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Multivariable PI control for a boiler plant benchmark using the Virtual Reference Feedback Tuning

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Abstract: In this work, the Virtual Reference Feedback Tuning is applied to the control of a boiler plant benchmark. Only data (without any modelling step) was used to compute a series of PI controllers for both a decentralized and a complete multi-loop control strategies. When compared with other PI controllers, it was found that a better tuning of the controller was achieved yielding better closed-loop results. The original VRFT method was enhanced with a series of constraints during the optimization process that allows the user to select the position of the zero of the controller.

Keywords: boiler plant, data-driven control, PI control, virtual reference

1. INTRODUCTION

The control of boilers has been an important problem for a long time. It is well known that the correct control of this plant can improve the performance with its corresponding economical savings and safety improvement. But it is not a simple task since non-minimum phase characteristics as well as not self-regulating behaviour are commonly found.

The literature on boilers and boiler control is extensive. In rather recent papers, pole placement control was applied to a six order boiler model in Anakwa and Swamy (1988) while General Predictive Control (GPC) was applied in Hogg and El-Rabaie (1991) in a coal fire boiler, in Rossiter et al. (1991) for a boiler in a power station and in Xu et al. (2005) in a cascade control topology for drum level control with identified CARIMA models. In Dimeo and Lee (1995), genetic algorithms are used to tune a PI controllers with extra proportional gains for decoupling for a boiler-turbine plant. The results were compared with a LQR control computed at nominal power. In Wang et al. (2002), a hybrid PID/Fuzzy control system is implemented for the control of the steam temperature and water level of a steam boiler in a large-scale thermal power plant. In Glickman et al. (2004), a PID optimization procedure is propose specially for power plants taking into account robustness restrictions. In Labibi et al. (2009), a robust decentralized PID tuning is proposed and implemented in a real boiler while sliding mode control and $\mathcal{H}_\infty$ control are applied in Moradi et al. (2009).

All of these methods have in common that a model (either non-linear or linearised) have to be first obtained in order to compute the controllers. In a new set of control strategies, the modelling step can be skipped in order to obtain the parameters of linear discrete-time controllers directly from the plant data. These methods are known as *data-driven control*.

Instead of using models, data-driven control uses experimental data to directly find a controller which, generally, is meant to minimize some control performance criterion. Some of the most remarkable methods within this control approach are the Iterative Feedback Tuning (IFT) (Gevers, 2002), the Correlation based Tuning (CbT) (Karimi et al., 2005) and the Virtual Reference Feedback Tuning (VRFT) (Campi et al., 2002). While the IFT is an iterative method (that is, several experiments on the plant have to be performed in order to find the controller) CbT and VRFT are one shot methods (only one set of data is needed to find the controller). For more information on this techniques, the reader is encourage to follow the given references and reference therein.

Given the complexity of the boiler models, it is interesting to avoid the modelling step and find the controller parameters with only experimental data. In this work, the VRFT is applied to a boiler plant in simulation in order to find decentralized PI controllers and complete decoupling controllers directly. VRFT is characterized to be a flexible method that has been applied in a variety of cases, for example the original single feedback controller, the two degrees of freedom case (Lecchini et al., 2002), non-minimum phase plants (Campestrini et al., 2011), neural

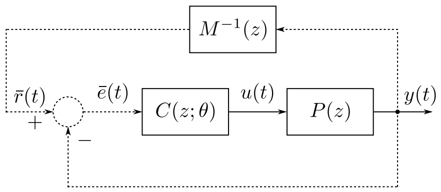

Fig. 1. The VRFT set up. The dashed lines represent the "virtual" part of the method.

network control (Esparza et al., 2011), and multiple-inputs multiple-outputs control (Nakamoto, 2004).

The rest of the paper is divided as follows, in section 2 the methods are presented, involving an overview on the VRFT and the presentation of the non-linear model of the boiler used for simulation purposes. In section 3 the results of the computed controllers are presented and compared with standard PI controllers. Conclusions are found in section 4.

