Computer Aided Tools for Designing Plant-wide Control Structures for Large-scale Industrial Processes

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Abstract. In this work a systematic design procedure of a plant-wide control structure is applied to a well known benchmark problem of a large-scale pulp mill process [2]. Because of the high dimension of this system it was necessary to develop some additional computer aided tools for support calculations. It is based on the minimization of the sum of squared deviations (SSD index) [19] which is done via the use of genetic algorithm. It represents a good trade-off between achieve acceptable results with less computational effort. Previous works presented alternative solutions but using several heuristic considerations for reducing the problem dimensionality. The obtained performance with the selected control structure and the decentralized strategy presented previously [3] are compared. Several closed-loop simulations for critical set point changes are rigorously evaluated here.

Keywords: computer aided design, plant-wide control, large-scale pulp industry, genetic algorithm, dynamic simulation, performance evaluation

1 Introduction

The academic and industrial communities have expressed great interest in studying realistic large-scale industrial process control problems [3,4,7,8,10,12,14,16]. In this context, [2] introduced a complete benchmark problem of a pulp mill process, including both the fiber line and the chemical recovery areas.

This benchmark presents great challenges in terms of plant-wide control as it has several features of interest including: lead/lag responses, long time delays, interactions from multiple loops, inverse responses and slow settling times. In addition, the dynamic simulations of the pulp mill process demand high computational times given the dimension of the system: approximately 8200 states, 114 controlled variables (CVs) and 82 manipulated variables (MVs).

There have been a large number of contributions on plant-wide control structure design based on heuristics and process knowledge. Among the most notable contributors are [11], [9] and co-workers. Plant-wide control is commonly seen as

composed of these main steps: determination of the MVs and the CVs, control configuration, and controller selection and design. The control configuration refers to determining the interconnections between the CVs and the MVs. The controller selection and design involve the determination of control algorithm as well as the tuning parameters for closed-loop operation. These steps could be addressed sequentially; however, all of them affect the others.

In this work, the application of a systematic methodology for the control structure design in the pulp mill benchmark problem is presented. Although the methodology was successfully tested in smaller benchmarks [12,13,14,20,21] the main contribution here is its implementation in a large-scale industrial case. This involves the development and utilization of some computational tools in order to find a good solution despite the complexity of this kind of systems.

The first step is to stabilize the process, which is carried out by seven control loops. This allows the application of a step-test identification technique in order to obtain both the steady-state gains and linear dynamic models for all the input-output variables involved in the process. From this steady-state process information, the problem to solve is the proper CVs selection together with the optimal sensors network definition.

In this context, it is usual finding in the literature the application of heuristic criteria for reducing the problem dimensionality and achieve an acceptable CVs selection. The objective here is to use a methodology that rigorously drives to the process control structure with as little as possible heuristic considerations. The methodology is based on the minimization of the sum of squared deviations (SSD) index [19] for searching the most suitable set of CVs to be considered in the control structure. This search represents a combinatorial problem that can be efficiently solved through the use of a genetic algorithm. For this case study the number of variables involved are 100 CVs and 65 MVs, hence the combinations to be tested are about 10^{27}.

The CVs-MVs pairing selection is performed in a systematic way through the use of the Normalized Relative Gain Array (NRGA) [6] which is based on the RGA matrix and its selection rules. Thus the pairing problem can be interpreted as an assignment problem and the Hungarian algorithm is applied in order to obtain the best pairing. These algorithms help on handling the large number of possible pairing sets involved in this system.

Finally, for testing the results the controllers tuning is performed through the internal model control (IMC) theory using the previously identified linear models.

The obtained process control structure and the decentralized strategy presented by [3] are compared based on their capacity to reduce the total error and maximize the operating profits. The control strategies are tested through closed-loop simulations of the rigorous nonlinear dynamic model including several set point changes.

The whole process simulator is implemented in Matlab 6. It consists of Simulink models, s-functions and numerous scripts (m-files and c-files) including configuration scripts for simulations [18].

