Application of Multivariable Virtual Reference Feedback Tuning with Anti-Windup to the Benchmark PID 2018 ⋆

Virginia Bordignon * **Lucíola Campestrini** *

* *Department of Automation and Energy, Universidade Federal do Rio Grande do Sul, Porto Alegre, Brazil (e-mails: {virginia.bordignon, luciola}@ufrgs.br).*

Abstract: This work presents an application of the Virtual Reference Feedback Tuning (VRFT) method to a multivariable refrigeration system benchmark. For the Benchmark PID 2018 problem, two approaches are developed: decentralized and centralized multivariable PID controllers are designed using only open-loop collected data. In order to cope with the saturation of the process' input variables, an anti-windup strategy is associated with the PID controllers. Finally, the closed-loop behavior achieved with VRFT is compared with the reference controller originally provided by the problem, where it can be noted that the performance is considerably enhanced by both proposed designs, with obtained combined indexes of 0.4134 and 0.3635 for the decentralized and centralized controller, respectively.

Keywords: Refrigeration system, data-driven control, VRFT, PID, anti-windup.

1. INTRODUCTION

The control of refrigeration systems has become an important research topic since the concern about energy efficiency has improved in the past decades. The objective of the controller is to provide the desired cooling power in steady-state for the closed-loop system, while minimizing transient behaviors. High performance controllers usually demand the identification of an accurate process model. However, refrigeration systems present strong nonlinearities and high coupling due to connections between pipes and valves, which make modeling or identification of such systems a hard task.

Many examples of refrigeration systems control exist in the literature. In Ekren et al. (2010), three different SISO control methods are employed and compared: classical PID controller using Ziegler-Nichols tuning method (Ziegler and Nichols, 1942); fuzzy logic controller, as also seen in Aprea et al. (2004), and model identification and controller design using an artificial neural network (ANN), where the latter provided overall better performance results, showing that when an accurate process model is used, usually better performance is obtained. In other works, the model identification stage is also performed before the control design: in Piedrahita-Velásquez et al. (2014) an autoregressive moving average with exogenous inputs (ARMAX) model is identified for a variable-speed compressor and a PI controller is tuned using a pole-placement method; in Dantas et al. (2017) a stochastic dynamic model identification is performed for an expansion valve actuator, so as to enable a stochastic model predictive control (MPC) implementation for superheat control.

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Another important characteristic that should be taken into account in the control design is the multivariable nature of the system, since the involved variables are strongly coupled. When this is the case, MIMO tuning rules should be used for high performance behavior. Multivariable controllers can be seen in Yin et al. (2016), where a multivariable cascade control is applied to a refrigeration cycle system, employing model identification to design an MPC and a PI control layer, and in Schurt et al. (2009), where, after identifying the refrigeration system, a MIMO controller is designed with the Linear Quadratic Gaussian (LQG) method.

If on the one hand Ziegler-Nichols tuning rules can be too simple for obtaining a high performance closed-loop behavior, on the other hand the modeling stage of vapor compression refrigeration systems can be rather complex, considering their nonlinear dynamics. An alternative within the control design theory is to employ data-driven control methods (Bazanella et al., 2012), which are used to design SISO or MIMO controllers based only on collected data from an experiment, without deriving a mathematical model for the process. These methods are more efficient than Ziegler-Nichols rules, since they use a batch of data, instead of two or three quantities provided by a specific experiment. Also, considering a fixed structure controller (PID for example) design, data-driven design can even outperform model-based design since they avoid identification and model reduction steps (Campestrini et al., 2017).

Among many data-driven design methods (Hjalmarsson et al., 1998; Campi et al., 2002; Karimi et al., 2004; Kammer et al., 2000), Virtual Reference Feedback Tuning (VRFT) (Campi et al., 2002) plays an important role: it estimates a fixed structure controller based on only one batch of input-output data collected in an experiment, which may be performed in open or closed loop. Recently some effort was put on extending data-driven methodologies to MIMO systems such as VRFT (Nakamoto, 2004) (Formentin and Savaresi, 2011) (Campestrini et al., 2016). Again, the VRFT formulation for MIMO systems presents the characteristic of needing only one experiment to design a centralized or descentralized controller.