2. METHODS

2.1 VRFT overview

In Campi et al. (2002), the method is presented for the tuning of feedback controllers. If the controller belongs to the controller class $\{C(z;\theta)\}$ given by $C(z;\theta) = \beta^T(z)\theta$, where $\beta(z) = [\beta_1(z) \cdots \beta_n(z)]^T$ is a known vector of transfer functions, and $\theta = [\theta_1\ \theta_2 \cdots \theta_n]^T$ is the vector of parameters, then the control objective is to minimize the model-reference criterion given by:

$$J_{MR}(\theta) = \left\| \left(\frac{P(z)C(z;\theta)}{1+P(z)C(z;\theta)} - M(z) \right) W(z) \right\|_2^2 \qquad (1)$$

where $P(z)$ is the unknown plant, $M(z)$ is the target closed-loop dynamics and $W(z)$ is a frequency weighting factor. However, since a model of the plant is unknown, this control objective cannot be solved. An alternative procedure is proposed: starting from a batch of open-loop data $\{u(t), y(t)\}$, a "virtual" signal is computed in such a way that, if the closed-loop system is fed with this virtual signal and the controllers in the loop were the ideal controllers that would achieve the predefined target closed-loop transfer function, then the input and output signals of the plant in closed-loop would be the same than the batch of open-loop data. The output of the controller should be equal to $u(t)$ and then, this controller can be found by *identifying* the transfer function which yields the output $u(t)$ when the input $\bar{e}(t) = \bar{r}(t) - y(t)$ is applied to the input as depicted in Fig. 1.

The original VRFT algorithm, as presented by the authors in Campi et al. (2002), is as follows: Given a set of measured I/O data $\{u(t), y(t)\}_{t=1,\ldots,N}$

(1) Calculate:
  - a virtual reference $\bar{r}(t)$ such that $y(t) = M(z)\bar{r}(t)$, and
  - the corresponding virtual tracking error $\bar{e}(t) = \bar{r}(t) - y(t)$
(2) Filter the signals $\bar{e}(t)$ and $u(t)$ with a suitable filter $L(z)$:

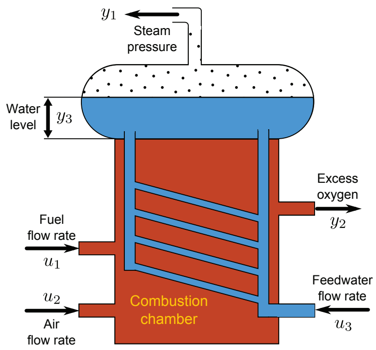

Fig. 2. Boiler plant layout. The plant correspond to a 3 inputs, 3 outputs system.

$$\bar{e}_L(t) = L(z)\bar{e}(t)$$
$$u_L(t) = L(z)u(t)$$

(3) Find the controller's parameters vector $(\hat{\theta}_N)$ that minimizes the following criterion:

$$J_{VR}^N(\theta) = \frac{1}{N}\sum_{t=1}^{N}\left(u_L(t) - C(z;\theta)\bar{e}_L(t)\right)^2 \qquad (2)$$

If $C(z;\theta) = \beta^T(z)\theta$, the criterion (2) can be rewritten as:

$$J_{VR}^N(\theta) = \frac{1}{N}\sum_{t=1}^{N}\left(u_L(t) - \varphi_L^T(t)\theta\right)^2 \qquad (3)$$

with $\varphi_L(t) = \beta(z)\bar{e}_L(t)$ and the parameter vector $\hat{\theta}_N$ is given by

$$\hat{\theta}_N = \left[\sum_{t=1}^{N}\varphi_L(t)\varphi_L(t)^T\right]^{-1}\sum_{t=1}^{N}\varphi_L(t)u_L(t) \qquad (4)$$

The authors, also showed that, the filter $L(z)$ should be the one that approximates the criterion (2) to (1). This filter should be designed to accomplish the constraint:

$$|L|^2 = |1-M|^2\,|M|\,|W|^2\,\frac{1}{\Phi_u} \qquad (5)$$

where Φ_u is the spectral density of $u(t)$

2.2 Boiler Benchmark

A boiler benchmark is considered to be the plant to control. This benchmark is used to perform the simulations with the computed controllers. It was proposed by Dr. Morilla as test problem for the Spanish IFAC meeting in 2010. The model of the boiler is based on Pellegrinetti and Bentsman (1996) and for more information, please see Fernández et al. (2011). Also the MATLAB files can be obtained at `http://www.dia.uned.es/~fmorilla/benchmark09_10/`.