The complete description of this work is given according to the following organization: in section 2 a brief description of the process and its objectives are presented. In section 3 the systematic methodology is detailed through its main steps. The various tools that allow a performance evaluation are discussed in section 4. In

section 5, the resulting dynamic behavior of the system and the operation costs are analyzed. Finally, in section 6 the conclusions and future works are exposed.

2 Case Study: Pulp Mill Process

2.1 Process Description

The Pulp Mill process is shown in Figure 1 in a simplified way as that given by [2]. The plant consists of two major areas such as the Fiber line and the Recovery Plant.

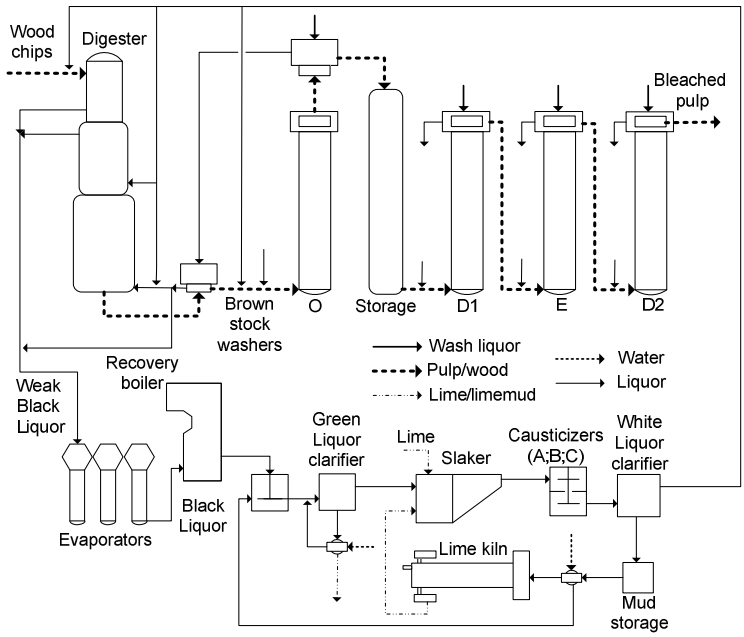

Fig. 1. The Pulp Mill Process.

The objective of the Fiber line area is to produce fibers from wood chips at a desired production rate and quality. Major raw materials of this process are wood chips and chemicals called white liquor (WL) which consists primarily of NaOH and NaSH. They are combined in a pressurized impregnation vessel, where wood chips are saturated in the white liquor. They then enter the Digester, where lignin in the wood starts to dissolve out. The main controlled variable in this unit is the Kappa Number, which is a measure of the amount of remaining lignin in the wood. Fibers are further washed in a Brown Stock drum washing section, to remove chemicals and residual lignin. Fibers then are bleached in several Bleaching Towers, to further

remove lignin and achieve a target brightness coefficient. The bleaching sequence includes post-delignification with Oxygen (O) and white liquor, Chlorine Dioxide (D1), Sodium Hydroxide (E), and brightening via Chlorine Dioxide (D2). At the end of each bleaching stage, pulp is washed to removed chemicals and lignin content before going to the next bleaching stage. On the other hand, the exit of the chemical streams from the Digester and washing stages now has many organic residuals and brown colour and, hence, are called ”Weak Black Liquors” (WBL). To recover chemical components and energy from these streams, the weak black liquors are sent to the Recovery Plant.

The most important objectives of the Chemical Recovery area are to obtain energy from the combustion of black liquor and regenerate the NaOH and Na2S from the weak black liquor coming from the Digester, extract liquor flows and the brown stock washing system. This regeneration procedure becomes the overall process economically feasible. In the multi-effect evaporation system the weak black liquor is converted in black liquor. The black liquor is sent to the recovery boiler where the combustion of the organic liquor provides the energy to produce high pressure steam and to carry out the reduction reactions to recover Na2S from Na2SO4 and other sulphur-based salts, and to recover Na2CO3. The black liquor solids is mixed with weak wash water to produce green liquor. The green liquor goes through the slaking/causticizing reactions to produce white liquor. This white liquor is sent back to the digester and the oxygen reactor. The lime mud from the white liquor clarifier is sent to the lime kiln to recover the lime.

