2018

Practical Guidelines for Tuning Model-Based Predictive Controllers for Refrigeration Compressor Test Rigs

Hiago A. S. Dangui
Federal University of Santa Catarina, Brazil, hiagodangui@gmail.com

Rodolfo C. C. Flesch
Federal University of Santa Catarina, Brazil, rodolfo.flesch@ufsc.br

Bernardo B. Schwedersky
Federal University of Santa Catarina, Brazil, bernardo.schwedersky@gmail.com

Practical guidelines for tuning model-based predictive controllers for refrigerant compressor test rigs

Hiago Antonio Sirino DANGUI[1], Rodolfo César Costa FLESCH[2]*, Bernardo Barancelli SCHWEDERSKY[1]

[1] Universidade Federal de Santa Catarina, Programa de Pós-Graduação em Engenharia de Automação e Sistemas,
Florianópolis, Santa Catarina, Brazil
Email address: {hiagodangui, bernardo.schwedersky}@gmail.com

[2] Universidade Federal de Santa Catarina, Departamento de Automação e Sistemas,
Florianópolis, Santa Catarina, Brazil
Tel.: +55 48 3721-7600. Email address: rodolfo.flesch@ufsc.br

* Corresponding Author

ABSTRACT

This paper presents a practical method for tuning the parameters of a model predictive control technique for controlling the suction and discharge pressures of refrigerant compressors in test rigs. The proposed method presents a clear interpretation, based on the process dynamics and its real operation. The rig considered in this paper has two outputs, which are the pressures at the inlet and outlet of the compressor under test, and two manipulated variables, which are two valve openings. In this study, the model predictive control technique known as generalized predictive control was used and, in addition to the experimental results, an analysis of the effects of the controller tuning parameters on the closed-loop results is presented. The obtained results are promising and show that the proposed method can be used as a starting point for the tuning of predictive controllers applied to test rigs and can contribute to make parameter tuning simpler and more intuitive.

1. INTRODUCTION

The refrigerant compressor industry makes large investment in research and development for the continuous improvement of its products and also for quality control purposes. One important aspect for this development is the ability to test in the compressors under the numerous operating conditions that can be found during its use. There are several tests generally executed, and some of them are regulated by international standards, such as performance evaluation tests, which are regulated by EN 13771-1 (CEN, 2016) and ANSI / ASHRAE 23 (2005). These standards specify the possible test methods, the operating conditions to which the compressor under test must be submitted during evaluation and the maximum admissible measurement uncertainties. In general, one key aspect of this kind of test is the closed-loop control of several process variables, needed to set the operating point at which the compressor will be evaluated.

In tests rigs, the operating condition of the compressor is usually defined by the regulation of variables around specific reference values. The most common variables are the temperature at the compressor inlet and the suction and discharge pressures. Those variables are traditionally controlled by two or more single-input and single-output (SISO) controllers, even when test rigs are multiple-input and multiple-output (MIMO) processes with total or partial coupling between variables, have nonlinear behaviors, and present time delays. These characteristics increase the complexity of the control problem and traditional controllers, such as Proportional-Integral-Derivative (PID) controllers, can present sluggish or oscillatory responses in closed loop, thus increasing the overall test duration (Flesch and Normey-Rico, 2010; Flesch *et al*., 2011; Flesch *et al*., 2012). Therefore, the use of advanced control strategies can increase the productivity and accuracy of the tests.

There are few references in the literature which explore the application of advanced control and optimization strategies in compressor test rigs, but several studies have demonstrated the benefits of implementing these techniques in refrigeration systems (Naidu and Rieger, 2011). For example, model-based predictive controllers (MPCs) are suitable for regulating the vapor compression cycle of refrigeration plants because the dynamic couplings and operational constraints can be considered directly in the determination of the optimum control signal to reduce the effect of transient disturbances and increase the system energy efficiency (Pollock *et al.*, 2014; Yang, Pollock and Wen, 2017).

Predictive controllers can be used, for instance, to minimize evaporator overheating (Fallahsohi *et al.*, 2009), to maximize COP (Ma *et al.*, 2010), and to reduce energy consumption and operating expenses of refrigeration systems without compromising the desired operating specifications (Schalbart, Leducq and Alvarez, 2015, Shafiei and Alleyne, 2015, Thiem *et al.*, 2017). The literature presents applications of MPCs in small-scale refrigeration systems, such automotive air-conditioning (Ng *et al.*, 2014), and also large-scale systems (Shafiei *et al.*, 2014).