In the benchmark application, the VRFT method presented in (Campestrini et al., 2016) is used to tune a multivariable PID controller based only on data collected from the process: first, a decentralized PID controller is designed and then a centralized one is proposed. The aim here is to provide in closed-loop efficient reference tracking for the cooling power delivered to the secondary flux and for the degree of superheating, while acting on the compressor speed and the valve opening variables. Besides, an anti-windup stage is included so as to cope with the manipulated variables' saturation.

This paper will be divided in the following fashion: section 2 presents the refrigeration system of the Benchmark PID 2018 as well as the proposed control strategy. In section 3, the multivariable control design using VRFT is thoroughly explained. Then, in section 4, the results obtained with the controllers are exposed and compared with the reference controller provided along with the Benchmark. Finally, section 5 presents some conclusions from the work.

Notation: throughout this paper, the variable t represents the discrete time variable and q, the discrete shift operator, i.e. $qx(t) = x(t + 1)$ for a signal $x(t)$.

2. REFRIGERATION SYSTEM BENCHMARK CONTROL APPROACH

2.1 Refrigeration System Control

The Benchmark PID 2018 consists in a refrigeration system based on vapor compression, inspired on modeling and identification works of Rodríguez et al. (2017) and Bejarano et al. (2016). The model itself is implemented as a black box in Simulink, therefore information about its mathematical expression is not given. Full documentation on the system and MATLAB files can be found in `http://servidor.dia.uned.es/~fmorilla/benchmarkPID2018/`.

A simplified diagram for the refrigeration cycle can be seen in Fig. 1, where some of the variables are indicated.

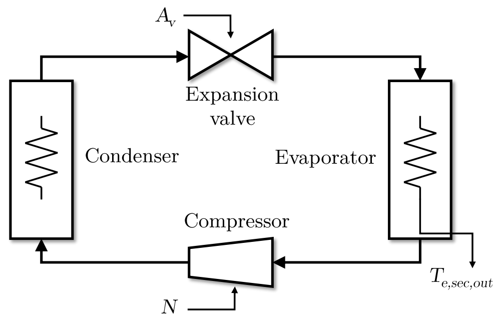

Fig. 1. Diagram of the refrigeration system benchmark.

The multivariable refrigeration system presents 2 outputs, the outlet temperature of the evaporator secondary flux $T_{e,sec,out}$ and the degree of superheating T_{SH}, to be controlled through 2 inputs, the compressor speed N and the expansion valve opening A_v. Also, the system is subjected to 7 disturbance signals (see Table 1). The Coefficient of Performance COP is also provided by the system so as to indicate steady-state performance quality.

Each input and disturbance variable must respect a particular range of accepted values (see documentation on the benchmark for more details). Particularly for the controller design phase, it is important to know the range of the control variables: $A_v \in [10 - 100]\,\%$ and $N \in [30 - 50]\,\text{Hz}$. Throughout this work, the initial operation point for the system's variables was chosen as shown in Table 1.

Moreover a distinctive characteristic of refrigeration systems is that the output variables are not completely independent. In the Benchmark case, for a given steady-state scenario for $T_{e,sec,out}$ and disturbance signals, there is a limited range of achievable steady-state for T_{SH}.

Table 1. Refrigeration system variables and chosen operation point.

Variable	Description	Value	Units
A_v	Expansion valve opening	48.79	%
N	Compression speed	36.45	Hz
$T_{e,sec,out}$	Outlet temperature of the evaporator second flux	-22.15	°C
T_{SH}	Degree of superheating	14.65	°C
$T_{c,sec,in}$	Inlet temperature of the condenser secondary flux	30	°C
$\dot{m}_{c,sec}$	Mass flow of the condenser secondary flux	150	g/s
$P_{c,sec,in}$	Inlet pressure of the condenser secondary flux	1	bar
$T_{e,sec,in}$	Inlet temperature of the evaporator secondary flux	-20	°C
$\dot{m}_{e,sec}$	Mass flow of the evaporator secondary flux	150	g/s
$P_{e,sec,in}$	Inlet pressure of the evaporator secondary flux	1	bar
T_{surr}	Surroundings temperature	25	°C