2.2 Process Objectives

The objectives of the process (product quality, production rate, product grades and reactor yields) and process constraints (operational, safety and environmental) are specified in Tables 1, 3 and 4 in [2]. The goal is to produce pulp at the desired brightness and production rate at a minimum cost.

In this work it is assumed that the process is operating under nominal conditions, with a production rate of 630 tons/day, E Kappa number of 2.50 and D2 Brightness equal to 0.81.

The details of the mathematical models as well as the source/binary code for all the unit operations are available as a benchmark problem for download from the Doyle’s Group web site [18].

3 Systematic Procedure for Plant-wide Control Structure Design

3.1 Initial Considerations

The fiber line sub process has 38 MVs and 40 CVs, and the chemical recovery sub process has 44 MVs and 74 CVs, for a total of 82 MVs and 114 CVs that are initially

available for control of the process. Tables A1, A2, A4 and A5 in [2] show the list of all the variables of the process.

In this work, the nomenclature used for all the variables is the same as in [2].

3.2 Process Stabilization

The pulp mill process open-loop response is unstable, so the first step is to stabilize it. From open-loop simulations, it was determined that the levels in: the storage tank (CV34), D2 tower (CV38), smelt dissolving tank (CV53), storage tank #1 (CV57), mud mixing tank (CV73) and storage tank #2 (CV74), and the smelt dissolving tank condensate temperature (CV55) should be controlled to maintain stability in the process.

The corresponding pairing between these CVs and MVs, and the controller selection for each loop was adopted to be the same as [3]. Table 1 shows that proportional (P) control was used for all the level control loops and proportional-integral (PI) control for the temperature control loop.

Table 1. Control loops for stabilizing the process.

CV Nº	MV Nº	Kc	Ti
34	18	-1,67	-
38	38	-5	-
53	62	5	-
55	81	-0,005	30
57	46	3	-
73	60	-2,92	-
74	63	-2,92	-

3.3 Model Identification

After all the unstable modes were stabilized, the open-loop rigorous nonlinear model was used to obtain both the steady-state gains and the dynamic models (transfer functions) of all the input-output of the process. These models were identified through an open-loop step-test, which begins with the excitation of each MV using a step of +1% above the nominal operation point, and a length of 3000 hours. The recorded data (sets of CVs) was collected using a sampling time of 5 minutes. The data was normalized using scaling factors as in [2]. As an example, for a given input mv_i and output cv_k the corresponding normalized steady-state gain $g_{k,i}$ is obtained as:

$$g_{k,i} = \frac{cv_{k_{final}} - cv_{k_{ss}}}{mv_{i_{final}} - mv_{i_{ss}}} \frac{\Delta mv_{i_{\max}}}{\Delta cv_{k_{\max}}} \tag{1}$$

where $cv_{k_{final}}$ and $mv_{i_{final}}$ are the unscaled final values, $cv_{k_{ss}}$ and $mv_{i_{ss}}$ are the steady-state values, and $\Delta cv_{k_{\max}}$ and $\Delta mv_{i_{\max}}$ are the maximum range of variation of the input mv_i and output cv_k respectively. The values of the scaling factors are available in the script "general_parameters.m" in the benchmark. The obtained $g_{k,i}$ for all the input-output pairs of the process conforms the normalized steady-state gain matrix G which has dimension 105-by-74.

The first order with and without time delay transfer functions were identified using the improved "pem" algorithm available in [17], obtaining linear, low-order, continuous-time transfer function ("idproc") type models. These linear models are suitable for the preliminary controllers tuning using the IMC tuning method presented by [15].

