Improved Bleach Plant Control Using Internal Model Control with Smith Predictor

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Abstract—This paper presents the improved control of a benchmark pulping process. Open-loop tests were conducted to obtain a multiple-input multiple-output process model in the form of transfer function matrices. Using this model, the best set of input-output pairings was selected by using relative gain array (RGA) and relative disturbance gain techniques, both in static and dynamic modes. These analyses confirmed the setting provided by the authors of the Benchmark, based on static RGA analysis. Controller settings for each control loop were calculated using different internal model control (IMC) tuning methodologies and the best set of controller parameters was chosen by evaluating the control system performance for set-point tracking and disturbance rejection in terms of the integral of absolute error, settling time, time constant and percentage of overshoot. PI controllers combined with Smith-predictors, and tuned with IMC, providing the set-points of the Kappa factor controllers related to the quality variables of the process and PI-only controllers tuned using IMC controlling the secondary variables give the best control performance. Smith predictors allow the controller designer to provide to the process controllers larger controller gains and smaller reset times, making the controlled response faster. Their ability to provide estimations of the process measurements when the real measurements are not available was especially useful in this process due to its large time delays.

I. INTRODUCTION

CASTRO and Doyle [1] presented a detailed control study of the fiberline of a pulp mill process. The process model consists of a set of equations with approximately 5000 states to capture the dynamics of the main unit operations: pulp digester, oxygen reactor, bleach towers, washers, and storage tanks. Heuristic methods were used to determine the primary control variables and relative gain array (RGA) analysis was performed to obtain the input-output pairings for decentralized control. The performance of model predictive control and decentralized single-input single-output control were compared, finding that the MPC offers a better framework when controlling the digester but no big differences between both techniques were found when controlling the bleach plant. Vanbrugge et al. [2] recalculated the RGA of the bleach plant and proposed a real-time optimization algorithm based on a modified version of an IMC-based optimization method. The performance was improved by on-line estimation of the process parameters and the total cost of the bleaching section was reduced by 10.6%. In 2004, Castro and Doyle [3] introduced a benchmark problem of a pulping process, including both the fiber line and the chemical recovery sections. The complete details of the pulp mill process were given, as well as the control objectives, modes of operation, process constraints, measurements and costs. The dynamic model, including the source/binary code of all the unit operations was made available to the process control community as a benchmark for its use in process system engineering studies. The benchmark also provides code for different controller structures, such as PID and MPC, including other decentralized advanced tools like feedforward controllers and Smith predictors.

Since its introduction, RGA has been a very important tool for determining the best input-output pairings for decentralized control. However, there are many control practitioners who doubt about its usefulness in some control applications because it does not include the effects of disturbances. Stanley et al. [4] proposed a new measurement, called relative disturbance gain (RDG) in order to include disturbances when selecting the input-output pairings. There is not an explicit study of RGD in the bleach plant supporting and confirming the proposed input-output pairings obtained using RGA or dynamic RGA. It should be therefore necessary to demonstrate that the input-output pairings given by Castro and Doyle [1] are suitable in the bleach plant in terms of disturbance rejection performance.

II. THE BLEACH PLANT

The main objective of the bleach plant is to remove lignin from the pulp and to obtain an appropriate brightness coefficient. This objective is achieved by using bleach towers, where the pulp is mixed together with oxidizing chemicals which make the lignin to be soluble in water. Fig.
1 shows a schematic of the bleaching plant considered by Castro and Doyle [3].

Fig. 1. Bleach plant flowsheet

After storage, the pulp is subjected to three bleach stages. The bleach towers are vertical cylindrical vessels. The pulp moves vertically in plug flow. Each tower has auxiliary equipment such as a chemical mixer, a washer and a seal tank.