In refrigerant compressor test rigs, MPC algorithms can be used to mitigate the coupling between suction and discharge pressures, which can improve the performance of control of the compressor operating condition and, therefore, the overall test performance. Besides that, MPC can consider the process constraints in its formulation and compensate dead time in closed loop. However, MPC tuning typically involves a large number of parameters, which in practice can make the task tricky (Garriga and Soroush, 2010; Shah and Engell, 2011). Thus, the development of a practical approach for tuning the MPC parameters can broaden its applications in refrigeration test rigs by making one of its main drawbacks, its tuning complexity, simpler and more intuitive.

This work proposes an experimental method for tuning the parameters of an MPC algorithm, known as generalized predictive control (GPC), to regulate the inlet and outlet pressures of refrigerant compressors in test rigs. This approach presents a clear interpretation, based on the process dynamics and its real operation. The method can be used as a starting point for MPC tuning and covers from the process model identification to the definition of the controller tuning parameters. The study presented in this paper is based on a specific test rig used in industry, but the method is presented in a general way so that it can be used as a practical guideline for tuning MPC for refrigerant compressor test rigs.

This paper is structured as follows. Section 2 presents the fundamental concepts of MPC strategies and details the formulation of the GPC algorithm. Section 3 presents the proposed tuning method. Section 4 shows the experimental evaluation of the method and the discussion of the results. Finally, Section 5 presents the conclusions of the paper.

2. MODEL-BASED PREDICTIVE CONTROL

Model-based predictive control is an advanced control technique which makes use of an explicit process model to predict its future behavior over a horizon N, and then calculates a control increments sequence, $\Delta\boldsymbol{u}$, which makes the future outputs of the process, $\hat{\boldsymbol{y}}$, track the future references, $\boldsymbol{w}$ (Camacho and Bordons, 2007). MPC consists in a receding horizon algorithm and its operation can be summarized as: the future process outputs are predicted based on past control signals and past and current process outputs; these predictions and the reference signals are used to obtain an optimal sequence of control increments ($\Delta\boldsymbol{u}$); the first control signal of the horizon for each input is applied to the process and, after that, the receding horizon rolls forward, beginning the next iteration of the algorithm. The main elements of any MPC are the prediction model, the objective function, and the optimizer.

The process model is the core element of an MPC strategy, since it is used to obtain the predictions of the system future outputs, $\hat{\boldsymbol{y}}$. Several model architectures have been used as prediction models in MPC algorithms, from simpler approaches, as the coefficients of the impulse or step response, to more complex architectures, as artificial neural networks (Pedersen *et al.*, 2017). One of the most studied MPC algorithms is the Generalized Predictive Control (GPC), which is considered in this work. It uses the Controlled Auto-Regressive Integrated Moving Average (CARIMA) model to obtain the predictions of the future process outputs (Clarke *et al.*, 1987). The CARIMA model is defined as:

$$A(z^{-1})y(t) = B(z^{-1})z^{-d}u(t-1) + \frac{C(z^{-1})p(t)}{\Delta}, \tag{1}$$

with $A(z^{-1})$, $B(z^{-1})$ and $C(z^{-1})$ representing polynomials in z^{-1}, z^{-d} representing the time delay of d time instants, $y(t)$ representing the process outputs, $u(t)$ representing the control signal, $p(t)$ representing a zero-mean white noise (which is the stochastic part of this model), and $\Delta = 1 - z^{-1}$. Based on Equation (1), the GPC prediction model can be obtained using a Diophantine equation and it can be split into two parts, the free and forced responses. The first one consists in the process response resulting of the past control actions, while the second one is the process response resulting of the future control actions. For a system with m outputs and n inputs, the outputs prediction can be written as:

$$\hat{\boldsymbol{y}} = \boldsymbol{G}\Delta\boldsymbol{u} + \boldsymbol{f} \tag{2}$$

with $\hat{\boldsymbol{y}} \in R^{\sum_{i=1}^{m} N_i}$ representing the prediction vector of the process outputs along the prediction horizon N of each output; $\boldsymbol{G} \in R^{\sum_{i=1}^{m} N_i \times \sum_{i=1}^{n} M_i}$ representing the system dynamic matrix, which is formed by blocks with a lower diagonal structure with the step response coefficients of each input-output pair; $\Delta\boldsymbol{u} \in R^{\sum_{i=1}^{n} M_i}$ representing the vector of future control increments, along each control horizon M_i; and $\boldsymbol{f} \in R^{\sum_{i=1}^{m} N_i}$ representing the free response of each system output along the prediction horizon N_i.