3.4 Optimal Selection of the Controlled Variables

This procedure takes into account the generalized control structure based on internal model control indicated in Figure 3 where y_s is the CVs vector, y_r is the non-controlled variables (NCVs) vector and u is the MVs vector, of dimension n-by-*1*, *(m-n)*-by-*1* and n-by-*1* respectively. The process can be divided into two parts: G_s of dimension n-by-n which includes the n CVs, and G_r of dimension *(m-n)*-by-n which includes the m-n NCVs. In addition, $\tilde{G}_s$ is a model of G_s, and G_c is the controller.

The methodology is based on perfect control in a mean square sense, given that n variables are perfectly controlled and minimizing the SSD of the m-n NCVs. In steady-state, assuming that $\tilde{G}_s = G_s$, the process outputs can be written:

$$y_s = y_s^{set}, \forall y_s^{set} \tag{2}$$

$$y_r = \left[G_r G_s^{-1} \right] y_s^{set} \tag{3}$$

Equation (3) can be written as:

$$y_r = S_{sp} y_s^{set} \tag{4}$$

$$S_{sp} = \left[G_r G_s^{-1} \right] \tag{5}$$

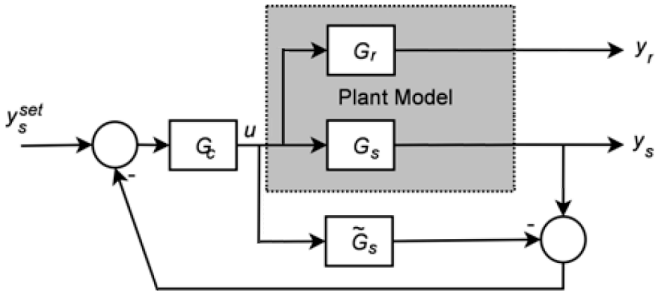

Fig. 3. Internal Model Controller structure.

As shown in equation (4), the error between the NCVs and their nominal operating point depends strongly on the selection of CVs. Then the idea is to find the optimal selection of the *n* CVs that minimizes:

$$\begin{aligned} SSD &= \sum_{i=1}^{n} \left\| e_{sp}(i) \right\|_2^2 \\ &= \sum_{i=1}^{n} \left\| S_{sp} y_{set}^n(i) \right\|_2^2 \end{aligned} \tag{6}$$

where e_{sp} refers to the steady-state error in the NCVs when are excited by set point changes. The vector $y_{set}^n(i)$ of dimension *n*-by-*1* has a value of one in position *i* and zeros at the remaining elements. From [19] it can be shown that:

$$\sum_{i=1}^{n} \left\| S_{sp} y_{set}^n(i) \right\|_2^2 = tr(S_{sp}^T S_{sp}) \tag{7}$$

The operation defined as *tr()* performs the sum of the elements located along the matrix diagonal. Then:

$$SSD = tr(S_{sp}^T S_{sp}) \tag{8}$$

The *n* selected CVs that minimizes SSD ensures that the process will remain as close as possible to its nominal operating point when be excited by set point changes.

3.5 Implementation via Genetic Algorithm

Given that n = 74 CVs from m = 105 potential CVs should be selected in order to match all the n MVs, then the total possibilities to be evaluated are $\frac{105!}{74!(105-74)!} \cong 4.10^{26}$.

From the process requirements, the D2 production rate (CV3), the digester kappa number (CV4), the O kappa number (CV19), the E kappa number (CV22) and the D2 brightness (CV26) have to be controlled. In addition, from the performed step-test it was seen that the time evolution of all the CVs were identical when exciting independently with MV48, or MV53 or MV73 to MV80. This is reflected in the normalized steady-state gain matrix columns associated with these MVs, which coincide element wise. It was decided to consider only one of these manipulated variables (MV53) and disregard the others for a possible input-output pairing. From these considerations, then the possibilities to be evaluated are $\frac{100!}{65!(100-65)!} \cong 1.10^{27}$. Given the magnitude of the number of possibilities, then the use of genetic algorithm (GA) is proposed because it is able to solve problems of very large dimension.