The washer is mounted in the bleach tower exit and it is used to eliminate dissolved chemicals from the pulp. It is a rotary drum washer, where clear water or recycled washer effluent coming from the following bleach tower is used to eliminate dissolved chemicals. The pulp enters in the rotating drum under vacuum. The outer surface of the drum is at higher pressure than its internal part, so the pulp enters in the drum through its porous surface. This causes the formation of a mat of pulp in the surface of the drum. Then, wash showers are used to remove further dissolved solids which may still in the pulp. Additional water is mixed together with the pulp to achieve the desired consistency. The temperature of this water is controlled with heat exchangers. The seal tank acts as storage or buffer for compensating variations in the composition of the liquor. The first and third bleach towers use chlorine dioxide as chemical agent to remove lignin from the pulp while the second uses sodium hydroxide.

The bleach plant has 11 controlled variables (CV), 14 possible manipulated variables (MV) and 10 potential disturbances (DV). Tables I, II and III show, respectively, the controlled, manipulated and disturbance variables.

**TABLE I. CONTROLLED VARIABLES OF THE BLEACH PLANT**

<table>
<thead>
<tr>
<th>CV</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>21</td>
<td>Temperature of bleach tower D1</td>
</tr>
<tr>
<td>22</td>
<td>Bleach tower E Kappa no.</td>
</tr>
<tr>
<td>23</td>
<td>Temperature of bleach tower E</td>
</tr>
</tbody>
</table>

**TABLE II. DISTURBANCE VARIABLES OF THE BLEACH PLANT**

<table>
<thead>
<tr>
<th>DV</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>13</td>
<td>D1 ClO2 stream temperature</td>
</tr>
<tr>
<td>14</td>
<td>D2 ClO2 stream composition</td>
</tr>
<tr>
<td>15</td>
<td>E caustic temperature</td>
</tr>
<tr>
<td>16</td>
<td>E caustic composition</td>
</tr>
<tr>
<td>17</td>
<td>E back-flush stream temperature</td>
</tr>
</tbody>
</table>

**TABLE III. MANIPULATED VARIABLES OF THE BLEACH PLANT**

<table>
<thead>
<tr>
<th>MV</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>17</td>
<td>E steam flow 3</td>
</tr>
<tr>
<td>18</td>
<td>Storage exit flow</td>
</tr>
<tr>
<td>19</td>
<td>D1 water flow</td>
</tr>
<tr>
<td>20</td>
<td>D2 ClO2 flow</td>
</tr>
<tr>
<td>21</td>
<td>D1 wash water flow</td>
</tr>
<tr>
<td>22</td>
<td>D2 steam flow</td>
</tr>
<tr>
<td>23</td>
<td>E caustic flow</td>
</tr>
</tbody>
</table>

**III. CONTROL STRUCTURE SELECTION USING RGA AND RDG ANALYSIS**

Controlled variables CV22 and CV26 are considered to be the quality variables of the bleach plant, so special care must be taken when designing a control system for these variables. Variable CV24 is not a quality variable, but it has a big influence in variable CV26. These three variables are assumed to be the primary controlled variables of the bleach plant. The rest of the controlled variables are the secondary controlled variables of the process.

**TABLE IV. RGA ANALYSIS**

<table>
<thead>
<tr>
<th>CV</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>24</td>
<td>E washer [OH]</td>
</tr>
<tr>
<td>25</td>
<td>Temperature of bleach tower D2</td>
</tr>
<tr>
<td>26</td>
<td>D2 tower brightness</td>
</tr>
</tbody>
</table>

The RGA technique was developed by Bristol [5] and has become the most important technique for measuring interaction and a very useful tool for decentralized control design. It is a valuable technique for the selection of manipulated-controlled variable pairings and it can also be used to predict the behaviour of controlled responses [6]. Grosdidier et al. [7] provided a derivation of the properties of the RGA. Additional properties were presented by Hovd and Skogestad [8], who extend the rules to the frequency domain. The RGA methodology requires the steady-state gains of the process to determine the best set of input-output pairings. The presence of the storage tank and the D2 bleach tower makes the process to be open-loop unstable. This is caused by the integrating nature of level systems. Before proceeding with the open-loop tests, two loops were closed to control the level of these two vessels. The manipulated variable selected to control the level of the...
storage tank was the storage exit flow. The manipulated variable chosen to control the level of the D₂ bleach tower was the D₂ exit flow. In order to avoid excessive variations of these two manipulated variables, two proportional-only controllers with default settings were used to perform this task. After removing these two input-output variables from the steady-state gain matrix, twelve candidate manipulated variables were available to control the remaining nine output variables. The generalization of the RGA for non-square plants was used to perform the RGA analysis. Then, the RGA, $\Lambda$, is given by:

$$
\Lambda = H \ast \left(H^T\right)^{-1}
$$

where $\ast$ represents element by element multiplication.

