Time and Frequency Data-driven PID retuning applied in MIMO process

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Abstract: This paper presents the application of the time and frequency domain data-driven methods to the iterative decentralized PID tuning of MIMO process. Each single loop is sequentially excited to generate data required for retuning. The initial PID tuning gains are adjusted in order to match the defined decentralized MIMO reference model. The proposed strategy is applied to process simulations and to an experimental coupled tanks pilot plant.

Keywords: PID control, Data-driven tuning, Iterative Tuning, Process Control

1. INTRODUCTION

Most industrial processes are multi-input/multi-output (MIMO). For such systems, the interactions between inputs and outputs make the feedback controller design more difficult comparing to single-input/single-output (SISO) process. By adjusting the controller parameters of one loop can affect other loops performance due to the coupling between them.

Decentralized PID MIMO control is still widely used at the lower-levels for regulatory control (Shen et al., 2010). This approach aims to tune the controllers based on SISO methods aiming at compensating loop iteractions (Acioli Júnior and Barros, 2012). According to the coupling level in the process, many decentralized techniques can be applied. For modest iteractions, detuning methods, sequential loop closing methods or equivalent transfer function methods can be used.

In the sequential loop closing methods (Mayne, 1979), the idea is to treat the decentralized controller design problem for process with n inputs n outputs as a sequence of n SISO projects. Thus, the loops are tuned and closed sequentially, one after another. One approach to tune SISO PID controllers is applying data-driven techniques. They determine parameters directly by using operational data or generated from an experiment (Gao et al., 2017). In most of the cases, it is used a reference model to describe the control system objective and an optimization is performed.

Data-driven MIMO PID tuning techniques have been proposed by extensions of SISO tuning versions. Those methods can be iterative as in Jansson and Hjalmarsson (2004), or based on a single experiment as in Campestrini et al. (2016). Most of those techniques are for discrete time domain controller, making more difficult to implement in PLCs (programmable logic controllers) or DCSs (distributed control systems). Moreover, most of these techniques use open-loop data for parameters computations. However, in some cases it is common to keep the loop closed due, for instance, to production constraints, safety reasons or unstable plants (Padilla et al., 2017).

In Gao et al. (2017), it is proposed a data-driven optimal tuning using the closed loop step response time domain data directly based on a reference model. In Moreira et al. (2018b), a frequency constraint is added to improve system robustness and stability. In Moreira et al. (2018a), it is proposed a technique to shape a desired closed-loop frequency response. These techniques only consider SISO systems. The iterative version of these techniques is presented in Moreira et al. (2018c).

In this article, the techniques presented in Gao et al. (2017), Moreira et al. (2018c) and Moreira et al. (2018a) are used to the PI/PID decentralized of MIMO plants readjust iteratively using sequential loop closing methods in closed-loop approach. The time and frequency data are generated by the sequentially application of a reference signal proposed in Barroso et al. (2015) in each loop. Optimal gains are computed for each loop by iteraction. Performance is evaluated using frequency and time indexes in order to evaluate the results for each resulting adjustment.

This paper is organized as: The problem statement is presented in Section 2. The experiment design is developed in Section 3. The data-driven tuning techniques chosen are explained in Section 4. The proposed procedure is summarized in Section 5. The reference model selection is explained in Section 6. Simulations results are presented in Section 7. Experimental results are presented in Section 8. The conclusions are discussed in Section 9.

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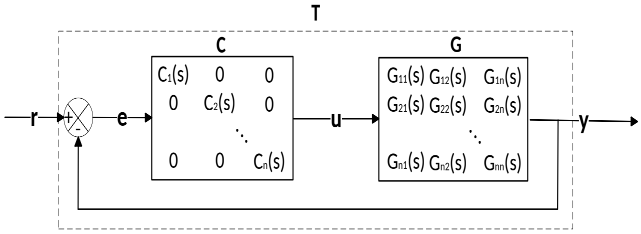

Fig. 1. MIMO Decentralized Closed Loop

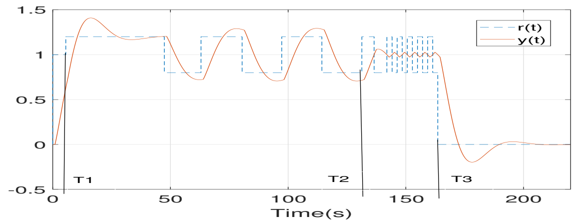

Fig. 2. Proposed Excitation Signal Example

2. PROBLEM STATEMENT

Consider a MIMO closed loop **T** as shown in Fig. 1, **r** is the reference n-vector, **e** is the error n-vector, **C** the initial decentralized PID controller matrix, **u** is controller action n-vector, **G** is the n-input × n-output process matrix and **y** is the output n-vector.