The boiler benchmark represents boiler number 2 at Abbott Power Plant in Champaign, IL. This boiler is used to produced both heating and electric energy. It has a vapor flow rate capacity of 22.10 kg/s with a pressure of 2.24 MPa. A diagram can be found in Fig. 2. The heat from the combustion in the chamber is transferred to the water, producing the water vapor. The residual gases from the combustion are vented to the atmosphere. Some constraints on the operation of the boiler have to be meet:

Table 1. Operation point of the boiler

Variable (%)	Value (%)
Fuel flow rate	35.21
Air flow rate	36.01
Water flow rate	57.57
Steam load	46.36
Steam pressure	60.00
Excess oxygen	50.00
Water level	50.00

- The flow rate and the temperature of the steam have to be maintained constant despite the variation in the load.
- The efficiency of the combustion reactions depends directly on the stoichiometry of the reactions. Therefore, it is necessary to control the excess of oxygen in the boiler.
- To avoid over-heating, it is mandatory to keep the water level in a predefined value.

The steam pressure (y_1), the excess oxygen (y_2) and the water level (y_3) are controlled by manipulating the fuel flow rate (u_1), the air flow rate (u_2) and the feedwater flow rate (u_3), respectively. The load (d_1) is assumed to be a measurable disturbance in the system. It is considered as a fourth input in the benchmark model. For simulation purposes, all this variables values have been scaled in the range 0-100%. The outputs are affected by noise to simulate measure distrubances. Input noise has been introduced as a non-measurable load and fuel characteristics disturbances.

The operation points considered in this paper are presented in Table 1. It is known that the air flow rate only affects the excess oxygen and not the other outputs. The model also presents non-minimum phase characteristics related with the fuel flow-rate and steam load.

Control of the boiler The basic control strategy for the boiler is a decentralized multivariable control. The benchmark suggest a PI controller with predefined parameters values that are able to stabilize the plant. The variable pairing is as follows: the steam pressure is controlled by manipulating the fuel flow rate, the excess oxygen is controlled using the air flow rate and the water level is controlled using the feed water flow rate.

The controllers are discrete time PI controllers with a sampling time of 0.2 s. It has to be stressed that a PI controller is a linear in the parameters controller since:

$$\begin{aligned} C(z,\theta) &= \frac{\theta_1 + \theta_2 z^{-1}}{1 - z^{-1}} \\ &= \left[\begin{array}{cc} \frac{1}{1-z^{-1}} & \frac{z^{-1}}{1-z^{-1}} \end{array} \right] \left[\begin{array}{c} \theta_1 \\ \theta_2 \end{array} \right] \\ &= \beta^T(z)\theta \end{aligned} \quad (6)$$

therefore, the parameters can be computed by solving a linear least squares problem within the VRFT framework. For a complete description of the boiler model, please refer to Pellegrinetti and Bentsman (1996) and references therein.

3. RESULTS AND DISCUSSION

In this section, the results of the application of the VRFT to the benchmark are presented. The controllers used are the same as in the original benchmark: discrete time PI controllers with sampling time equal to 0.2s. The tuning methodology is the VRFT with an additional constraint to ensure that the zero of the controllers lie inside the unit circle to avoid instability. This restriction is depicted in Fig. 5. If the controllers are given by:

$$C(z,\theta) = \frac{\theta_1 + \theta_2 z^{-1}}{1 - z^{-1}} \quad (7)$$

then the pole is located in $z = -\theta_2/\theta_1$. Then, to constrain the position of this real zero inside the unit circle (that is $|-\theta_2/\theta_1| < 1$, the following three restriction has to be satisfied for a security margin Δ:

$$\begin{aligned} (-1+\Delta)\theta_1 + \theta_2 &\leq 0 \\ (-1+\Delta)\theta_1 - \theta_2 &\leq 0 \\ -\theta_1 &< 0 \end{aligned} \quad (8)$$

This restriction is useful for the cases where the unconstrained result gives a positive value for θ_1. The data for the optimization was found simulating a random input around the operation point presented in Table 1. Two different control strategies were tested: first a decentralized approach where each loop controller was found separately and a complete approach where a proportional gain was computed as a controller between the error signal of one loop and the control signal of the other loops. The decentralized approach is depicted in Fig 3 while the complete strategy is presented in Fig.4. For the complete control strategy, the optimization problem can be found following the same procedure as in the single-input single-output.