The gain matrix $G$ can be decomposed, using singular value decomposition, as:

$$
G = U D V^T
$$

where $U$ and $V$ are orthogonal matrices and $D$ is a diagonal matrix containing only the positive singular values. In Eq(1), $H$ is the pseudo-inverse of matrix $G$. It was observed that the sum of terms of the columns related to manipulated variables “MV24”, “MV19” and “MV19” were much lower than one, so these variables were removed from the RGA to obtain a square matrix. The resulted RGA is presented in Fig. 2. Due to the sequential nature of the bleach plant, the RGA is almost a diagonal matrix. All diagonal terms are close to one and off-diagonal terms are negligible.

After approximating the open-loop responses with continuous first-order-plus-time-delay transfer functions, the RGA was calculated as a function of frequency to find if the pairings calculated using static RGA are still appropriate from a dynamic point of view. Fig. 3 shows the obtained results for two of these diagonal terms, which are those with the most deviation from the unity value.

$$
\begin{align*}
\text{Fig. 2. Relative Gain Array of the bleach plant} \\
\text{Fig. 3. Diagonal terms of the dynamic RGA}
\end{align*}
$$
system. The extension for an $n \times n$ case is straightforward. The steady-state gain matrix for a $2 \times 2$ system including the gains of a load disturbance, $d$, is:

$$
\begin{bmatrix}
  x_1 \\
  x_2
\end{bmatrix} =
\begin{bmatrix}
  K_{i1} & K_{i2} & K_{F1} \\
  K_{i1} & K_{i2} & K_{F2}
\end{bmatrix}
\begin{bmatrix}
  m_1 \\
  m_2
\end{bmatrix}
$$

The RGD, $\beta_i$, is defined as the ratio of changes in the controller output that is required to bring $x_1$ back to its desired set-point when the load disturbance, $d$, is introduced into the system under two situations: multi-loop control and single loop control. Mathematically, $\beta_i$ is defined as a ratio of two gains:

$$
\beta_i = \frac{\frac{\partial m_1}{\partial d}_{x_1,x_2}}{\frac{\partial m_1}{\partial d}_{x_1,m_2}}
$$

Thus, $\beta_i$ can also be interpreted as a comparison between multi-loop control and ideal decoupled control. This means that if $\beta_i > 1$, then the controller effort within a multi-loop environment is bigger than the one required for a SISO system and therefore a decoupler is recommended. A small value of the RDG means that the controller output does not have to move too far from its steady-state to compensate the effects of the load disturbance. Mathematically, multi-loop control is preferred when [4]:

$$
|\beta_1| + |\beta_2| < 2
$$

From the ten possible load disturbances, it was observed that just five play a significant role in the process. These load disturbances are DV14, DV16, DV18, DV19 and DV22. Each of the load disturbances DV18, DV19 and DV22 only affects one controlled variable CV25, CV26 and CV25 respectively. The load disturbance DV14 affects the controlled variables CV22 and CV26 while the load disturbance DV16 affects the controlled variables CV24 and CV26. Therefore, the RDG analysis only makes sense when studying the disturbance variables DV14 and DV16. Fig. 4 shows the effects of the disturbance variable DV16 on controlled variables CV24 and CV26 in terms of RDG. Fig. 5 gives the RDG terms related to disturbance DV14. As observed, the sum of RDG does not surpass considerably the upper limit in the whole frequency range. This means the control loop pairings obtained using RGA are appropriate for disturbance rejection is this process.