The second main element of MPC is the cost function, which defines the control problem objective. In general, a cost function is selected to guarantee that the future process outputs track setpoint changes and, at same time, penalizes the control efforts. A general equation, which is used in the GPC algorithm, is (Camacho and Borbons, 2007):

$$J = \sum_{i=1}^{m} \sum_{j=N_{1,i}}^{N_{2,i}} \delta_i(j)[\hat{y}_i(t+j|t) - w_i(t+j|t)\,]^2 + \sum_{i=1}^{n} \sum_{j=1}^{M_i} \lambda_i(j)[\Delta u_i(t+j-1)]^2, \tag{3}$$

with $\hat{y}(t+j|t)$ representing the prediction of the process outputs for $t+j$ taken at time instant t; $w(t+j|t)$ representing the future setpoints, known at time instant t; N_1 and N_2 representing the minimum and maximum prediction horizons, with $N = N_2 - N_1 + 1$ being the prediction horizon; M representing the control horizon; and the coefficients $\delta_i(j)$ and $\lambda_i(j)$ representing weighting sequences for the setpoint tracking error and control effort, respectively. They can be chosen as constant values or can assume different values for each of the instants of the prediction and control horizons.

To obtain the optimal values of $\boldsymbol{\Delta u}$, the cost function J has to be minimized. The optimal solution is the one that minimizes the cost function J respecting the imposed constraints, being this optimization problem formulated as:

$$\begin{array}{cc} \min\limits_{\Delta \boldsymbol{u}} & J \\ \text{subject to} & \mathbf{A}\Delta\mathbf{u} \leq \mathbf{b} \end{array}. \tag{4}$$

In this case, matrix **A** and vector **b** define the control problem constraints, which are typically related to the limits in amplitude and variation of the control signal or process variables. Details about constraints and their representation in an MPC problem can be found in Camacho and Bordons (2007). If the problem does not consider constraints, it has an analytical solution, since the cost function is a quadratic form with respect to the control increment. On the other hand, if constraints are considered, the problem of Equation (4) can be solved with quadratic programming methods.

3. PROPOSED CONTROLLER TUNING

This section presents the practical tuning method proposed for refrigerant compressor evaluation test rigs. The tuning method is described for closed circuit tests rigs with control valves installed at the suction and discharge of the compressor. The section is divided into three subsections. Subsection 3.1 shows how the dynamic models of the compressor pressures can be identified. Subsection 3.2 shows how to choose the prediction and control horizons. Finally, Subsection 3.3 presents the tuning of the weights $\delta_i(j)$ and $\lambda_i(j)$.

3.1 Dynamic model identification

The identification of the dynamic behavior of the compressors suction and discharge pressures can be made using a step response test. In this test, the pressures are set manually at the desired operating point and then abrupt changes are made in the manipulated variables (control valve openings). When the pressures reach steady state, the dynamic relationship between a specific input-output pair can be approximated by a first order model as:

$$H(s) = \frac{y(s)}{u(s)} = \frac{Ke^{-\theta s}}{\tau s + 1}, \tag{5}$$

with s representing the complex variable used in the Laplace transform; $y(s)$ and $u(s)$ representing the Laplace transforms of the output and the input signals, respectively; K representing the static gain defined by the ratio of the output variation by the amplitude of the applied step; τ representing the time constant, which is the time required for the system to reach approximately 63.2% of its steady state value; and θ representing the time delay, which is equal to the time required for the output to change after application of the step.