For the $n \times n$ case, it is assumed that a batch of N samples of open-loop data is available for each of the n loops as $\{u_1(t), u_2(t), \ldots, u_n(t), y_1(t), y_2(t), \ldots, y_n(t)\}_N$ ($u(t)$ represents the inputs and $y(t)$ the outputs). It is necessary that this data excites the dynamics of the process that is intended to be controlled, just as with any other identification procedure. Given the desired closed-loop target transfer functions $M_1(z)$, $M_2(z)$, ... , $M_n(z)$, the virtual reference signals are computed as:

$$\begin{aligned} \bar{r}_1 &= M_1^{-1}(z) y_1 \\ \bar{r}_2 &= M_2^{-1}(z) y_2 \\ \vdots &= \vdots \\ \bar{r}_n &= M_n^{-1}(z) y_n \end{aligned} \quad (9)$$

and the matrix of controllers is given by

$$C(z) = \begin{pmatrix} C_{11}(z,\theta_{11}) & C_{12}(z,\theta_{12}) & \cdots & C_{1n}(z,\theta_{1n}) \\ C_{21}(z,\theta_{21}) & C_{22}(z,\theta_{22}) & \cdots & C_{2n}(z,\theta_{2n}) \\ \vdots & \vdots & \vdots & \vdots \\ C_{n1}(z,\theta_{n1}) & C_{n2}(z,\theta_{n2}) & \cdots & C_{nn}(z,\theta_{nn}) \end{pmatrix} \quad (10)$$

If the controllers are linear in the parameters as:

$$C_{ij}(z,\theta_{ij}) = \beta_{ij}^T(z) \cdot \theta_{ij} \quad (11)$$

where $i = 1, \ldots, n$ represents the ith manipulated variable, $j = 1, \ldots, n$ represents the jth virtual error signal $\bar{e}_j = \bar{r}_j - y_j$, θ_{ij} is the vector of parameters of the controller and $\beta_{ij}(z)$ is its corresponding base function vector, the optimization problem is defined as

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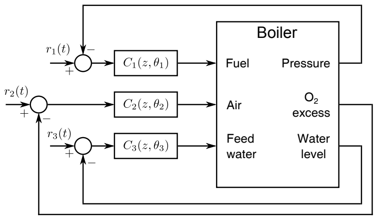

Fig. 3. Decentralized approach.

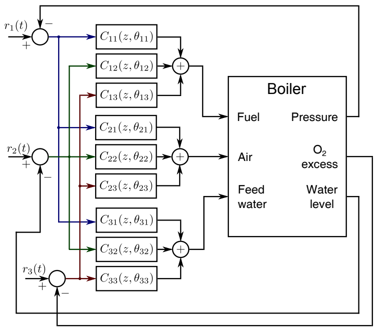

Fig. 4. Complete approach.

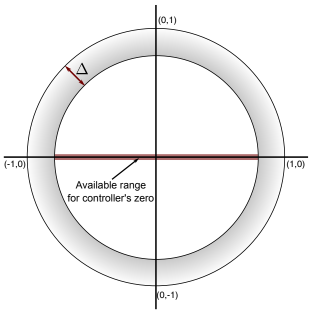

Fig. 5. Representation of the restriction included for the computation of the VRFT controllers.

$$\underset{\Theta_1,\Theta_2,\ldots,\Theta_n}{\arg\min} \; J_{VR}\left(\Theta_1,\Theta_2,\ldots,\Theta_n\right) \tag{12}$$

with

$$J_{VR}\left(\Theta_1,\Theta_2,\ldots,\Theta_n\right) = \left\| \begin{bmatrix} u_1 \\ \vdots \\ u_n \end{bmatrix} - \Psi \begin{bmatrix} \Theta_1 \\ \vdots \\ \Theta_n \end{bmatrix} \right\|^2$$

$$\Theta_i = \left[\theta_{i1}^T,\ldots,\theta_{in}^T\right]^T$$

$$\Psi = \begin{bmatrix} \Phi_1 & 0 & 0 & 0 \\ 0 & \Phi_2 & 0 & 0 \\ & & & \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & \Phi_n \end{bmatrix}$$

$$\Phi_i = \left[\beta_{i1}^T \bar{e}_1 \cdots \beta_{in}^T \bar{e}_n\right]$$

which is a standard least-squares problem, where the interaction between the loops is taken into account at the same time as the problem is solved. For the case of control strategy for the boiler, only the 3×3 case is considered.

The closed-loop model target for each loop was set as a first order model given by

$$M(z) = \frac{(1-x)z^{-1}}{1-xz^{-1}} \tag{13}$$

where x represents how fast the closed-loop is (for smaller x, the closed-loop is faster). The values of x depends of the characteristics of the plant, the control strategies and the control configuration. To select this value, prior knowledge of the plant is needed, despite the fact that an explicit model of the plant is not necessary.