Using the AG concepts, the problem can be parameterized as a function of the selected CVs. That is, state the problem as a function of the chromosome $I_j = \left[g_1, g_2, ..., g_{N_c} \right]$, where j = 1, …, N_i with N_i the initial population dimension, N_c the number of potential CVs and g_i the genes belonging to the binary alphabet with i = 1, …, N_c. A value of one in a particular gene means that the corresponding variable is selected, and a value of zero implies the variable is not selected to be controlled.

Finally, the minimization of equation (8) as a function of I_j allows for the optimally selection of the CVs:

$$\min_{I_j} SSD(I_j) = \min_{I_j} \left\{ tr[S_{sp}^T(I_j) S_{sp}(I_j)] \right\} \tag{9}$$

S_{sp} is a function of I_j given that G_s and G_r are modified according to the different chromosomes.

The algorithm toolbox developed by [5] was used here. The main parameters adopted for running the algorithm are shown in the Table 2. The length of the chromosome is 100 because it must be decided which variables have to be controlled over 105, but 5 of them are previously chosen to be controlled from the process requirements. Given computational constraints, N_i = 13000 was adopted. As a result, it was necessary to repeat several times the execution of the GA in order to confirm the obtained solution. The selection method used was the roulette wheel.

Table 2. Genetic Algorithm parameters setting.

N_i: initial population	N_c: nº of potential CVs	N_g: nº of generations	Mutation Probability	Crossover Probability
13000	100	700	0,7 / Nc	0,7

3.6 Control Configuration and Controller Design

The control configuration involves determining the interconnections between the CVs and the MVs. Each CV-MV pair forms a single-input single-output (SISO) control loop, where the other MVs of the process behave as perturbations to the current loop. An appropriate pairing of the CVs-MVs of the process should minimize this interaction effect.

Although there are different methods, relative gain array (RGA) [1] analysis allows to determine the MVs-CVs pairings for deciding the process control structure.
The RGA matrix can be calculated as [1]:

$$\Lambda(G_s) = G_s \otimes (G_s^{-1})^T \tag{10}$$

where $\otimes$ denotes element-by-element multiplication and G_s the square *n*-by-*n* matrix obtained from the GA solution. Values of RGA elements close to 1 means that a slight interaction effect in the corresponding control loop is performed when the other loops are closed. Values less than 0.5 indicate a certain interaction effect and negative values are not desirable. Therefore, values close to 1 represents the best condition to avoid the interaction effect.

For small-scale processes it is possible to see which would be a good configuration from the selection rule given above. But for the pulp mill process the number of possible pairing sets increases significantly. However, is extremely complicated to apply the selection rule without the use of an algorithm that automates the searching.

Through the use of the Normalized Relative Gain Array (NRGA) concept as in [6] it is possible to interpret the pairs selection as an assignment problem which can be solved by Hungarian algorithm [6]. Thus the pairing selection can be performed in a systematic way.

Figure 4 shows the RGA matrix of the process obtained by equation (10) where all the MV-CV pairs selected according to [6] can be seen. The MVs (x-axis) and CVs (y-axis) have been rearranged to make the matrix as close as possible to a diagonal matrix. Only for the purpose of better visualization, RGA values were filtered between 0 and 9.

The controller selection and design involve the determination of control algorithm as well as the controller parameters for closed-loop operation.

A close examination of the Figure 4 shows that there are sub-blocks where the input-output interactions are important. This has serious difficulties for adjusting and implementing the PI controllers.

Fig. 4. Steady-state RGA matrix of the process.

