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Plantwide Control of A Benchmark Bleach Plant

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Abstract— **This paper presents a study on the plantwide control of a benchmark pulping process. Control structure determination was based on Relative Gain Array (RGA) and Relative Disturbance Gain (RGD) analysis. RGA and RDG were calculated based process a multiple-input multiple-output (MIMO) process transfer model identified from open-loop tests. Both static and dynamic RGA and RDG were calculated and analysed. These analyses confirmed the setting provided by the authors of the Benchmark, based on static RGA. Controllers in the individual control loops were tuned using 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 (IAE), setting time, time constant and percentage of overshoot. The Kappa factor, a key quality variable, was controlled by PI controllers combined with Smith-predictors and tuned with IMC. PI-only controllers tuned using IMC were used to control the secondary variables. With Smith predictors larger controller gains and smaller reset times can be used leading to faster control response. The proposed control strategy is successfully implemented on the benchmark simulation.**

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I. INTRODUCTION

In a pulp mill, the main objective is to produce pulp of a certain Kappa number (measurement of lignin content) and brightness (traditional measurement of blue reflectance) using the minimum energy resources, utilities and chemicals. 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.

Vanbrugghe 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 academic 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 parings 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.

The paper is organized as follows. Section II presents the benchmark simulated bleach plant. Control structure selection using RGA and RDG analysis is presented in Section III. Section IV gives the control system performance. Some concluding remarks are presented in Section IV.

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 [3].

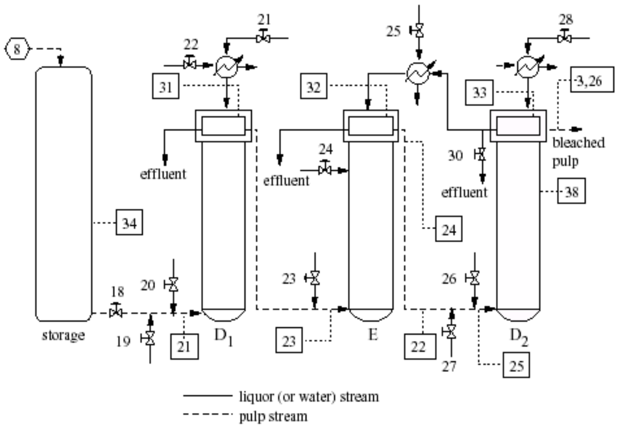


Fig. 1. Bleach plant flowsheet

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 benchmark 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

CV	Description	CV	Description
21	Temperature of bleach tower D_1	31	Washer 5 dilution factor
22	Bleach tower E Kappa no.	32	Washer 6 dilution factor
23	Temperature of bleach tower E	33	Washer 7 dilution factor
24	E washer $[OH^-]$	34	Storage volume
25	Temperature of bleach tower D_2	38	D_2 tower volume
26	D_2 tower brightness		

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 II.
DISTURBANCE VARIABLES OF THE BLEACH PLANT

DV	Description	DV	Description
13	D_1 ClO_2 stream temperature	18	D_2 ClO_2 stream temperature
14	D_1 ClO_2 stream composition	19	D_2 ClO_2 stream composition
15	E caustic temperature	20	D_2 caustic temperature
16	E caustic composition	21	D_2 caustic composition
17	E back-flush stream temperature	22	Wash washer temperature

TABLE III.
MANIPULATED VARIABLES OF THE BLEACH PLANT

MV	Description	MV	Description
17	O steam flow 3	24	E back-flush flow
18	Storage exit flow	25	E steam flow
19	D_1 water flow	26	D_2 ClO_2 flow
20	D_1 ClO_2 flow	27	D_2 caustic flow
21	D_1 wash water flow	28	D_2 wash water flow
22	D_1 steam flow	30	Split fraction 4
23	E caustic flow	38	D_2 exit flow

III. CONTROL STRUCTURE SELECTION

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 D_2 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 D_2 bleach tower was the D_2 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, Λ, is given by:

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

where * represents element by element multiplication.

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

$$G = UDV^{T} \qquad (2)$$

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.