After the identification of the models, the dynamic behavior of the pressures can be represented as MIMO system with two inputs and two outputs as:

$$\begin{bmatrix} y_s(s) \\ y_d(s) \end{bmatrix} = \begin{bmatrix} H_{11}(s) & H_{12}(s) \\ H_{21}(s) & H_{22}(s) \end{bmatrix} \begin{bmatrix} u_s(s) \\ u_d(s) \end{bmatrix}, \tag{6}$$

with $y_s(s)$ representing the suction pressure; $y_d(s)$ representing the discharge pressure; and $u_s(s)$ and $u_d(s)$ representing the manipulated variables associated with the valves installed at the suction and discharge of the compressor, respectively. Subsections 3.2 and 3.3 shows how the parameters of Equations (5) and (6) can be used to obtain the GPC tuning.

3.2 Horizons *N* and *M*

The prediction horizon defines a time window in which the behavior of the system will be predicted and N is the number of predicted samples of the outputs. Higher values of N provide the controller with a prediction of the behavior of the system until a time instant closer to the steady state. On the other hand, lower values of N provide a prediction which is limited to the transient. According to Clarke et al. (1987), the choice $N = 10$ is reasonable for various classes of processes, being considered as the default horizon for GPC implementation. Theoretically, the maximum prediction horizon N_2 must be at least greater than the degree of the polynomial $B(z^{-1})$ of Equation (1), thus all states of the system will be included in the cost of Equation (3) (Clarke et al., 1987). In practice, N is defined long enough that between 60% and 95% of the steady state value is understood by the horizon (Garriga and Soroush, 2010). Thus, the following guideline for the prediction horizon choice is suggested to predict the behavior of the pressures:

$$N = \max\left[10, \operatorname{int}\left(\frac{5\tau}{T}\right)\right], \tag{7}$$

with T representing the sampling period. According to Equation (7), if $5\tau/T > 10$, then N can be chosen as the nearest integer to $5\tau/T$, which means that the prediction horizon will be equal to the number of samples needed to predict 99.3% of the steady-state value. If the ratio is smaller than 10, the default value $N = 10$ is adopted. If the time delay θ is known, the horizon N_1 can be chosen as $N_1 = \operatorname{int}(\theta/T) + 1$ to reduce the amount of computation, since the system output is affected by a change in the system input just after the time delay has elapsed.

The control horizon M defines the size of the future control increment sequence, $\boldsymbol{\Delta u}$, calculated at each iteration by the optimizer. Higher values of M lead to a controller which is more robust, while lower values lead to a control which is more susceptible to parametric process variations (Clarke et al., 1987). In addition, higher values of M increases the complexity of the quadratic optimization problem and, therefore, the calculation time of the control law, which in practical applications should be substantially smaller than the sampling period (Camacho and Bordons, 2007). In the literature, $M = 1$ is considered as the default value for the control horizon (Garriga and Soroush, 2010). In test rigs, due to its use in different operating conditions, it is important that M may be chosen to fulfill a compromise between the robustness of pressures regulation and the calculation time. Following this specification, M can be chosen as a value between 5% and 25% of the value of the prediction horizon N (Trierweiler et al., 2003).

3.3 Weights $\boldsymbol{\delta_i(j)}$ and $\boldsymbol{\lambda_i(j)}$

This work makes use of constant weights along N so, from this subsection on, $\delta_i(j)$ and $\lambda_i(j)$ will be denoted only by δ_i and λ_i. In addition, the subscripts s and d will be used to denote the parameters associated with suction and discharge pressure, respectively.

The tuning of δ_i and λ_i allows the adjustment of the rising time and the control signal smoothness. Large values of δ_i penalize the setpoint tracking error, resulting in faster settling times. Meanwhile, greater values of λ_i result in costs that penalize the control signal variation, thus, reducing the control effort and resulting in more robust solutions (Camacho and Bordons, 2007). Therefore, the tuning of δ_i and λ_i affects directly the performance of the compressor tests and must be defined according to the test rig desired dynamic characteristics and the test routine itself. Typically, in test rigs similar to the one specified at the beginning of Section 3, the settling time of the discharge pressure is larger than that of the suction pressure. In addition, variations in the valve opening installed at the compressors suction also modify the discharge pressure. On the other hand, variations in the valve opening installed at the compressor discharge do not imply variations in the suction pressure. Thus, the following two criteria can be considered for the tuning of δ_i

and λ_i: (I) the controller must be robust to regulate the pressures under different operating conditions, so the responses must be smoother, which implies in $\lambda_i > \delta_i$; (II) softer variations in the opening of the suction valve reduce the disturbances in the discharge pressure, therefore $\lambda_s > \lambda_d$.