4 Performance Evaluation

For the performance evaluation of the control strategies, two different indexes, the error improvement percent (EIP) and the profit improvement percent (PIP) were used. The first one reflects the dynamic performance and the second concerns the economic benefits. These indexes are based on the time evolutions of the dynamics of the CVs and the MVs. The EIP is defined as:

$$EIP = 100\frac{IAE^{base} - IAE^{new}}{IAE^{base}} \tag{11}$$

The superscript *base* refers to the control strategy proposed by [3] and the superscript *new* refers to the actual control strategy for the process. The Integral Absolute Error (IAE) is defined as:

$$IAE = \sum_{k} \left| k(k) - y(k) \right| \tag{12}$$

where y is the output and r corresponds to the desired value. The PIP is defined as:

$$PIP = 100\frac{TOP^{new} - TOP^{base}}{\left|TOP^{base}\right|} \tag{13}$$

The PIP reveals how much the economic benefits were increased by the utilization of the new control strategy with respect to the one used as base. The Total Operating Profit (TOP) is defined as:

$$TOP = Sales - Penalty\ \ Costs - Raw\ \ Costs \tag{14}$$

The TOP is the economic benefit calculated for each unit of the process. The *Raw Costs* are the costs of raw materials used, the *Penalty Costs* are the costs relative to penalties from environmental regulations or violations of product quality, and *Sales* represents a proportional value to the production of the unit. A good control strategy should be able to reduce the error and improve the process economics simultaneously.

5 Results

For the performance evaluation of the obtained process control structure versus the control strategy presented by [3], closed-loop simulations of the rigorous model were performed with both strategies, including critical set point changes. The set point sequence used is described in Table 3. The total simulation time was 200 hours.

Table 3. Sequence of set point changes applied to the process.

Time [hr]	Event	New Value
0	Kiln CaCO3 % change	0,0151
91,6	Bleach Pulp Production change	692,8
100,2	E Tower Temperature change	356,5
101,5	D2 Tower Temperature change	355,5
101,5	D2 Brightness change	0,86

Figures 5 to 7 show the closed-loop dynamics of key CVs during the set point changes described for both control strategies. The set point is represented in dash dot black, the new control in solid red and the control proposed by [3] in dotted blue.

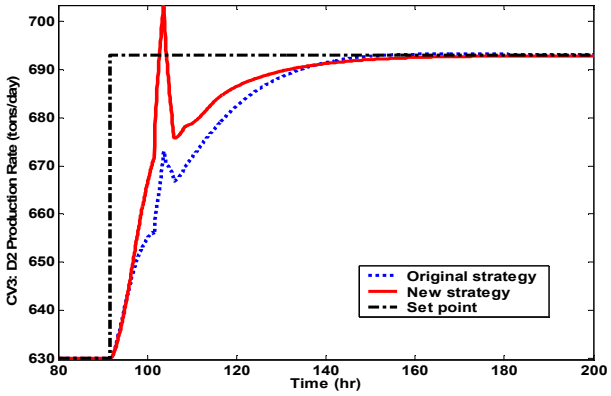

Fig. 5. CV3 (D2 Production Rate).

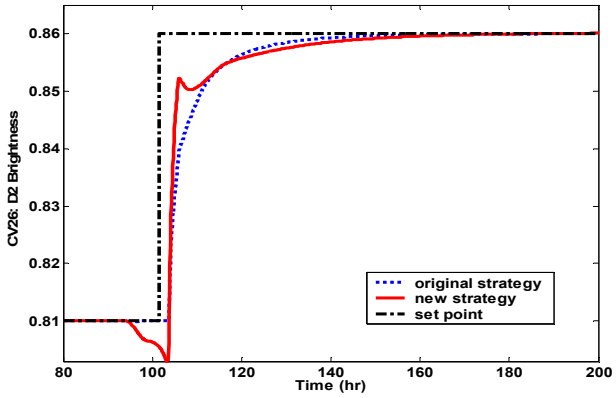

Fig. 6. CV26 (D2 Brightness).

The simulation results show that the obtained control structure fulfils with the operating objectives showing a similar dynamic performance against set point changes as that presented in [3]. Table 4 shows the IAE and EIP indexes for key CVs corresponding to the closed-loop simulation with set point changes.