Each SISO PID controller in **C** has the following form:

$$C_i(s) = K_p + \frac{K_i}{s} + K_d s \tag{1}$$

where K_p, K_i and K_d are the respective Proportional, Integral and Derivative gains.

Assume initial controllers are known. The problem discussed in this paper can be stated as: Given a decentralized stable MIMO $n \times n$ closed loop **T** with known stabilizing PID controllers $C_i(s)$. Without a parametric identification of the model **G**, find appropriate tuning gain values to shape and match a defined reference model $\mathbf{T_r}$ as close as possible.

3. EXPERIMENT DESIGN

The proposed strategy consists of an iterative procedure. An excitation signal is sequentially applied to the MIMO closed loop system. This excitation signal is applied to each single loop sequentially to generate the required time and frequency domain data to retune the current PID controller. The procedure is repeated sequentially for all single loops to adjust the controller gains. In the next iteraction, each control loops is excited again until there is a convergence in PID parameters computation. The excitation signal data can also be applied to compute performance assessment indexes.

The chosen reference signal is explained in the next subsection. It is designed to generate frequency and time domain data to retune the controllers. Moreover, it is possible to estimate frequency domain performance indexes as gain and phase margins.

3.1 Closed Loop Excitation Signal

The reference signal is composed as the sequence of three different signals: a step, a standard relay test (Åström and Hägglund, 1984) and a phase margin experiment (de Arruda and Barros, 2003). An example of this excitation signal applied to each loop is shown in Fig. 2.

Delay Estimation The cross-correlation method is applied in this paper in output $y(t)$ and reference $r(t)$ signals in the time interval where the step signal was applied ($t = 0$ and $t = T_1$), by the following formula:

$$\widehat{\tau}_d \approx \frac{1}{N} argmax_{\tau_d} \sum_k y(k) r(k - \tau_d), \tag{2}$$

where N is the number of collected samples.

Gain and Phase Margins Estimation From the experiment data, the crossover and critical frequencies, $\widehat{\omega}_g$ and $\widehat{\omega}_c$ respectively, can be estimated by measuring a stable limit cycle period during the time intervals $[T_1; T_2]$ and $[T_2; T_3]$. The process frequency response for those frequencies, $(G(j\widehat{\omega}_g)$ and $G(j\widehat{\omega}_c)$, can be estimated using the Discrete Fourier Transform (DFT) data from the chosen stable limit cycles.

As the controller transfer function $C_i(s)$ is known, it is possible to compute the frequency responses $C_i(j\widehat{\omega}_g)$ and $C_i(j\widehat{\omega}_c)$. Therefore, the gain $\widehat{A}_m$ and phase margins $\widehat{\phi}_m$ are estimated by:

$$\widehat{A}_m = \frac{1}{|G_i(j\widehat{\omega}_c) C_i(j\widehat{\omega}_c)|} \tag{3}$$

$$\widehat{\phi}_m = \pi + \angle G_i(j\widehat{\omega}_g) C_i(j\widehat{\omega}_g) \tag{4}$$

Moreover, the estimated margins $\widehat{A}_m$ and $\widehat{\phi}_m$ can be used to evaluate the control system performance by comparing with the reference margins A_{ref} and ϕ_{ref} stated by the reference model $T_r(s)$.

4. SISO DATA-DRIVEN TUNING TECHNIQUES

The retuned controller $\overline{C}_i(s)$ is described by the following equations:

$$\overline{C}_i(s) = (K_p + K_p^{\Delta}) + \frac{K_i + K_i^{\Delta}}{s} + (K_d + K_d^{\Delta}) s \tag{5}$$

where K_p^{Δ}, K_i^{Δ} and K_d^{Δ} are the Proportional, Integral and Derivative gains increments respectively.