In practice, the tuning of the weights defines the importance of each part of Equation (3) in the total cost of J. For the case of the system defined in Equation (6) the cost J can be calculated as:

$$J = \delta_s \sum_{j=1}^{N_s} e_s(t+j|t)^2 + \delta_d \sum_{j=1}^{N_d} e_d(t+j|t)^2 + \lambda_s \sum_{j=1}^{M_s} \Delta u_s(t+j-1)^2 + \lambda_d \sum_{j=1}^{M_d} \Delta u_d(t+j-1)^2, \tag{8}$$

with $e(t+j|t) = w(t+j|t) - \hat{y}(t+j|t)$ representing the values of the reference tracking error obtained at time instant t. Equation (8) can be simplified using the average value of $e(t+j|t)$ along horizon N defined in the time domain by Equation (9):

$$\bar{e}(t) = \frac{1}{NT}\int_0^{NT} (w(t) - \hat{y}(t))\,\mathrm{d}t. \tag{9}$$

Assuming the application of a control increment Δu in the first-order model identified in subsection 3.1, the output can be described as $\hat{y}(t) = (1 - e^{-t/\tau})K\Delta u$. With the assumptions that the Δu applied to the system was calculated by the optimizer and that the prediction horizon is long enough to let the system reach steady state, the tracking error is null in steady-state. Then, at the end of the horizon $N = 5\tau/T$ the output value is approximately equal to the reference $w(t)$, i.e. $y(5\tau) \cong w(t) \cong K\Delta u$. Thus:

$$\bar{e}(t) = \frac{1}{5\tau}\int_0^{5\tau} w\left[1 - \left(1 - e^{-t/\tau}\right)\right]\mathrm{d}t = \frac{w}{5\tau}\int_0^{5\tau} e^{-t/\tau}\,\mathrm{d}t = \frac{K\Delta u}{5\tau}\left[\tau - \frac{\tau}{e^5}\right]. \tag{10}$$

Therefore, $\bar{e}(t) \cong K\Delta u/5$. Applying this result in Equation (8) leads to the following simplification:

$$J \cong \frac{N_s\delta_s}{25}[K_{11}\Delta u_s + K_{12}\Delta u_d]^2 + \frac{N_d\delta_d}{25}[K_{21}\Delta u_s + K_{22}\Delta u_d]^2 + M_s\lambda_s\Delta u_s^2 + M_d\lambda_d\Delta u_d^2, \tag{11}$$

with K_{11}, K_{12}, K_{21} e K_{22} representing the static gains of the transfer functions of Equation (6).

Equation (11) can be used to tune δ_i e λ_i in accordance with criteria (I) and (II). Comparing the first two terms of Equation (11) and assuming $\delta_d = 1$ (one of the tuning parameters can be arbitrarily chosen, since the relative importance among the terms defines the optimization problem), δ_s can be chosen as a function of the static gains and the prediction horizons N_d and N_s, as shown in Table 1. Thus, the differences associated with the reference tracking error terms of J are compensated and the choice of δ_s is reduced to the tuning of parameter α. Higher values for α result in the prioritization of the suction reference tracking; on the other hand, if α is small, the tracking of the discharge reference is prioritized. The expression for λ_d in Table 1 is obtained by considering criterion (II), so that the condition $\lambda_s > \lambda_d$ holds. In this case, $\Delta u_s < \Delta u_d$, so it is assumed that $\Delta u_s \ll \Delta u_d$ and the term $[K_{21}\Delta u_s + K_{22}\Delta u_d]^2$ can be approximated by $K_{22}^2\Delta u_d^2$. By using this approximation and assuming the same importance of the second and the fourth terms of Equation (11), λ_d can be expressed as a function of N_d, M_d and K_{22}. A tuning parameter β was included to tune the relative importance of both terms. If the value of β is larger than one, the response is smoother and more robust; on the other hand, if β is made small, reference tracking performance is prioritized. Finally, equating the last two terms of J leads to the expression for the tuning of λ_s, which is defined as a function of λ_d and the ratio between the control horizons M_d and M_s. The value $\beta = 5$ has shown to be a good choice for compressor test rigs.