Along with the refrigeration system description, the documentation of the Benchmark PID 2018 also provides a reference controller $C_r(q)$ for comparison. The reference controller consists in a decentralized structure with $c_{r11}(q)$ a general discrete-time controller and $c_{r22}(q)$ a PI controller, the second of which employing a built-in Simulink anti-windup solution. The reference controller expression is given as

$$C_r(q) = \begin{bmatrix} \frac{-1.0136q^2 - 0.0626q + 0.9988}{(q-1)(q-0.9853)} & 0 \\ 0 & \frac{0.42q - 0.02}{(q-1)} \end{bmatrix}. \quad (1)$$

2.2 Control strategy

The objective of the refrigeration system control is to provide the desired amount of cooling power to the flow on the evaporator, here represented as a reference signal on the $T_{e,sec,out}$ variable, $Ref\,T_{e,sec,out}$. Also, a reference signal on the T_{SH} output is imposed, $Ref\,T_{SH}$. Therefore, the controller should be able to track both reference signals as efficiently as possible, despite disturbances' action.

Motivated by the lack of a mathematical model to describe the process, this work proposes a data-driven approach to identify a multivariable PID controller. In this framework, we consider the problem of providing A_v and N for tracking reference signals $Ref\,T_{e,sec,out}$ and $Ref\,T_{SH}$, which results in a 2-dimensional controller structure. The control signal is calculated as

$$u(t) = C(q, P)(r(t) - y(t)), \tag{2}$$

where

$$u(t) \triangleq [\, A_v \;\; N \,]^T$$
$$y(t) \triangleq [\, T_{e,sec,out} \;\; T_{SH} \,]^T$$
$$r(t) \triangleq [\, Ref\,T_{e,sec,out} \;\; Ref\,T_{SH} \,]^T$$

and $C(q, P)$ is a discrete-time controller parametrized by P. This MIMO controller can be either decentralized or centralized. In the first design, a decentralized PID controller is considered, given as

$$C(q, P) = \begin{bmatrix} c_{11}(q, \rho_{11}) & 0 \\ 0 & c_{22}(q, \rho_{22}) \end{bmatrix} \tag{3}$$

where each subcontroller is parametrized as in

$$c_{ij}(q, \rho_{ij}) = \rho_{ij}^T \bar{C}(q) = [\, k_{ij}^P \;\; k_{ij}^I \;\; k_{ij}^D \,] \begin{bmatrix} 1 \\ \frac{q}{(q-1)} \\ \frac{q-1}{q} \end{bmatrix}, \tag{4}$$

and $P = \left[\, \rho_{11}^T \;\; \rho_{22}^T \,\right]^T$. The second approach consists in designing a centralized PID controller, structured as

$$C(q, P) = \begin{bmatrix} c_{11}(q, \rho_{11}) & c_{12}(q, \rho_{12}) \\ c_{21}(q, \rho_{21}) & c_{22}(q, \rho_{22}) \end{bmatrix} \tag{5}$$

with each subcontroller parametrized as in (4) and

$$P = \left[\, \rho_{11}^T \;\; \rho_{12}^T \;\; \rho_{21}^T \;\; \rho_{22}^T \,\right]^T. \tag{6}$$

Feedforward compensation has not been considered in the control design. The closed-loop results obtained with each of the controllers are compared with the reference controller (1) provided by the Benchmark PID 2018 problem.

It is important to notice that both control variables are susceptible to saturation within their respective ranges. It is advisable therefore to include a anti-windup strategy in the control design, so as to avoid windup effects in the PID's integral element (Åström and Hägglund, 2006). In this application, the back-calculation anti-windup method was employed, whose diagram for a SISO PID controller can be seen in Fig. 2, where $u(t)$ is the calculated control signal and $u_s(t)$ is the measured (or estimated) saturated control signal and $e(t) = r(t) - y(t)$. The back-calculation gain was designed as $K^T = K^I/K^P$ as proposed in Bohn and Atherton (1995). Fig. 3 shows the extension of the anti-windup scheme for the control signal $u_i(t)$ in a multivariable application.

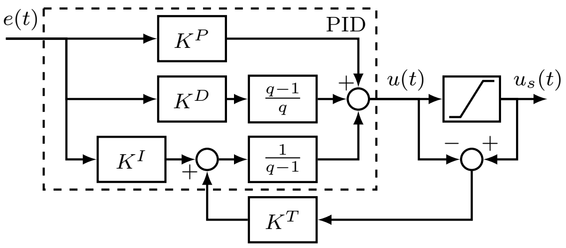

Fig. 2. PID controller diagram with anti-windup loop.