4.1 Time shaping

The time shaping follows from Gao et al. (2017). The technique is stated as follows.

Using time domain data collected from a closed-loop step change experiment or generated in operational procedures, the optimal increments vector $\theta_0 = \left[K_p^{\Delta}\ K_i^{\Delta}\ K_d^{\Delta}\right]^T$ that solves the following optimization problem:

$$\min_{\theta_0} J_1 = ||\Omega - \Phi \theta_0||_2^2 \tag{6}$$

where $\Omega = [H_r(T_s) - H_T(T_s) \ \dots \ H_r(NT_s) - H_T(NT_s)]^T$,

$$\Phi = \begin{bmatrix} H_{\Delta}^1(T_s) & H_{\Delta}^2(T_s) & H_{\Delta}^3(T_s) \\ \vdots & \vdots & \vdots \\ H_{\Delta}^1(NT_s) & H_{\Delta}^2(NT_s) & H_{\Delta}^3(NT_s) \end{bmatrix},$$

H_Δ^i are the step response of the terms $T(s)\Delta_i(s)$ and

$$\Delta_1(s) = \frac{1}{K_p + \frac{K_i}{s} + K_d s}, \quad \Delta_2(s) = \frac{1/s}{K_p + \frac{K_i}{s} + K_d s},$$
$$\Delta_3(s) = \frac{s}{K_p + \frac{K_i}{s} + K_d s}.$$

As optimization problem (6) is convex and the matrices are constant, the solution vector θ_0 can be obtained by:

$$\theta_0 = (\phi^T \phi)^{-1} \phi^T \Omega \tag{7}$$

4.2 Time shaping with frequency constraint

The optimization problem described in section 4.1 can be extended to guarantee some frequency domain conditions. These are important to improve the system robustness and stability characteristics as gain or phase margins. Hence, it can be required in a control system project that the frequency response in a certain points must be equal or closer to the reference model.

Thus, a constraint in the frequency domain is inserted in (6) (Moreira et al., 2018b):

$$\begin{aligned} &\min_{\theta} J_2 = ||\Omega - \Phi\theta||_2^2 \\ &\text{subject to } \mathbf{A}\theta - \mathbf{b} = \mathbf{0} \end{aligned} \tag{8}$$

As optimization problem (8) is convex and the matrices are constant, the solution vector θ can be obtained by the constraint least square estimator analytic formula:

$$\theta = \theta_0 - (\Phi^T \Phi)^{-1} \mathbf{A}^T [\mathbf{A} (\Phi^T \Phi)^{-1} \mathbf{A}^T]^{-1} [\mathbf{A}\theta_0 - \mathbf{b}] \tag{9}$$

where θ_0 is the solution of the unconstrained least square problem, $\mathbf{A} = \begin{bmatrix} 1 & 0 & \dfrac{T_f \omega^2}{1 + (T_f \omega)^2} \\ 0 & -\dfrac{1}{\omega} & \dfrac{\omega}{1 + (T_f \omega)^2} \end{bmatrix}$,

$\mathbf{b} = \left[\Re\left(\dfrac{L_r(j\omega) - L(j\omega)}{G(j\omega)} \right) \ \Im\left(\dfrac{L_r(j\omega) - L(j\omega)}{G(j\omega)} \right) \right]^T$ and L is the Loop Gain Function, T_f is the derivative filter

4.3 Frequency shaping

The optimization problem described in section 4.1 uses only time domain data to be performed. However, frequency data can be also used to obtain the new gains.