Table 1: Guidelines for tuning the weights

Weight	Tuning guideline
δ_d	1
δ_s	$\frac{N_d}{N_s}\frac{(K_{21}+K_{22})^2}{(K_{11}+K_{12})^2}\alpha^2$
λ_d	$\frac{N_d}{M_d}\frac{K_{22}^2}{25}\beta^2$
λ_s	$\lambda_d\frac{M_d}{M_s}\beta^2$

4. EXPERIMENTAL EVALUATION AND DISCUSSION

This section presents the experimental evaluation of the tuning method proposed in Section 3. Subsection 4.1 describes the test rig and the identification of dynamic pressure models. Subsection 4.2 presents the evaluation of controller tuning and discussion of results. Finally, Subsection 4.3 presents a comparison between GPC and the PID controllers typically used in the test rig.

4.1 Test rig description

The test rig considered in this paper is illustrated in Figure 1. This test rig is used in the refrigeration industry to emulate the operating conditions to which refrigerant compressors are submitted in real cooling systems. The operating conditions are defined by the regulation of the pressures at the compressor inlet and outlet, defined respectively as suction pressure, y_s, and discharge pressure, y_d. Using R-134a (tetrafluoroethane) as refrigerant, the test rig is able to impose operating conditions in the range of 0.5 bar (50 kPa) to 3.4 bar (340 kPa) for y_s and 5 bar (500 kPa) to 20 bar (2000 kPa) for y_d. In terms of evaporating temperatures, the range goes from about –40 ºC to +5 ºC, while the condensing temperature range goes from about 25 ºC to 65 ºC.

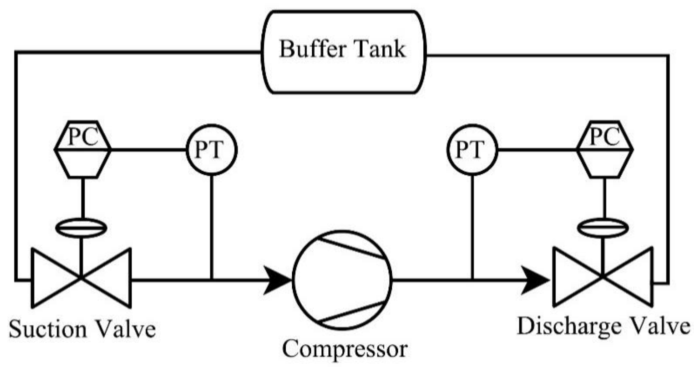

Figure 1: P&ID diagram of the test rig

The pressures are controlled by manipulation of the suction valve (SV) and discharge valve (DV) openings. The range of actuation of both valves is set between (0 and 10) V. Therefore, the test rig is a MIMO process with two inputs, the voltages u_s and u_d applied to SV and DV respectively, and two outputs, y_s and y_d. Figure 2 illustrates the step response test performed to identify the dynamic models. The chosen operating point represents 50% of the rig operating capacity. It can be seen that at 5 s of test, the application of a 1 V step in SV results in a variation of y_s and also an expressive variation of y_d, so there is a dynamic coupling between u_s and y_d. On the other hand, at 85 s the application of a 1 V step in DV causes a negligible variation in y_s. This result is due to the installation of the buffer tank, which mechanically reduces the coupling between the pressures in the discharge-suction direction. The process models identified are described by Equation (12):

$$\begin{bmatrix} y_s \\ y_d \end{bmatrix} = \begin{bmatrix} \frac{0.96}{3.6s+1} & 0 \\ \frac{6.86}{10.2s+1} & \frac{4.71}{12s+1} \end{bmatrix} \begin{bmatrix} u_s \\ u_d \end{bmatrix}. \tag{12}$$

The data were collected using a sampling period equal to $T = 0.2\ s$. The transport delays were not included in the models because they are numerically negligible when compared to the identified time constants.

