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Improvement of model predictive control on a depropaniser: an industrial case study

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Abstract: In this work, improvements to a model predictive controller in an industrial facility is presented. A depropaniser column used to separate propane and propylene from heavier components was experiencing sporadic process instabilities which was impacting product purities. A soft sensor to measure C_4 hydrocarbons was inaccurately predicting the actual composition, which caused the controller to behave erratically. A simple linear regression implementation improved the accuracy of the soft sensor significantly, which allowed further optimisation of the controller. Large benefits in process stability and propylene recovery were observed.

Keywords: model predictive controller, depropaniser, inferential, soft sensor, industrial case study

1. INTRODUCTION

The use and applications of model predictive controllers have grown significantly since its inception (Qin and Badgwell, 2003). These controllers provide process improvements at comparatively low capital cost (Bauer and Craig, 2008). The use of soft sensors to infer process variables which are not measured or infrequently measured have also become more prevalent (Fortuna et al., 2005, Küsel et al., 2020, Pani et al., 2016).

However, the performance of model predictive controllers can become ineffective due to changing process conditions, which can lead to operator intervention through switching off the controller or limiting variable movement, which ultimately translates into sub-optimal control.

In this paper, an industrial case study of improvements to a model predictive controller on a depropaniser distillation column is presented.

2. PROCESS AND CONTROL DESCRIPTION

2.1 Process description

The depropaniser receives feed from various upstream units. The feed consists of a mixture of propylene, propane and heavier hydrocarbons. The intent of the depropaniser is to separate propane and propylene from the mixture, while minimising propylene losses to the bottoms of the column. The feed enters the column on tray c. Heavier hydrocarbons report to the bottoms, while propane and propylene report to the side draw, which is extracted from tray e. The overheads of the column is condensed and refluxed on the top tray f.

The feed rate to the column is dependent on the upstream units, but the intent is to maximise the feed rate up to the design feed rate. The bottoms level in the column is controlled by bottoms flow rate, while the heating medium flow rate to the reboiler is controlled by the column pressure controller. The side draw flow rate is controlled by a ratio controller, which ratios the feed rate and the side draw flow rate. There is an online gas chromatograph on the side draw which measures the concentration of C_4 hydrocarbons. Samples are taken on the feed and the bottoms stream to measure the composition.

The overhead pressure is controlled by the overhead flow rate, while the reflux drum pressure is controlled by the hot vapour bypass. The level in the reflux drum is controlled by the reflux flow rate.

2.2 Control description

The depropaniser is equipped with a model predictive controller to optimise the process control objectives. The controller has several controlled variables and manipulated variables, each with low and high limits. The controlled variables are:

- C_4 concentration in the side draw
- Column pressure
- Bottom temperature
- Reboiler flow rate
- Reboiler valve opening
- Side draw valve opening

The C_4 concentration is used as a control variable and has an optimisation objective function to target. The aim is to maximise the C_3 extraction by operating the C_4 specification as close to the specification limit as possible.

The other controlled variables are all constraint variables with the bottoms temperature being the constraint that is predominantly active.

The manipulated variables are:

- Side draw to feed ratio
- Column differential pressure

The C_4 content in the side draw was estimated using a mathematical equation.

$$x_{C_4} = \beta_0 + \beta_1 P + \beta_2 T_e \quad (1)$$

Where x_{C4} is the concentration of C_4 components in the side draw, P is the column pressure, T_e is the tray e temperature, and $\beta_0, .., \beta_2$ are regression coefficients.

The advantage of using an estimated C_4 concentration is that the update frequency of the reading is near continuous which then allows for continuous optimisation of the side draw flow. In this application the C_4 analyser does update quite frequently, but the inferential still provides a slight advantage in predicting the C_4 content before the analyser reports the concentration.

3. PERFORMANCE EVALUATION

Large propylene losses to the bottoms of the column were experienced, even though the efficiency metrics indicated satisfactory performance. The propylene losses were inferred by frequent drops in the bottom temperature of the column. The propylene composition in the bottoms of the column is measured every 24 hours by taking a sample of the stream and performing gas chromatography analysis in the laboratory.