Lemma 1. From collected frequency response data using a defined frequency range: $\omega = [\omega_1 \ \omega_2 \ \dots \ \omega_n]$, it is possible to compute the optimal increments by solving the two optimization problems:

$$\min_{K_p^\Delta} J_1 = \|\Omega_r - \Phi_r K_p^\Delta\|_2^2 \tag{10}$$

$$\min_{K_i^\Delta, K_d^\Delta} J_2 = \|\Omega_i - \Phi_i \left[K_i^\Delta \ K_d^\Delta \right]^T \|_2^2 \tag{11}$$

where $\Omega_r = \begin{bmatrix} \Re\left([S(j\omega_1) - S_r(j\omega_1)] \dfrac{C(j\omega_1)}{S_r(j\omega_1) T(j\omega_1)} \right) \\ \vdots \\ \Re\left([S(j\omega_n) - S_r(j\omega_n)] \dfrac{C(j\omega_n)}{S_r(j\omega_n) T(j\omega_n)} \right) \end{bmatrix}$,

$\Phi_r = [1 \ 1 \ \cdots \ 1]^T$,

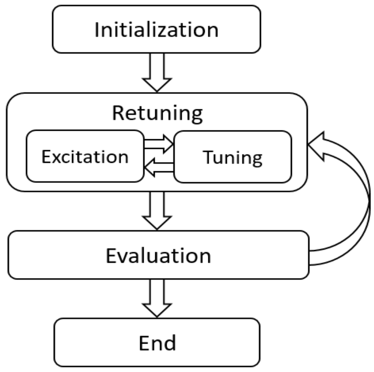

Fig. 3. Iterative MIMO tuning block diagram

$$\Omega_i = \begin{bmatrix} \Im\left([S(j\omega_1) - S_r(j\omega_1)] \dfrac{C(j\omega_1)}{S_r(j\omega_1) T(j\omega_1)} \right. \\ \vdots \\ \Im\left([S(j\omega_n) - S_r(j\omega_n)] \dfrac{C(j\omega_n)}{S_r(j\omega_n) T(j\omega_n)} \right) \end{bmatrix},$$

$$\Phi_i = \begin{bmatrix} -1/\omega_1 & \omega_1 \\ \vdots & \vdots \\ -1/\omega_n & \omega_n \end{bmatrix}.$$

Proof. See Moreira et al. (2018a). Q.E.D.

5. ITERATIVE MIMO TUNING PROCEDURE

The developed procedure can be summarized in the following steps:

(1) Initialization: From the initial decentralized MIMO system $\mathbf{T}$. Obtain the initial controllers $\mathbf{C}$, define the desired references models $\mathbf{T_r}$ and a convergence tolerance ϵ.
(2) Retuning: Repeat steps (a) and (b) until all controllers have been tuned
    (a) Experiment: Apply the proposed reference signal excitation in the selected single control loop to collect the response data.
    (b) Tuning: Use a data-driven SISO PID tuning technique to adjust the controller.
(3) Evaluate: Compute the optimal gains increments
    (a) Return to the step (2): case the optimal gains increments were bigger than the specified tolerance ϵ.
    (b) End: case the optimal gains increments were smaller than the specified tolerance ϵ.

The procedure block diagram is shown in Fig. 3.

6. REFERENCE MODEL SELECTION

To apply the tuning strategy described in previously, it is necessary to define a reference model $T_r(s)$ for each single loop. In this paper, it is assumed that the reference model is tuned according to the IMC PI rules from Rivera et al. (1986). Hence, the reference model is a first order process with time delay:

$$T_r(s) = \frac{1}{\tau_c s + 1} e^{-\tau_d s} \tag{12}$$

Table 1. Controllers gains for Time Shaping

Iteraction	Controller 1			Controller 2		
	K_p	K_i	K_d	K_p	K_i	K_d
1	1.585	0.250	0.020	3.523	0.263	0.102
2	1.612	0.251	0.021	3.590	0.428	0.110
3	1.612	0.253	0.024	3.593	0.370	0.108

where τ_c is the closed loop tuning parameter and τ_d is the process delay.

For this control system design, it is possible to define the $T_r(s)$ by selecting the desired gain A_m or phase margins ϕ_m. This is done by the development in Acioli Júnior and Barros (2011) and Ho et al. (2001) that obtained the following equations:

$$\tau_c = \beta\tau_d \tag{13}$$

$$\beta = \frac{2A_m}{\pi} - 1 \tag{14}$$

$$\phi_m = \frac{\pi}{2}\left(1 - \frac{1}{A_m}\right) \tag{15}$$

According to the equations above, by measuring the time delay τ_d and defining β, A_m or ϕ_m it is possible to obtain the reference model as equation (12). In this paper, the gain margin is defined.