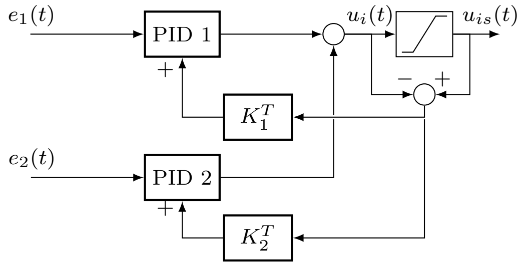

Fig. 3. Multivariable PID controller diagram with anti-windup loop.

3. DATA-DRIVEN CONTROLLER DESIGN

Data-driven methods aim to tune the controller parameters from input-output data obtained through experiments performed on the process, without deriving a process model. The ease of implementation justifies the successful use of such methods in many control applications (Formentin et al., 2013; Radac and Precup, 2016).

The VRFT is one of these methods, which tunes a fixed-structure controller by solving a model-matching problem. A classical model-matching, or model-reference (MR), formulation is given as follows: consider a discrete-time MIMO process with n inputs and n outputs, represented by vectors $u(t)$ and $y(t)$ respectively, where for a linear system

$$y(t) = G(q)u(t)$$

in which $G(q)$ represents the process' unknown transfer function. The control signal is designed as in (2) so the system in closed-loop becomes

$$y(t) = T(q, P)r(t),$$

with $T(q, P) = [I + G(q)C(q, P)]^{-1}G(q)C(q, P)$.

The controller parameters are tuned by solving

$$\min_P J^{MR}(P)$$
$$J^{MR}(P) \triangleq \sum_t \|(T(q, P) - T_d(q))r(t)\|_2^2. \tag{7}$$

where $T_d(q)$ is a chosen transfer matrix and represents the desired closed-loop behavior for reference tracking and is known as the *reference model*. However, since $T(q, P)$ depends on the unknown process' model, data-driven approaches minimize a different criteria, whose minimum is near the minimum of (7), and is based only on data collected on the process, without using a mathematical model.

More specifically, one-shot methods, as the one used in this work, estimate the optimal controller based on one sufficiently rich batch of measured input-output data

$$Z_M = \{u(t),\; y(t)\}, \text{ for } t = 1, \ldots, M$$

collected either in open or closed loop.

3.1 Multivariable VRFT Overview

A multivariable formulation for the classical VRFT method is presented in (Campestrini et al., 2016). As in the consolidated VRFT method for SISO systems (Campi et al., 2002), the purpose is to design an optimal controller which approaches in closed-loop a desired behavior specified by $T_d(q)$.

From the measured output $y(t)$ and the chosen reference model $T_d(q)$, a virtual reference (VR) signal is calculated as $\bar{r}(t) = T_d(q)^{-1}y(t)$. Now the problem of determining the optimal $C(q,P)$ is rewritten as

$$\begin{aligned}&\min_P J^{VR}(P)\\ &J^{VR}(P) \triangleq \sum_t^M \|F(q)[u(t) - C(q,P)(\bar{r}(t) - y(t))]\|_2^2\end{aligned} \tag{8}$$

where M is the number of data samples and $F(q)$ a filter, whose role is to approximate the minima of (8) and (7).

The problem in (8) can be easily solved through least-squares method if the controller is linearly parametrized in P, as the decentralized and centralized PID controllers presented in (3) and (5) with (4), respectively.

The solution of problem (8) is given as

$$\hat{P} = \left[\sum_{t=1}^M \phi(t)\phi^T(t)\right]^{-1} \sum_{t=1}^M \phi(t)w(t) \tag{9}$$

where

$$w(t) = F(q)u(t) \quad \phi(t) = [\, A_1(t) \, \dots \, A_n(t) \,] \tag{10}$$

$$A_x(t) = \begin{bmatrix} F_{x1}(q)E(t) \\ \vdots \\ F_{xn}(q)E(t) \end{bmatrix} \qquad E(t) = \begin{bmatrix} \bar{C}(q)\bar{e}_1(t) \\ \vdots \\ \bar{C}(q)\bar{e}_n(t) \end{bmatrix} \tag{11}$$

for $x = 1, \dots, n$, with $\bar{e}(t) \triangleq \bar{r}(t) - y(t)$. Notice that in the benchmark problem $n = 2$.

