenuated by the feedback controller action, it constitutes a more interesting reference than $y_{sim}$ for evaluating the impact of model quality in the controller performance.

Figure 6 shows the results of the model quality evaluation (first stage of the performance assessment). Each bar corresponds to the average $I_{avr}$ indicator for the respective assessed period. The variability of $I_{avr}$ for each CV highlights the importance of performing the assessment at different plant conditions for a more consistent analysis. The variability of results among CVs shows that the magnitude of the modelling uncertainties is not the same for all the variables, corroborating with the idea of ranking the variables in order to limit the scope of the controller revamp.
The controlled variables to be evaluated in the second stage of the assessment were selected based on the average of the $I_{var}$ indicator for the three periods. This criterion eliminated CVs 3 and 11 from the analysis, because the average of $I_{var}$ remained within the reference limits ($0.8 \leq I_{var} \leq 1.2$). All other CVs were evaluated in the second stage of the assessment.

Figure 7 shows the results of the second stage of the controller assessment. The correlation indicators between $e_0$ and $y_0$ correspond to the average of the three periods. Considering the reference limit for determining the dominant modelling problem, CVs 5, 7, and 10, are the ones mainly affected by unmeasured disturbances. The main problem of the other controlled variables is related to the discrepancy between the model and the actual plant dynamics.

It is also important to point out that both statistic coefficients proposed for comparison (skewness and kurtosis) provided consistent diagnosis for all the variables. In the case of CV2, for which the indicator based on skewness diagnosed MPM, whereas the indicator based on kurtosis diagnosed UD, the methodology suggests that the result of one indicator suffices for the MPM diagnosis.

The identification work was performed in the native modelling environment of the controller software, using state subspace methods and historical process data available at the process information management system.

For the variables dominantly affected by model-plant mismatch problems (CVs 1, 2, 4, 6, 9 and 12), the identification was carried out using the same manipulated and disturbance variables of the original models. For variables 5, 7, and 10, diagnosed as mainly affected by unmeasured disturbances, a study was conducted to include models with additional variables, considering additional channels of the existing controller matrix, as well as the addition of external variables to the controller.

During the identification stage, an analysis of the historical data of CV8 showed it was not the best variable to represent the constraint. For this reason, it was excluded from the assessment.

After the identification work, the performance assessment was repeated in order to evaluate the impact of the new models in the controller's performance. Besides, the new assessment was performed using the same $S_0$ function used in the controller's audit.

Figure 8 shows the comparison between the controller's model quality evaluations using the original and the updated models. The identification of CVs 1 and 6 placed both variables in the discrepancy allowable range. Also, a significant improvement was observed for CVs 2, 5, and 10, which presented significant reduction on the $I_{var}$ indicator. The results also suggest that the controller performance with the new models for CVs 9 and 12 will not improve, because $I_{var}$ indicator is farther from the desired range than with the original model.
Figure 9 shows the results of the second stage of the controller’s performance assessment with the new models. The reduction on the skewness and kurtosis indicators observed when comparing Figures 7 and 9 shows the efficiency of the performed identification.

Fig. 9. Correlation results between $e(t)$ and $y_d$ based on kurtosis and skewness statistics for the controlled variables evaluated in the re-audit of the controller.

The diagnosis of unmeasured disturbances for CVs 2 and 12 suggests that although the identification work was effective at reducing the MPMs, these CVs are also affected by unmeasured disturbances. Finally, the controller was updated in the production environment and is running with improved performance.

5. CONCLUSIONS

The present work proved that the methodology for performance assessment of multivariable controllers working with variables controlled by ranges proposed by Botelho et al. (2015a, b, c) can be used to complement the scope of revamp projects for existing controllers, limiting the remodelling effort to only the controlled variables whose modelling uncertainties are degrading the controller performance.

It is a consistent method that can be successfully adapted to industrial DMC controllers, which usually contain the variables that are controlled within ranges.

The methodology also allows comparing the controller performance using the old and new models employing the same dataset collected for the assessment. This is an advantage in relation to the traditional identification work, because it empowers the engineer with information other than the prediction error on the impact of the new model before commissioning the updated controller.

As a complementary work, it is suggested that the performance assessment of the controller with the new models should be evaluated using an $S_0$ function computed based on the new controller matrix. The comparison of these results with the ones presented in this work could be used to investigate the impact of updating $S_0$.

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