7. SIMULATION RESULTS

To evaluate the proposed MIMO decentralized PID strategy, consider the reflux and vapor flow and the temperatures of plates 4 and 17 of the destilation collunm from Luyben and Vinante (1972). The model is:

$$\begin{bmatrix} R \\ V \end{bmatrix} = \begin{bmatrix} \frac{2.2}{7s+1}e^{-s} & \frac{1.3}{7s+1}e^{-0.3s} \\ \frac{2.8}{9s+1}e^{-1.8s} & \frac{4.3}{9.2s+1}e^{-0.35s} \end{bmatrix} \begin{bmatrix} T_4 \\ T_{17} \end{bmatrix} \tag{16}$$

The initial decentralized PID controllers are obtained from example 1 of Vázquez and Morilla (2002):

$$C_1(s) = 0.88 + \frac{0.4835}{s} + 0.0308s \tag{17}$$

$$C_2(s) = 2.70 + \frac{1.5084}{s} + 0.1971s \tag{18}$$

According to the IMC PI design equations (14 and 15), the reference closed-loop transfer functions ($T_r(s)$) are different for various delays estimations. A Gaussian noise with zero mean and variance of 0.0001 is added in system outputs signals in all simulations.

The estimated delays are 1.06 and 0.31 seconds for each single loop. For the reference margins $A_{ref} = 3$ and $\phi_{ref1} = 60°$ the reference model is defined as:

$$\mathbf{T_r} = \begin{bmatrix} \frac{1}{0.9645s+1}e^{-1.06s} & 0 \\ 0 & \frac{1}{0.2821s+1}e^{-0.31s} \end{bmatrix} \tag{19}$$

The iterative procedure is applied to the system for all data-driven techniques discussed with a tolerance $\epsilon = 0.1$. The respective controllers gains for each method are listed in Tables 1, 2 and 3. For all techniques the procedure converged in a few iteractions.

Table 2. Controllers gains for Time with Frequency Constraint

Iteraction	Controller 1			Controller 2		
	K_p	K_i	K_d	K_p	K_i	K_d
1	1.579	0.256	0.021	3.475	0.155	0.106
2	1.565	0.245	0.024	3.529	0.231	0.157

Table 3. Controllers gains for Frequency Shape

Iteraction	Controller 1			Controller 2		
	K_p	K_i	K_d	K_p	K_i	K_d
1	1.643	0.308	0.349	3.983	0.316	0.157
2	1.839	0.290	0.236	4.012	0.309	0.213

Table 4. Frequency Domain Performance Indexes

	A_{m1}	A_{m2}	$\phi_{m1}(°)$	$\phi_{m2}(°)$
Initial	4.521	3.978	32.265	50.143
Time Shape	3.131	2.879	59.746	59.447
Time w/ Constraint	3.227	3.017	60.547	62.621
Freq. Shape	3.064	2.683	59.789	58.993

Table 5. Time Domain Performance Indexes

	$NRMSE_1$	$NRMSE_2$	IAE_1	IAE_2
Initial	0.39	0.14	108.14	20.07
Time Shape	0.33	0.14	68.26	35.28
Time w/ Constr.	0.33	0.15	69.23	51.77
Freq. Shape	0.31	0.14	60.09	40.68

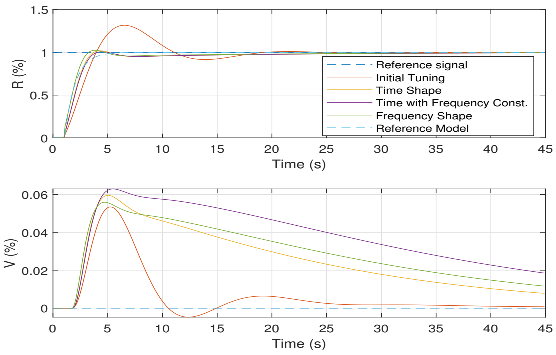

Fig. 4. Reference Step Experiment at Loop 1

Each tuning performance is assessed with the gain and phase margin estimation shown in Table 4. As expected, all indexes have converged to similar values.