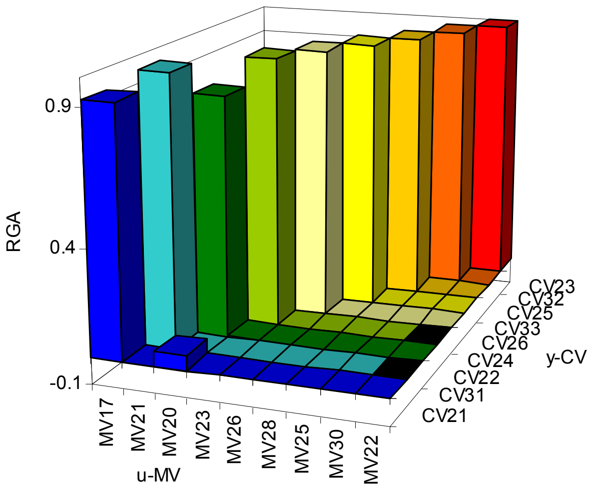


Fig. 2. Relative Gain Array of the bleach plant

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. All diagonal terms of the RGA remain closed to one in the whole frequency range, which indicates the proposed set of input-output pairings is also suitable from the dynamic point of view. Fig. 3 shows the first three diagonal elements of the dynamic RGA.

Since its introduction, RGA has been widely used in industry to configure multi-loop control systems [9]. McAvoy [10] has shown that there is a strong link between the RGA and the stability and design of a control loop. However, the RGA has been the subject of controversy [11]. Some engineers think that it does not have any use while others strongly rely on it.

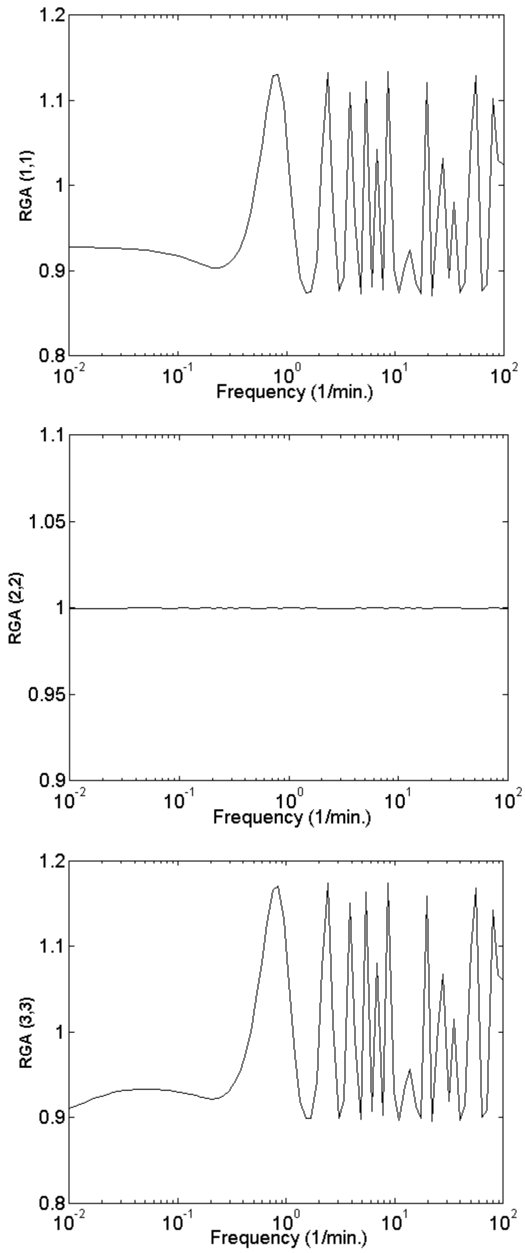


Fig. 3. The first three diagonal terms of the dynamic RGA

RGA is generally considered having two main disadvantages. Firstly, RGA is calculated from steady-state data only and therefore dynamic interactions may cause it to provide wrong conclusions. This problem was overcome by introducing dynamic interaction measures [12], [13]. Secondly, RGA is independent of load disturbances affecting the control loop. Stanley et al. [4] defined RDG in order to include disturbances in the analysis of the control loop performance. RGD is similar to RGA in the sense that it involves the ratio of two different steady-state gains: perfect control gains to open-loop gains. RDG can be calculated from steady-state information only but it can also be extended to take into account dynamic interactions. For simplicity, the definition of the RDG is presented for a 2×2 system. The extension for an $n \times n$ case is straightforward. The steady-state gain matrix for a 2×2 system including the gains of a load disturbance, d, is:

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} K_{11} & K_{12} & K_{F1} \\ K_{21} & K_{22} & K_{F2} \end{bmatrix} \begin{bmatrix} m_1 \\ m_2 \\ d \end{bmatrix} \quad (3)$$

The RGD, β_1, 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, β_1 is defined as a ratio of two gains:

$$\beta_1 = \frac{\left.\frac{\partial m_1}{\partial d}\right|_{x_1, x_2}}{\left.\frac{\partial m_1}{\partial d}\right|_{x_1, m_2}} \quad (4)$$

Thus, β_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]:

$$|\beta_1| + |\beta_2| < 2 \quad (5)$$

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. Control Performance

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]:

$$K_f = a_n K_{in}^n + a_{n-1} K_{in}^{n-1} + \ldots + a_1 K_{in} + a_0 \quad (6)$$

$$F_x = K_f F_p C_p K_{in} / X \quad (7)$$

where K_f, F_x, X, F_p, C_p and K_{in} 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.