3.2 Design of filter $F(q)$

When none of the existing controllers within the chosen controller class can satisfy $J^{MR} = 0$, the minimum of (8) will be biased (Campestrini et al., 2016). In order to reduce such bias and approximate the minima of (7) and (8), Campestrini et al. (2016) shows that a good choice for $F(q)$ is

$$F(e^{j\omega}) \approx T_d(e^{j\omega})(I - T_d(e^{j\omega}))\Phi_r^{1/2}(\omega)\Phi_u^{-1/2}(\omega), \tag{12}$$

with $\Phi_r^{1/2}$ being the spectral factor of the power spectrum of $r(t)$ and $\Phi_u^{1/2}$, the spectral factor of the power spectrum of $u(t)$. Since data is collected in open-loop, using a combination of steps, we can approximate $\Phi_r^{1/2}(\omega) \approx \Phi_u^{1/2}(\omega)$ and the filter is easily obtained as

$$F(q) = T_d(q)(I - T_d(q)),$$

which is the filter used in the application of VRFT to the refrigeration system control.

3.3 Choice of $T_d(q)$

Once the controller class is defined (decentralized or centralized PID controller) and the data-collection experiment is defined (an open-loop experiment, where a combination of steps is applied to both inputs), the only quantity that is left to be chosen is the reference model $T_d(q)$.

The selection of $T_d(q)$ has an important effect on the method's performance. An unrealistic choice of $T_d(q)$ may often lead to a poor tuning of the controller within the chosen controller class. In MIMO systems, the selection of the reference model describes both the performance behavior of each output, as settling time and overshoot, for example, and the coupling between loops. If total decoupling is desired, then a diagonal matrix should be chosen. A thorough research on the subject or multivariable systems is presented in Gonçalves da Silva et al. (2018) and Gonçalves da Silva et al. (2016).

In this work, the desired reference model $T_d(q)$ for both controller approaches has been chosen as the decoupled transfer function matrix

$$T_d(q) = \begin{bmatrix} \frac{0.9}{(q-0.1)} & 0 \\ 0 & \frac{0.9}{(q-0.1)} \end{bmatrix}. \tag{13}$$

Such choice translates the desire of achieving null steady-state error, a 2 s settling time and no overshoot on both loops for step changes.

4. RESULTS

In order to implement the VRFT method, a batch of open-loop data with 800 samples and sampling period $T_s = 1$ s is collected from the system around the chosen operation point seen in Table 1. A step of -5 % was applied to input A_v at instant $t = 200$ s and a step of -5 Hz, to input N at $t = 500$ s. The disturbance signals are kept as constant values at the operation point. The input signal and the system's response can be seen in Fig. 4 and 5.

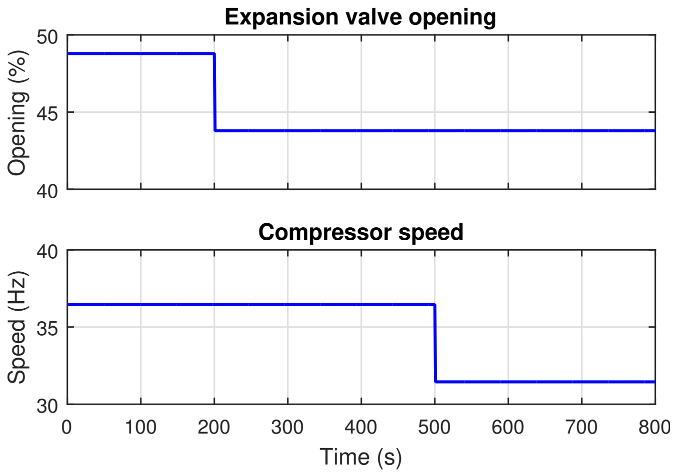

Fig. 4. Collected open-loop input data.

The obtained controller' parameters for both centralized and decentralized approaches can be seen in Table 2. From these parameters, it was possible to calculate the anti-windup gains K^T for each PID subcontroller. The simulation results in closed-loop can be seen in Fig. 6, where the expansion valve opening A_v and compressor speed N are compared for all three controller (the reference (1) and the two VRFT designed controllers), and in Fig. 7, where behavior of the outlet temperature of the evaporator secondary flux $T_{e,sec,out}$ and the degree of superheating T_{SH} are balanced as well.