The time domain tracking performance is assessed using the normalized root mean square (NRMSE) criteria and the coupling effect is computed by the integral absolute error (IAE) for step reference signals as listed in Table 5. The respective outputs for a step reference signal are shown in Figs. 4 and 5. It is noticed an improvement for NRMSE indexes for loop 1 and all data-driven techniques applied. The IAE indexes for controller 1 decreased considerably while for loop 2 all of them increased but all have a small effect. Based on the indexes computed, any of them can be applied to compute a proper MIMO PID decentralized controller to improve time and domain performance.

8. EXPERIMENTAL RESULTS

The proposed procedure was applied also to a pilot system composed by two tanks with same size and a reservoir, two

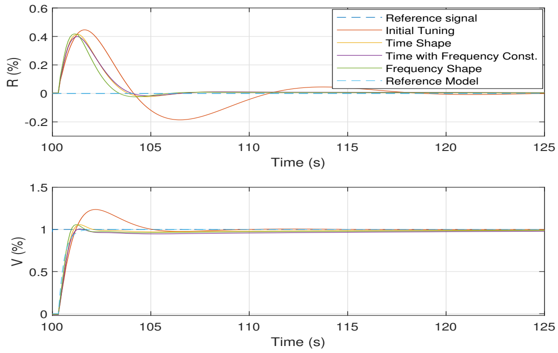

Fig. 5. Reference Step Experiment at Loop 2

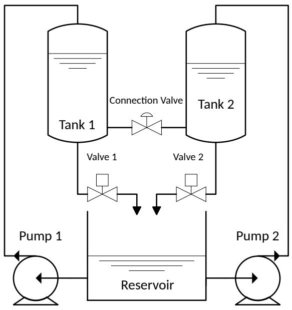

Fig. 6. Coupled Tanks Pilot Plant Schematic

hydraulic pumps, two frequencies inverters, two differential pressure transmitters, two electric valves, one manual valve, PLC and a PC with SCADA. The pilot plant schematic is shown in Fig. 6. It was chosen as input the frequency applied to each the hydraulic pumps (%) and as output each tank level (%).

The valve that connects the tanks is kept constant during the experiments. The initial reference for the controllers are 52 % and 50 % for loop 1 and 2 respectively. For the reference margins are $A_{ref} = 5$ and $\phi_{ref} = 72°$ for both loops the initials decentralized PID controllers are:

$$C_1(s) = 2 + \frac{0.09}{s} + 3s \tag{20}$$

$$C_2(s) = 2.5 + \frac{0.02}{s} + 3.5s \tag{21}$$

The estimated delays were 1.8 seconds for both loops. Moreover, the reference models were defined as:

$$\mathbf{T_r} = \begin{bmatrix} \frac{1}{3.93s+1}e^{-1.8s} & 0 \\ 0 & \frac{1}{3.93s+1}e^{-1.8s} \end{bmatrix} \tag{22}$$

The data is collected with a time sampling of 0.1 seconds. The iterative procedure is applied to the system for all data-driven techniques discussed with a tolerance $\epsilon = 0.01$. The respective controllers gains for each method are listed in Tables 6, 7 and 8. Moreover, the frequency constraint used in the time shape with frequency constraint it is the critical frequency.

For all techniques, the procedure have converged almost within the same number of iteractions for different solutions. The difference in the final controllers gains can be

Table 6. Controllers gains for Time Shaping - Pilot Plant

Iteraction	Controller 1			Controller 2		
	K_p	K_i	K_d	K_p	K_i	K_d
1	1.953	0.102	3.071	2.451	0.041	3.584
2	1.914	0.112	3.128	2.399	0.065	3.635
3	1.877	0.122	3.178	2.352	0.086	3.696
4	1.836	0.133	3.238	2.297	0.111	3.763

Table 7. Controllers gains for Time with Frequency Constraint - Pilot Plant

Iteraction	Controller 1			Controller 2		
	K_p	K_i	K_d	K_p	K_i	K_d
1	2.680	0.103	3.271	2.367	0.041	0.780
2	2.900	0.113	2.229	1.837	0.063	0.158
3	2.767	0.125	1.463	1.573	0.085	-0.052
4	2.607	0.140	1.256	1.591	0.110	-0.093