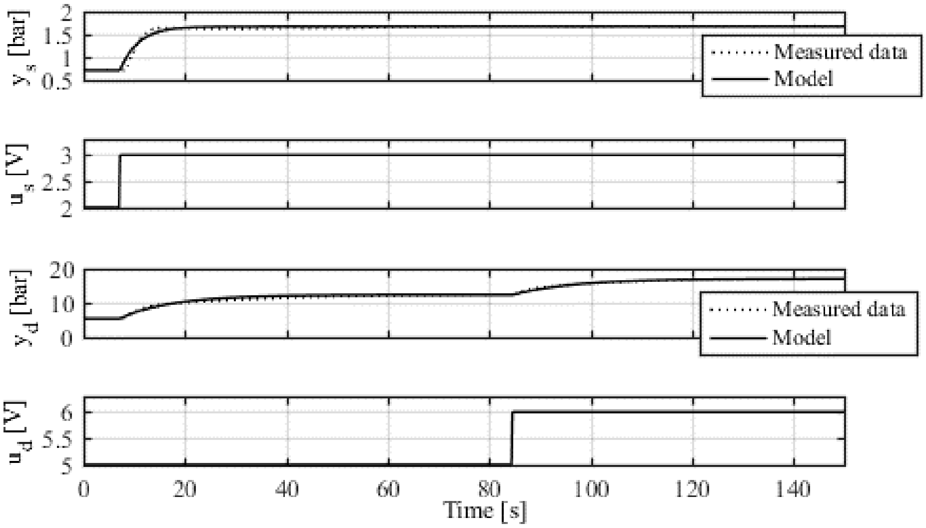

Figure 2: Step-response test

4.2 Tuning evaluation

Following the method described in Section 3, the tuning of GPC controller parameters begins with the choice of prediction and control horizons. From Equation (7) and the time constants identified in Equation (12) the prediction horizons are $N_s = \text{int}\left[\frac{5(\tau_{11})}{T}\right] = 90$ samples and $N_d = \text{int}\left[\frac{5(\tau_{22})}{T}\right] = 300$ samples, with $T = 0.2$ s. It is worth noting that for the choice of N_d the slowest time constant associated to the discharge pressure was used, that is $\tau_{22} = 12$ s. Then the control horizons were defined as 5% of the prediction horizon values, resulting in $M_s = 4$ samples and $M_d = 15$ samples. Finally, by adopting $\beta = 5$ the tuning of the weights based on Table 1 was as follows: $\delta_d = 1$, $\delta_s = 1.21\alpha^2$, $\lambda_d = 450$ and $\lambda_s = 1500$. Figure 3 shows the tuning performance for two different values of α.

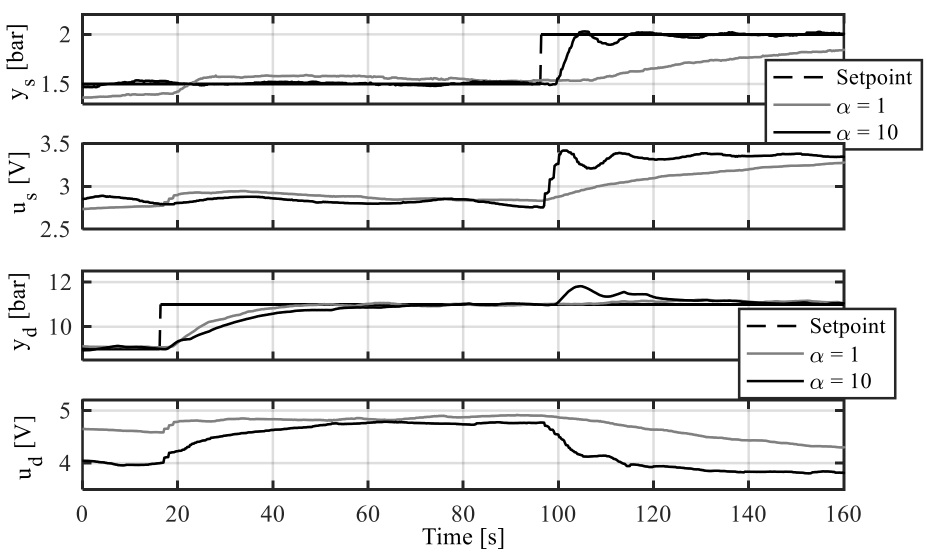

Figure 3: Tuning method evaluation. Closed-loop responses for different values of parameter α.