The simulation scenario considered the initial operation point as in Table 1. The same scenario is described in the Benchmark PID 2018 documentation and used as standard simulation framework. It consists in a step of -0.5 °C applied to $Ref\, T_{e,sec,out}$ at $t = 120$ s. At instant $t = 540$ s,

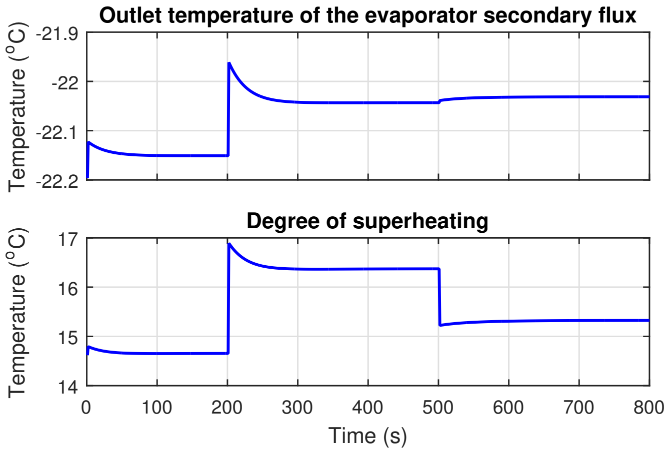

Fig. 5. Collected open-loop output data.

Table 2. Controllers' parameters obtained with VRFT method for decentralized and centralized controller approaches.

P	Decentralized	Centralized
ρ_{11}	[-20.513, -0.248, -0.313]	[-13.870, -0.120, -0.145]
ρ_{12}	-	[-0.6382, -0.009, -0.013]
ρ_{21}	-	[-30.167, -30.509, -0.127]
ρ_{22}	[0.809, 0.827, 0.007]	[2.883, 2.868, -0.005]

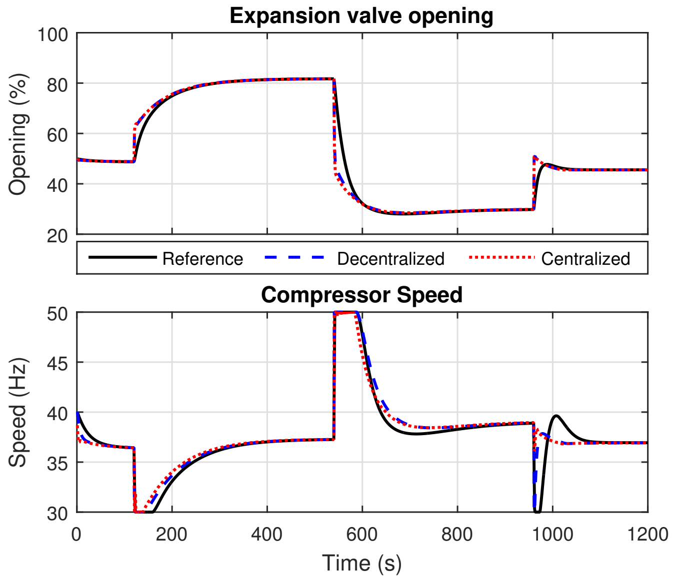

Fig. 6. Comparison of the refrigeration systems' inputs in closed-loop.

a step of $-1\,°\mathrm{C}$ is applied to disturbance $T_{e,sec,in}$. And at instant $t = 960\,\mathrm{s}$, steps of $1\,°\mathrm{C}$ and $-3\,°\mathrm{C}$ are imposed on disturbances $T_{e,sec,in}$ and $T_{c,sec,in}$ respectively. Reference signal T_{SH} is properly adjusted at each of these instants in order for the desired $T_{e,sec,out}$ steady-state to be achieved.