Troubleshooting revealed that the calculated C_4 concentration in the side draw varied greatly from the analyser value (see Figure 1). Since the side draw to feed flow ratio is used to control the C_4 concentration, the side draw flow rate was erratic, which caused major process instabilities in both the temperature profile and flow rates (see Figure 2).

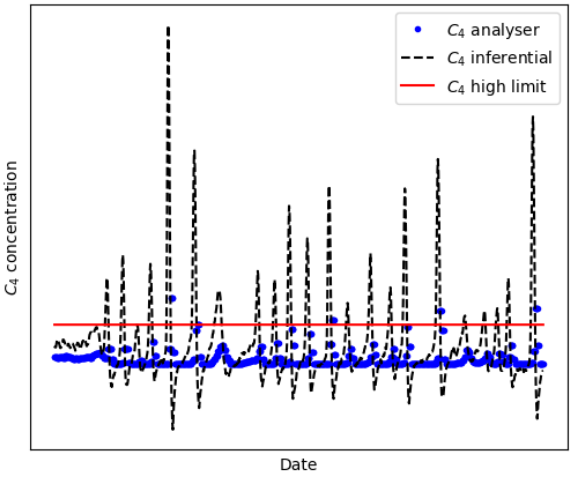

Figure 1: C_4 concentration (analyser and calculated value)

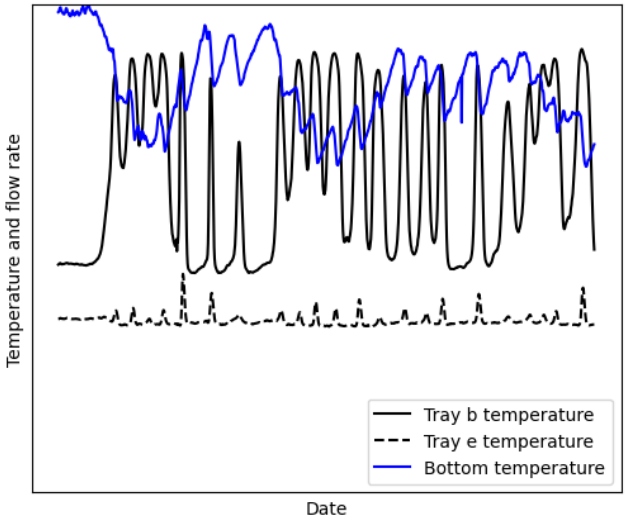

Figure 2: Tray b and e temperatures and side draw flow rate

Carry-over of C_4 components above the specified limit to the side draw is unwanted, since it impacts the downstream product quality. Operators would therefore intervene by limiting the side draw flow rate, or by dropping it completely from the controller. When the model predictive controller aimed to increase the side draw flow rate, it could not increase past the high limit. Insufficient extraction of propylene would occur, and propylene would report to the bottom stream, thereby decreasing the bottom temperature. This is shown in Figure 3. Discussions with the operators were invaluable to understand the shortcomings of the controller from their perspective.

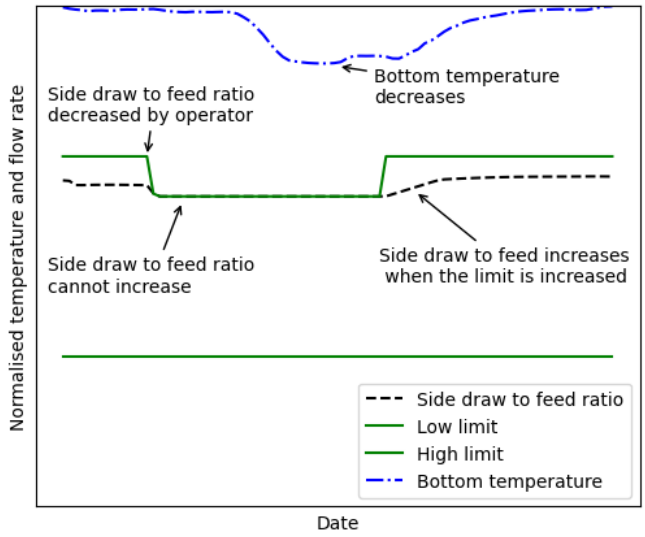

Figure 3: Side draw limit decreased causing a drop in the bottom temperature

4. IMPROVEMENTS

4.1 Updated calculation of C_4 concentration

Figure 4 shows the design temperature profile of the depropaniser, which was further verified by process simulation to match plant data. It clearly indicated that the temperature profile at tray e is less sensitive to composition changes when compared to tray b, indicating a need for a new mathematical formula to be developed to better approximate the C_4 concentration.