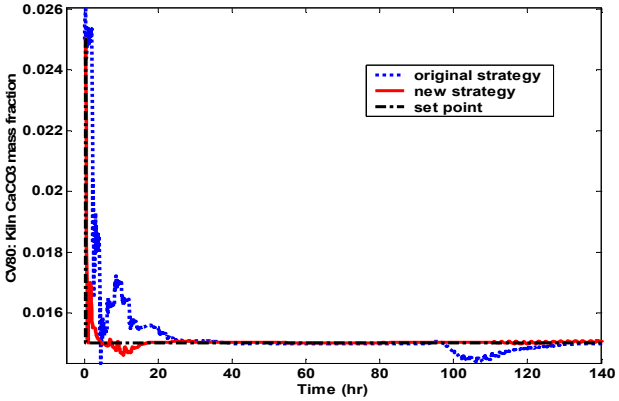

Fig. 7. CV80 (Kiln CaCO3 mass fraction).

Table 4. Dynamic performance comparison.

CV Nº	Description	IAE (Base)	IAE (New)	EIP %
3	D2 Production Rate	93,3	72,1	22,7
23	E Tower Temp.	1,89	1,57	16,9
25	D2 Tower Temp.	2,01	2,27	-12,7
26	D2 Brightness	426,5	445,5	-4,4
80	Kiln CaCO3	53,7	21,0	60,9

Tables 5 and 6 show the economic performance of both control strategies. It is observed that the new control structure was able to improve total profits by 5,66%. This is mostly due to the fact that it performs the production rate and the D2 brightness set point changes faster than the original strategy, which increased product sales and minimized the brightness penalty during the operation mode transition. This bearing in mind that if the pulp brightness exceeded ±1% of the set point, it could not be sold.

Table 5. Economic performance. Original control structure

Operation Unit	Raw Costs ($)	Penalty Costs ($)	Sales ($)	TOP ($)
Digester	788.710	-	2.610.900	1.822.200
Brown Stock	1.676	-	-	-1.676
Oxygen Tower	33.988	-	-	-33.988
Bleach Plant	252.910	125.620	-	-378.530
Evaporators	402.550	-	269.440	-133.120
Recaust	86.083	-	-	-86.083
Lime Kiln	32.791	2	-	-32.793
Total	1.598.700	125.620	2.880.300	1.156.000

Table 6. Economic performance. New control structure

Operation Unit	Raw Costs ($)	Penalty Costs ($)	Sales ($)	TOP ($)	PIP %
Digester	780.390	-	2.615.300	1.834.900	0,70
Brown Stock	1.695	-	-	-1.695	-1,14
Oxygen Tower	31.187	-	-	-31.187	8,24
Bleach Plant	278.670	55.708	-	-334.370	11,66
Evaporators	399.360	-	268.850	-130.500	1,96
Recaust	84.992	-	-	-84.992	1,26
Lime Kiln	30.761	-	-	-30.761	6,19
Total	1.607.100	55.708	2.884.200	1.221.400	5,66

6 Conclusions

A systematic methodology based on genetic algorithm which takes into account as little as possible heuristic considerations was used to develop a decentralized large-scale process control structure. It showed an acceptable performance against critical set point changes when compared with the proposed by [3].

This work is meant to give the necessary tools for implementing the systematic methodology for plant-wide control of the pulp mill benchmark problem and not to present the best or the only workable control structure. Several topics should be addressed in order to achieve improvements, like determining the minimum number of manipulated variables to be considered by the genetic algorithm so as to minimize the number of control loops. In addition the use of the SSD index considering disturbance changes in order to treat a more realistic case.

As future work the idea is to improve the overall dynamic performance of the system from the implementation of a new methodology based on the net load evaluation index as in [12]. This methodology provides a trade-off solution between servo and regulator behavior depending on the control objectives, enabling improved disturbance rejection.

Finally, given the high computational times involved, it is possible to consider if parallel computing or similar could assist in order to accelerate the dynamic simulations for obtaining results.

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