Table 2. Values of x for each loop

Closed-Loop Target	Value of x
$M_1(z)$	0.9512
$M_2(z)$	0.7515
$M_3(z)$	0.6065

Table 3. IAE and SADU results for a change in the steam load

Cases		IAE	SADU
Loop 1	Original	281.68	51.26
	Decentralized	143.14 (-49.2%)	54.004 (5.4%)
	Complete	165.51 (-41.2%)	29.02 (-43.4%)
Loop 2	Original	2837.79	50.90
	Decentralized	3219.73 (13.5%)	53.98 (6.0%)
	Complete	2757.02 (-2.8%)	28.61 (-43.8%)
Loop 3	Original	560.34	53.41
	Decentralized	353.81 (-36.9%)	54.16 (1.4%)
	Complete	356.22 (-36.4%)	30.23 (-43.4%)

How to select the control specifications for data-driven methodologies is still an open subject of research (not only for the VRFT, but for all the data-driven methodologies). In this work the procedure to select the value of x is as follows: from the knowledge of the velocity of the plant, an initial value of x is selected. Then the value is decreased until the control performance starts to degrade. With this procedure, the selection of the value of x is similar to the selection of the desired closed-loop bandwidth. In this work, the values of x were found to be as presented in Table 2. The constraint in the position of the zero of the controller was found using the same heuristic. This restriction is specially important for the water level loop since the system has an “integrator dynamic” in this section.

The resulting controllers were compared with the original PI controllers of the benchmark for a change in the steam load. To compare, the integral of the absolute error (IAE) and the sum of the absolute value of the difference of the input signals (SADU) are both computed and presented in Table 3. All the signals were sampled with sampling time $T_s = 0.2s$, which is the same period as the controllers and was decided in the benchmark. From the data obtained in the simulation of the nonlinear model, it was clear that output y_1 and y_3 are not affected by input u_2, while output y_2 is not affected by input u_3. Based on decoupling principles (Morilla et al., 2008), controllers $C_{12}(z)$ and $C_{32}(z)$ were constraint to be equal to zero to avoid unnecessary coupling between loops. In the case of $C_{23}(z)$, it was only constraint to have its zero within the unit circle and the optimization gave zero to its parameters automatically.

The resulting controller parameters are presented in Table 4. The original controllers are continuous time PI parameters but in the table, the corresponding “bilinear transform” values are given. The simulations results are presented in Figures 6 to 11. In Fig. 6 the comparison of

Table 4. Controller parameters, (θ_1, θ_2)

Controller	Original	Decentralized	Complete
C_{11}	(5.02,-4.98)	(18.71,-18.61)	(14.27,-14.20)
C_{12}	-	-	(0.00,0.00)
C_{13}	-	-	(3.48,-3.47)
C_{21}	-	-	(1.31,-1.29)
C_{22}	(0.20,-0.198)	(0.058,-0.054)	(0.0443,-0.0399)
C_{23}	-	-	(0.00,0.00)
C_{31}	-	-	(-12.97,12.94)
C_{32}	-	-	(0.00,0.00)
C_{33}	(2.51,-2.49)	(9.84,-9.80)	(11.90,-11.85)

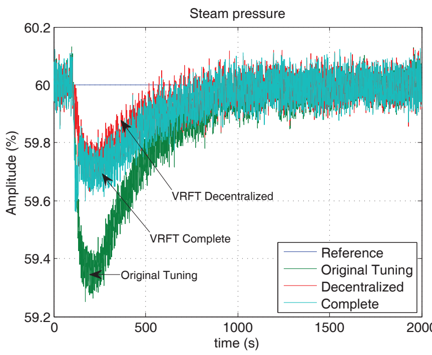

Fig. 6. Comparison of the steam pressure results.

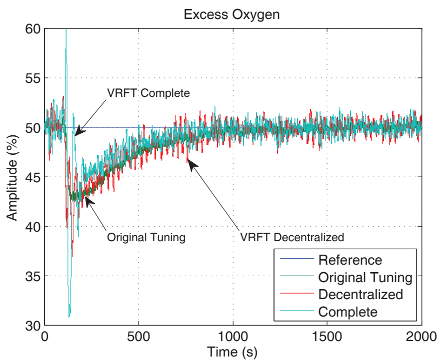

Fig. 7. Comparison of the excess oxygen results.