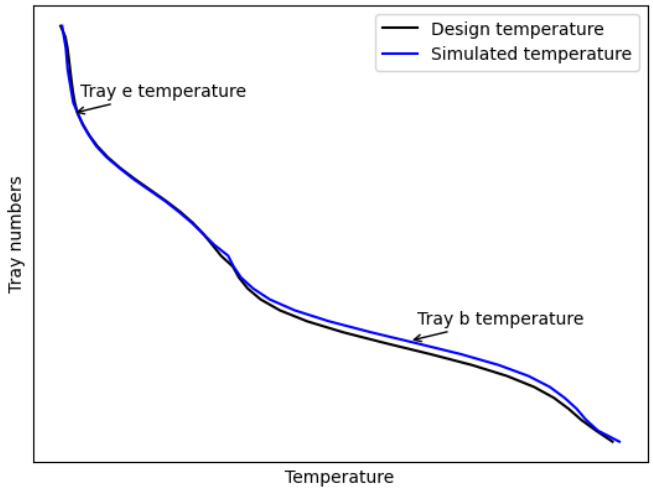

Figure 4: Temperature profile

The development of the new formula included:

- The selection of new process variables that are good predictors of the side draw C_4 composition.
- Implementing lag functions between the selected process variables and the side draw C_4 component composition into the new formula. This is needed to account for timing differences inherent in the process dynamics of a distillation column.

4.2.1. Selection of new variables

The process variables that were used as the features for the new calculation were selected from insight that was obtained from the process plant operators and the application of the domain knowledge that exists for distillation column operation. Six variables were tested, which were further reduced through the identification and removal of cross correlating variables. This was achieved by specifying a cross correlation threshold for Pearson's correlation coefficient of 0.9 and selecting the feature with the strongest correlation. This resulted in a reduced feature set of 4 process variables. These are:

i. The reflux flow rate
ii. The column pressure
iii. Tray b temperature
iv. Tray e temperature

4.2.1. Determination of values for process lag

Analysis of the historised model predictive controller parameters and process data showed that there was a lag in the response of the C_4 composition with respect to changes in the measurements of the selected process variable features. An estimate of the process lag was determined by performing a process delay shift for each of the process variables and selecting the lag that resulted in the highest Pearson's correlation coefficient relative to the C_4 composition. The results for this analysis is presented in Figure 5.

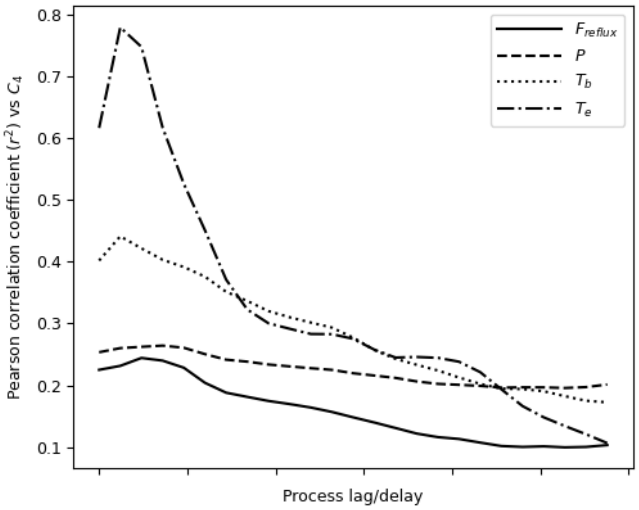

Figure 5: Effect of process lag on the r^2 of the features used for estimating C_4 composition

The results show that a stronger correlation was achieved for all the process variables with respect to the C_4 composition when compensating for process lag.