Table 8. Controllers gains for Frequency Shape - Pilot Plant

Iteraction	Controller 1			Controller 2		
	K_p	K_i	K_d	K_p	K_i	K_d
1	2.749	0.053	3.123	2.391	0.105	0.988
2	2.992	0.058	1.962	1.808	0.110	0.438
3	2.745	0.070	1.461	1.624	0.086	0.006
4	2.575	0.060	1.216	1.566	0.093	0.328
5	2.499	0.065	1.191	1.585	0.085	0.128

Table 9. Frequency Domain Performance Indexes - Pilot Plant

	A_{m1}	A_{m2}	$\phi_{m1}(°)$	$\phi_{m2}(°)$
Initial	3.827	3.286	69.965	93.741
Time Shape	4.622	4.837	63.588	79.374
Time w/ Constr.	3.436	3.506	73.294	78.432
Freq. Shape	3.650	3.850	71.734	79.590

Table 10. Time Domain Performance Indexes - Pilot Plant

	$NRMSE_1$	$NRMSE_2$	IAE_1	IAE_2
Initial	79.11	78.17	3.40	10.39
Time Shape	69.97	71.91	3.27	2.85
Time w/Constr.	70.71	71.01	2.52	2.90
Freq. Shape	92.38	72.05	4.15	3.77

analyzed in the performance indexes listed in Tables 9 and 10 for frequency and time domain respectively.

For the time shaping technique and time shaping with frequency constraint, it is noticed a better fit for the frequency domain, specially in phase margin, and a small deceasing in the NRMSE criteria. The frequency shaping tuning technique improves the $NRMSE_1$ and the margins however it decreases the $NRMSE_2$. Those small difference in the time domain performance is justified by the initial controllers that have a good fit. It also can be noticed a high improvement in the coupling effect in the loop 2 by the IAE index while in the loop 1 it remains in similar values. The respective outputs for a step reference signal are shown in Fig. 7 and 8.

9. CONCLUSIONS

In this paper, it was discussed time and frequency domain data-driven methods to a iterative decentralized PID tuning to MIMO systems. Using the procedure that excites

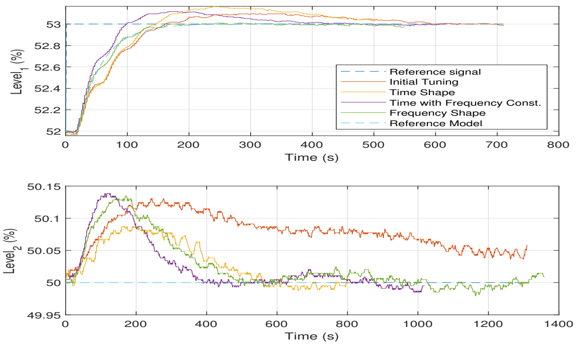

Fig. 7. Reference Step Experiment at Loop 1 - Pilot Plant

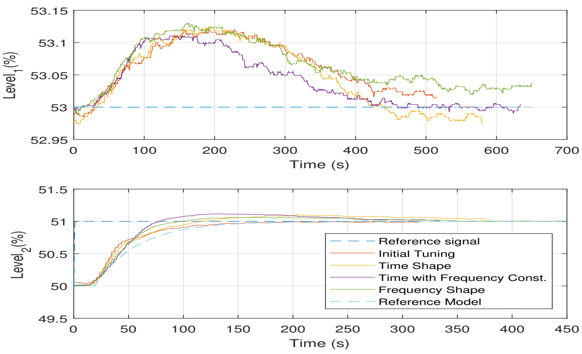

Fig. 8. Reference Step Experiment at Loop 2 - Pilot Plant

each single loop sequentially to obtain the required time and frequency domain data, the PID optimal gains are computing using data-driven SISO techniques to adjust the closed loop to match a decentralized MIMO reference model. Three data-driven techniques are applied to the proposed procedure to evaluate efficiency.

Based on the simulation and the experimental results, it was possible to verify the efficiency of the SISO methods applied sequentially to MIMO plants. The resulting controllers were capable to adjust the system performance to make the closed loops have a similar response to the defined reference model and the desired frequency and time specifications, even with the controller structure limitations. The best results obtained with the methods time shaping and time shaping with frequency constraint.

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