IV. CONTROLLER TUNING

The primary variables were controlled by a combination of Kappa Factor control with conventional feedback control while the secondary outputs using only PI controllers. The Kappa Factor control is a particular controller used in Pulp Mills especially designed for disturbance rejection. Its operation together with PI controllers allows free-offset set-point tracking. Essentially, the Kappa factor can be understood as the ratio between lignin content in the pulp and the chemical agent entering the bleach tower. The general equations of the Kappa Factor are defined as [2]:

$$
F_x = K_f F_r C_p K_m / X
$$

where $K_f$, $F_r$, $X$, $F_p$, $C_p$, and $K_m$ are, respectively, the Kappa factor, chemical flow rate (manipulated variable), chemical composition, pulp flow rate, pulp consistency and pulp upstream Kappa no. The product of variables $K_f$, $C_p$ and $F_p$ determines the amount of lignin entering the bleach tower. Coefficients $a_0$ to $a_n$ define a polynomial of order $n$ which expresses the functionality between the Kappa Factor and the incoming Kappa no. Based on industrial experience it is possible to determine this functionality.
$$G(s) = \frac{K e^{-\alpha s}}{1 + \frac{\tau}{\alpha}}$$ (8)

Table IV. IMC Tuning Formulae

<table>
<thead>
<tr>
<th>Controller Type</th>
<th>$K_c$</th>
<th>$\tau_1$</th>
<th>Recommended $\lambda$</th>
</tr>
</thead>
<tbody>
<tr>
<td>PI</td>
<td>$\tau_1(\lambda K)$</td>
<td>$\tau$</td>
<td>$\lambda \alpha &gt; 1.7$</td>
</tr>
<tr>
<td>Improved PI</td>
<td>$(2\tau + \alpha)(2\lambda K)$</td>
<td>$\tau + \alpha/2$</td>
<td>$\lambda \alpha &gt; 1.7$</td>
</tr>
</tbody>
</table>

Fig. 5. Dynamic RDG for disturbance variable DV14 and controlled variables CV22 and CV26

A conservative value of $\lambda = 2.5\alpha$ was used in order to avoid excessive control action due to model-plant mismatch. For variables with no time delay, the value of $\lambda$ was adjusted by inspection of the controlled responses. Additionally, controller settings were calculated using Smith-Predictors in the quality variables. Using Smith-Predictors, instead of tuning each controller without considering the time delay of the process, a value of $\lambda = 2\alpha$ was introduced in the classical IMC formulae. The best setting of controller parameters was chosen by the behaviour of the system for set-point tracking and disturbance rejection performance. Integral of absolute error (IAE), settling time, time constant and percentage of overshoot were the parameters used for evaluating these performances. PI controllers combined with Smith-predictors, and tuned with classical IMC, providing the set-points of the Kappa factor controllers related to the quality variables of the process and PI-only controllers tuned using IMC controlling the secondary variables give the best control performance. Smith predictors allow the controller designer to provide to the process controllers larger controller gains and smaller reset times, making the controlled response faster.

Fig. 6. Set-point tracking and disturbance rejection performances for CV22

Fig. 6 (a) and Fig. 7 (a) show the set-point tracking performances of the primary variables CV22 and CV24. Examples of disturbance rejection performances for the three primary variables are shown in Fig. 6 (b), Fig. 7 (b) and Fig. 8. Fig. 6 (b) represents the disturbance rejection performance of the primary variable CV22 under a positive step change of magnitude 0.25 in the disturbance variable DV14. By the same way, Fig. 7 (b) and Fig. 8 represent, respectively, the disturbance rejection performance of the primary variables CV24 and CV26 under a positive step change.
change of magnitudes 0.25 in respectively the disturbance variables DV16 and DV19. As it can be observed, the use of Smith predictors significantly improves the control performance.

V. CONCLUSIONS

Using the benchmark simulator introduced by Castro and Doyle [3], a decentralized control strategy for a bleach plant is developed with emphasis on Kappa number control and brightness control. Dynamic RDG analysis confirms the input-output setting provided by the authors of the benchmark based on RGA analysis. Additionally, it is demonstrated that PI controllers combined with Smith-predictors, and tuned with classical IMC, providing the set-points of the Kappa factor controllers related to the quality variables of the process offers an appropriate methodology to control the main objectives of the plant in terms of set-point tracking and disturbance rejection performances.

REFERENCES