4.2.3. Final calculation

The new calculation, shown in equation (2), is still a linear approximation, but provided a more accurate estimation due to the feature selection approach that was implemented, together with the compensation for process lag.

$$x_{C_4}(t) = \beta_0 + \beta_1 F_{reflux}(t - t_{D1}) + \beta_2 P(t - t_{D2}) + \beta_3 T_b(t - t_{D3}) + \beta_4 T_e(t - t_{D4}) \quad (2)$$

Where $x_{C_4}(t)$ is the composition of C_4 components at time t, F_{reflux} is the reflux flow rate, P is the column pressure, T_b is the tray b temperature, T_e is the tray e temperature, $\beta_0, .., \beta_4$ are regression coefficients, and $t_{D1}, .., t_{D4}$ are the process lag/delay between the C_4 composition and the respective process variables. The test dataset comparison between the actual and predicted C_4 composition for the new calculation is presented in Figure 6.

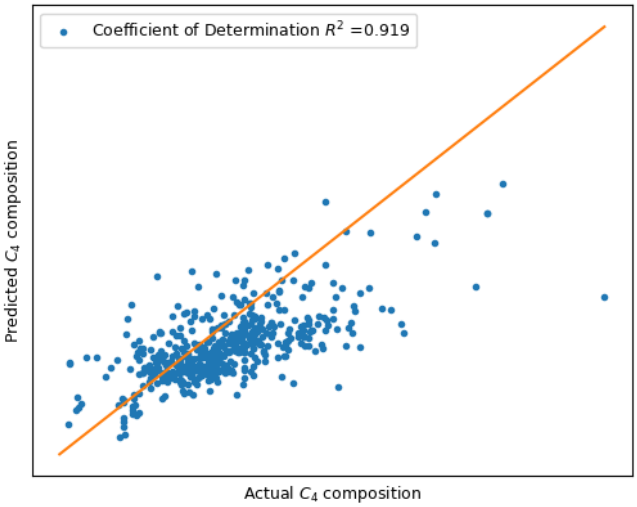

Figure 6: Parity plot comparing the test data set actual vs predicted C_4 composition for the new calculation

This comparison shows that the new calculation achieves a coefficient of determination R^2 value of 0.919. The simplified mathematical equation was more than adequate to predict the C_4 content in the side draw. More complex methods would have been considered if this simplified approach did not display acceptable performance.

The new calculated composition was much more accurate compared to the previous method, as shown in Figure 7. This allowed the controller to quickly find the optimal side draw to feed ratio which resulted in more stability and less process fluctuations. There was also less operator intervention required. The model presented here is contrasted with work done by (Küsel et al., 2020), which used first principles to derive the C_5 composition in a debutaniser column, and with (Pani et al., 2016), who also used a linear equation, but applied principal component analysis on the variables, whereafter the composition was predicted. For this application, it was found that the simple linear model provided satisfactory performance.

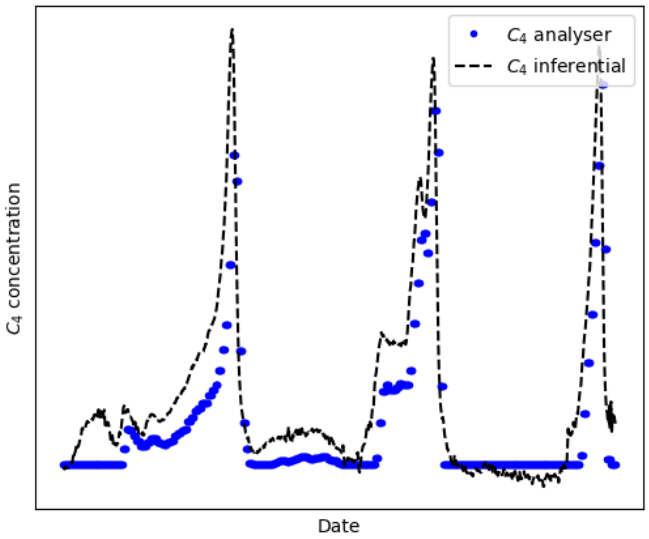

Figure 7: C4 composition (analyser and calculated value) after the new calculation was implemented

Figure 7 also shows that the inferential seems to lead the analyser result. This could potentially be due to the inherent delays present in the time it takes the analyser to complete its analysis of the samples taken.