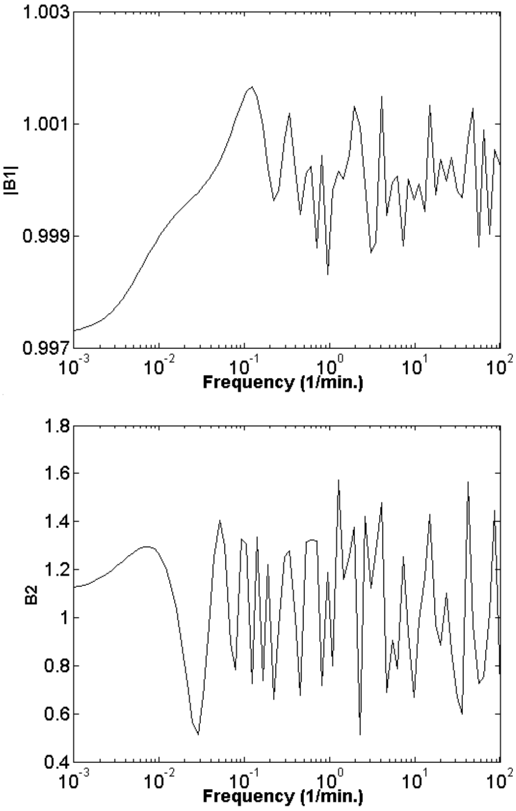


Fig. 4. Dynamic RDG for disturbance variable DV16 and controlled variables CV24 and CV26

Controller settings for each control loop were calculated using different internal model control tuning (IMC) methodologies. Rivera et al [14] have proposed tuning methods for PID controllers based on the IMC methodology. Table 4 gives the IMC tuning rules for the following first order plus delay model:

$$G(s) = \frac{Ke^{-\alpha s}}{1 + \tau s} \tag{8}$$

TABLE IV.
IMC TUNING FORMULAE

Controller Type	K_c	τ_I	Recommended λ
PI	$\tau/(\lambda K)$	τ	λ/α>1.7
Improved PI	$(2\tau+\alpha)/(2\lambda K)$	$\tau+\alpha/2$	λ/α>1.7

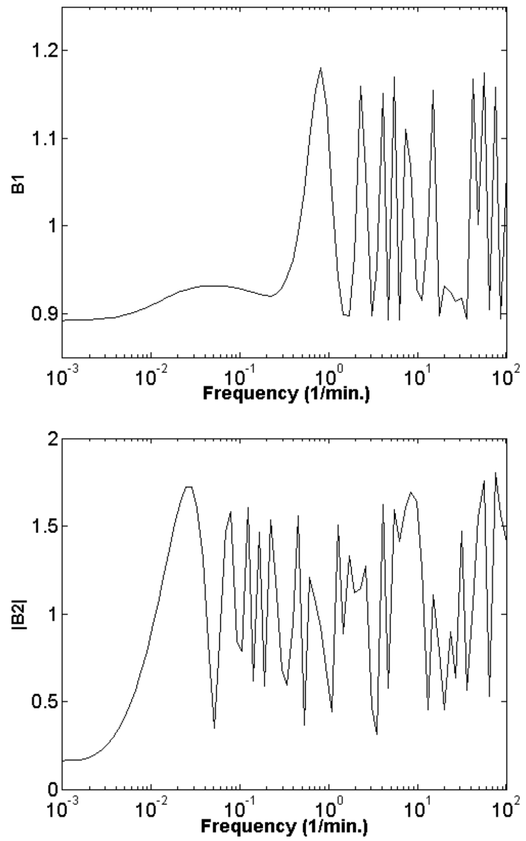
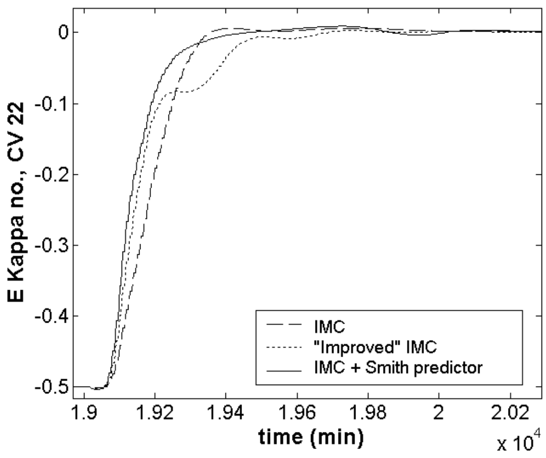
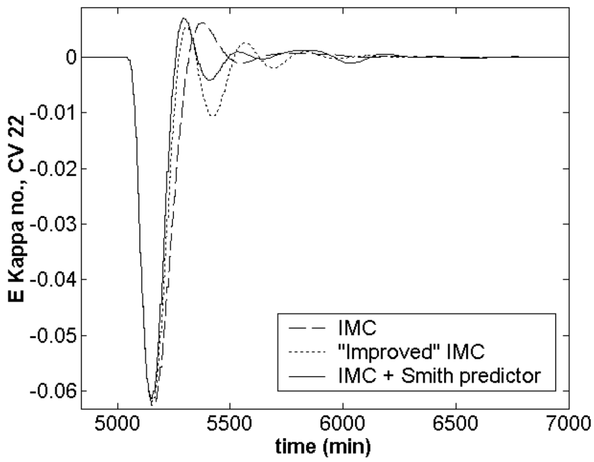