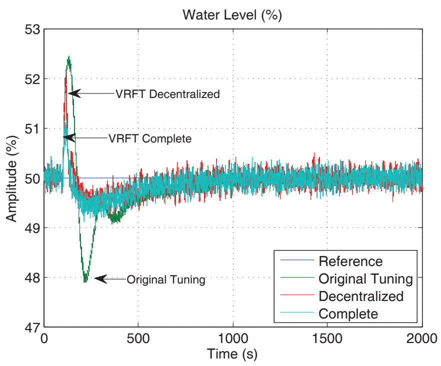

Fig. 8. Comparison of the water level results.

the controlled steam pressure is presented, in Fig. 7 the excess oxygen results are shown and in Fig. 8 the results in the controlled water level. The corresponding flow rates are presented in Fig. 9 for the original controller, in Fig. 10 for the decentralized VRFT strategy and in Fig. 11 for the complete case.

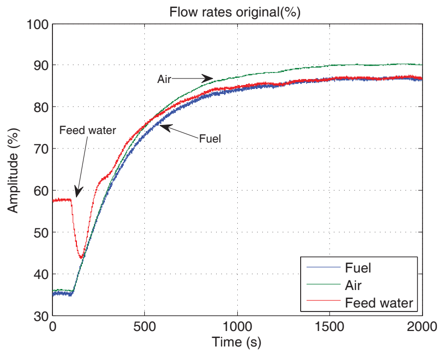

Fig. 9. Flow rates of the original controllers.

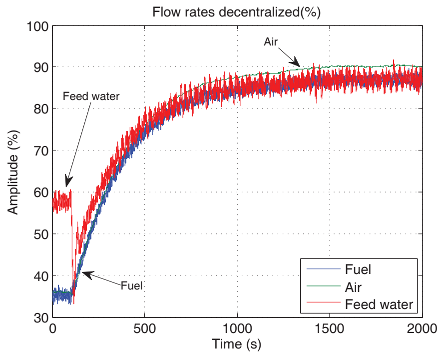

Fig. 10. Flow rates of the decentralized controllers.

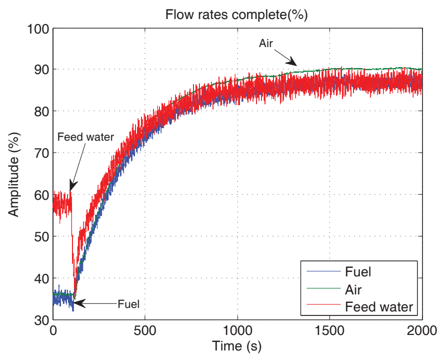

Fig. 11. Flow rates of the complete controllers.

Overall, using the VRFT controllers it was possible to improve the response of the system towards the change in the steam load. However it was found that the results are more oscillatory, possible due to the effect of the noise in the system. The decentralized strategy is able to improve the response for loop 1 and 3 by 49.2% and 36.9% with almost the same control effort (represented by the SADU), but with a worse response for loop 2. On the other hand, the complete strategy improves the response for all the loops, but the response is slightly worse than the decentralized case for loop 1 and almost the same for loop 3. However, it is interesting to note that in all cases the SADU gives a lower value than in the original response. This results shown that the VRFT is an excelent and easy to use procedure for the tune of PI controllers, even for complicated non-linear plants as the boiler benchmark. Nevertheless, it is clear that the controllers are not filtering the noise efectively (it can be seen in Table 4 that the values of the parameters are quite different between the orignal and the VRFT cases). In this case the use of filters in the output of the controllers is desirable to take into account this issue. However, this is an extra step that has to be performed in paralell with the computation of the VRFT controllers.

4. CONCLUSIONS

The VRFT was applied to the control of a boiler plant benchmark without any modelling step. The parameters of the PI controllers where found without any modelling step, just an open-loop experiment was necessary to minimize a least square problem yielding the optimal PI parameters (in a least-squares sense). Two control strategies were tested: a decentralized approach and a complete (decoupling) approach. For the disturbance rejection case both VRFT approaches give better results than the original tuning but the response is more affected by the noise than in the reference case. The VRFT method was complemented with a series of restriction during the optimization step to prevent the controllers to yield non-minimum phase zeros. This was very important to prevent instability, specially for the third loop case. This application shows the goodness and easiness of the VRFT when applied to complex, non-linear plants as boilers.

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