4.2 Tuning and other improvements

Tuning of the controller was also done to ensure more gradual moves when the controller makes changes to the manipulated variables.

The amount a controlled variable is allowed to deviate from the limits can be changed – previously the limits for the bottom temperature was not stringent enough, causing the bottom temperature to be allowed to decrease, leading to propylene losses. Therefore, the prioritisation of keeping the bottom temperature within the specified limits was also increased.

5. RESULTS

5.1 Bottom temperature

The bottoms temperature, which is used as a proxy for the propylene content in the bottoms, is shown in Figure 8. The variability in the bottoms temperature has improved dramatically, leading to an increase in propylene extraction and financial improvements.

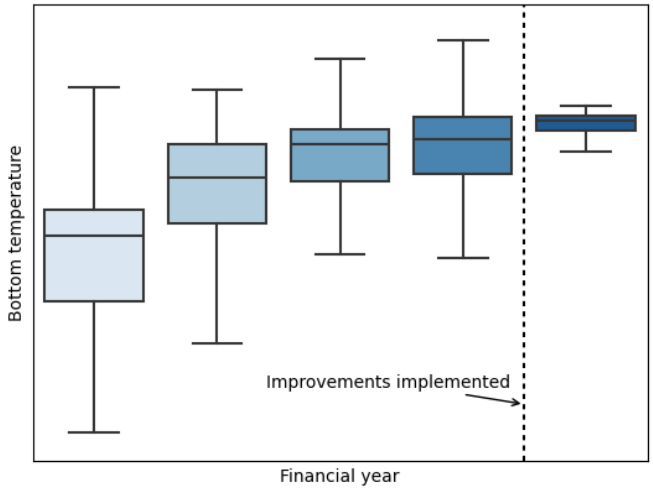

Figure 8: Boxplot of bottoms temperature for different financial years

5.2 Propylene recovery

The propylene recovery, as calculated from flow rates and sample results, is shown in Figure 9. The propylene recovery results lack granularity since the sample results are not as frequently updated as an online measurement, but still shows a significant improvement compared to previous years.

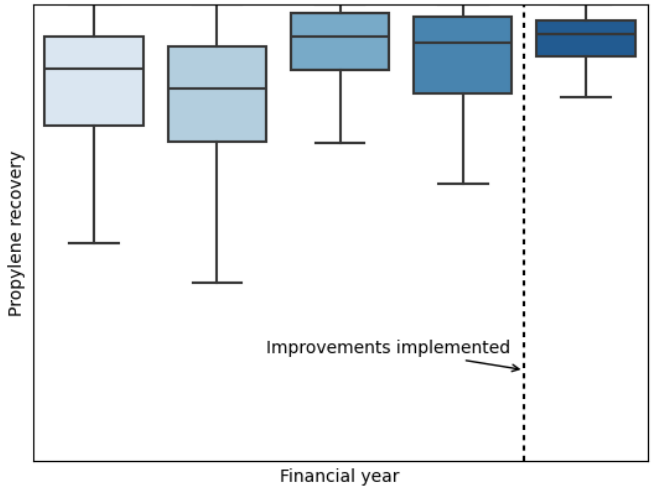

Figure 9: Propylene recovery for different financial years

6. CONCLUSIONS

Continuous monitoring, specifically the status of controlled variables and the limits as specified by the operator, was critical in troubleshooting problems with the model predictive controller.

The new mathematical equation to calculate the C_4 concentration in the side draw was a simple linear function, but proved effective to enable process improvement in the form of improved propylene recovery. Variable selection, such as choosing a tray temperature that is sensitive to composition changes, and adding process lags, improved the accuracy of the calculation. Together with tuning and prioritisation of the bottoms temperature, process improvements and financial benefits were observed.

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