Fig. 5. Dynamic RDG for disturbance variable DV14 and controlled variables CV22 and CV26

A conservative value of λ=2.5α was used in order to avoid excessive control action due to model-plant mismatch. For variables with no time delay, the value of λ 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 λ=2α 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.



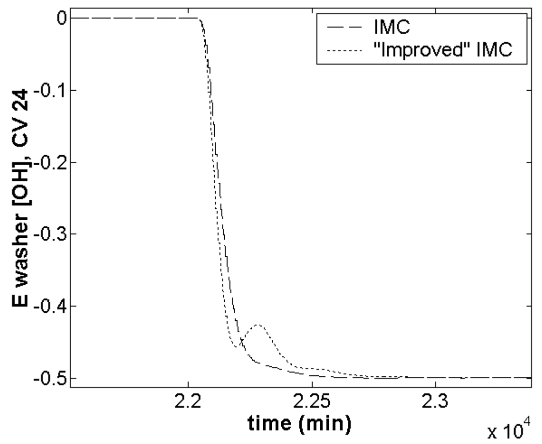
(a)



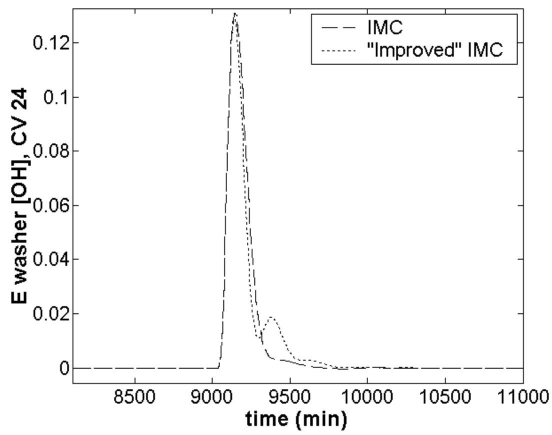
(b)

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 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.



(a)



(b)

Fig. 7. Set-point tracking and disturbance rejection performances for CV24

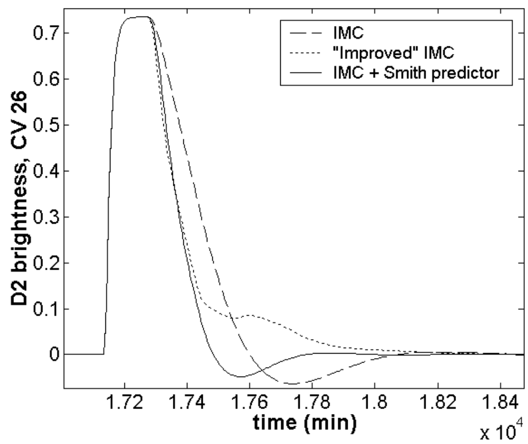


Fig. 8. Disturbance rejection performance for CV26

V. CONCLUSIONS

Plant wide control of simulated benchmark bleach plant with emphasis on Kappa number control and brightness control is presented in this study. 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.

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