Qualitatively speaking, the performances obtained with the centralized and decentralized PID controllers tuned with VRFT are significantly improved if compared to the reference controller, both in reference tracking and disturbance rejection. Also, the settling time achieved for $T_{e,sec,out}$ is approximately in accordance with the reference model $T_d(q)$ specifications. However the settling time for

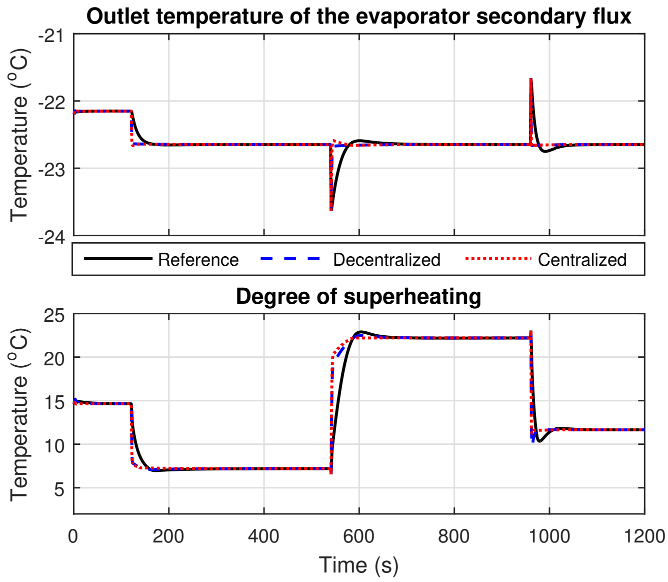

Fig. 7. Comparison of the refrigeration systems' outputs in closed-loop.

T_{SH} seems to be damaged by the saturation of input N (18 s for both centralized and decentralized controllers).

Now in order to compare the three approaches performance in a quantitative way, the Ratio of Integrated Absolute Error ($RIAE$) index is used for evaluating the reference tracking for the outlet temperature of the evaporator secondary flux and the degree of superheating ($RIAE_1$ and $RIAE_2$ respectively). The $RIAE$ is calculated as a ratio between the Integrated Absolute Errors (IAE) of the reference tracking provided by two controllers. Similarly the Ratio of Integrated Time multiplied Absolute Error ($RITAE$) is calculated for each of the reference signal changes (one for $T_{e,sec,out}$, $RITAE_1$ and three for T_{SH}, $RITAE_2^1$, $RITAE_2^2$ and $RITAE_2^3$). At last, the control effort is evaluated through the Ratios of Integrated Absolute Variation of Control signal ($RIAVU$) for the expansion valve opening and the compressor speed, $RIAVU_1$ and $RIAVU_2$ respectively. The combined index J is calculated as a mean value and can be interpreted as an overall relative performance index.

In Table 3, all indexes have been calculated for both centralized and decentralized PID controller using as reference the provided controller seen in (1). An index resulting in a value smaller than 1 indicates that the evaluated controller's performance is relatively improved (the individual IAE, ITAE and IAVU indexes values are decreased).

From Table 3, all performance indexes are considerably enhanced by both controllers evaluated. The exception being the control effort in the expansion valve, which is 5 % higher than the one provided by the reference controller. In general, the combined index J indicates that the global quality of the closed-loop is increased on both control approaches.

5. CONCLUSIONS

In this paper, the VRFT method was used to tune a multivariable PID controller for a refrigeration system

Table 3. Ratios of IAE and IAVU indexes and combined index relative to the reference controller.

Index	Decentralized	Centralized
$RIAE_1$	0.1569	0.1597
$RIAE_2$	0.3338	0.2102
$RITAE_1$	0.7193	0.7870
$RITAE_2^1$	0.3466	0.2009
$RITAE_2^2$	0.3704	0.1176
$RITAE_2^3$	0.0867	0.0437
$RIAVU_1$	1.0499	1.0513
$RIAVU_2$	0.9301	0.9032
J	0.4134	0.3635

benchmark. A model identification step was hence avoided, and the controller was designed using only one batch of open-loop data measured from the process. In the proposed controller approach, two MIMO PID structures were employed: decentralized and centralized MIMO PID, all of which associated with an anti-windup strategy for handling the control variables saturation. The results showed that the overall closed-loop performance was improved for both PID structures, if compared with the given reference controller. Besides, the VRFT implementation shows that good PID tuning can be achieved with very little computational burden (in the VRFT, only a least-squares problem is solved) and no knowledge of the plant's model, as long as data from the process is available and the output variables remain in a linear region of operation. Future extensions of this work include employing a two-degree-of-freedom controller structure, taking into account disturbance measurements in the controller design.

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