In Figure 3, a set-point change for y_d occurs at 18 s and a set-point change for y_s occurs at 95 s. For $\alpha = 1$ ($\delta_s = 1.21$), the reference tracking is equally prioritized in both variables, which results in similar settling times for suction and discharge pressures. In this situation, a small effect of the dynamic coupling is observed in y_d because the discharge actuator can be used to reject the disturbances caused by changes in the suction valve opening. On the other hand, for $\alpha = 10$ ($\delta_s = 121$), the suction-pressure reference-tracking dynamics is prioritized, which results in a faster and more aggressive response for suction pressure. This tuning also results in a slower settling time for y_d, but the change of about 10 s with respect to the case with α = 1 is not as expressive as the change observed in the dynamics of y_s. In addition, the fast change of the suction valve necessary to obtain a fast response in the suction pressure results in an expressive effect on the discharge pressure because the discharge actuator cannot operate quickly enough to compensate the disturbance. Therefore, it can be concluded that α can be tuned so that the behavior of the closed-loop system presents a compromise between the performance of setpoint tracking and the attenuation of the effect of the dynamic coupling in y_d. For this test rig, a good compromise can be achieved using $\alpha = 5$, so the nominal tuning for the weights is considered to be: $\delta_d = 1$, $\delta_s = 30$, $\lambda_d = 450$, and $\lambda_s = 1500$. This tuning is used in Subsection 4.3 to compare the performance of the system when controlled by a GPC and a PID controller.

4.3 Comparison with PID controllers

The purpose of this subsection is to present a performance benchmark for the GPC controller by comparing its results to the ones obtained with a control technique commonly used in the test rig. For this comparison, a SISO PID controller was implemented for each output. Both PIDs were tuned to obtain the same closed-loop setting times as GPC. The result of the comparison between the controllers for the regulation of y_d is presented in Figure 4. In this test, a change of setpoint for y_d occurs at 10 s and disturbance due the change of y_s occurs at 60 s.

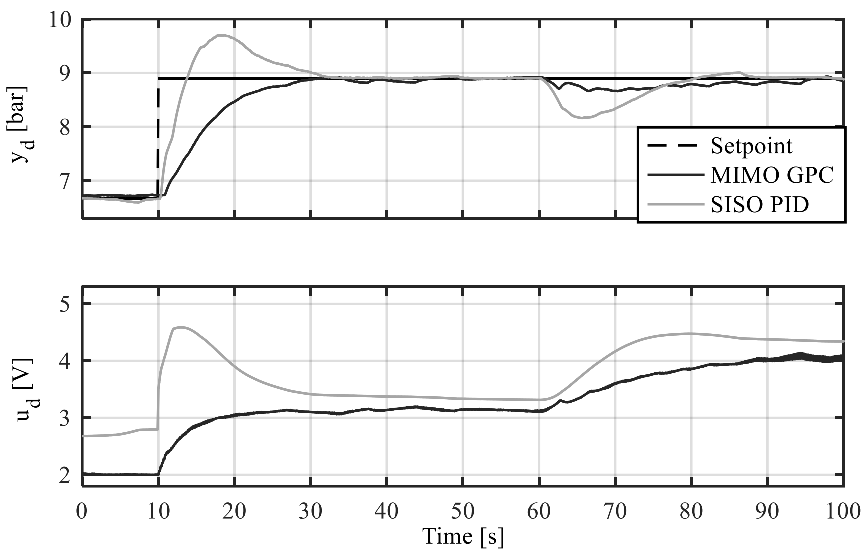

Figure 4: Comparison between closed-loop responses of GPC and PID controllers for the regulation of y_d

Figure 4 shows that GPC can attenuate the dynamic coupling between variables, since the deviation of y_d from its reference value when a step reference change in y_s occurs is considerably smaller than that observed with PID (around 60 s). Besides, a peak occurs in the response to the reference change for the case of SISO PID, but this behavior can be attenuated with the inclusion of a reference filter. However, in this work the filter was not adopted because in such test rigs the controllers typically do not use reference filters. It should be noted that the response to the SISO PID was defined from the response obtained with GPC for comparison purposes, but other PID tunings may present more appropriate behaviors. The comparison for the suction pressure was omitted, since the results did not present novelties in relation to what was discussed for y_d.

5. CONCLUSIONS

In this paper, a practical method for tuning the parameters of a model predictive control technique for controlling the suction and discharge pressures of refrigerant compressors in test rigs was presented. The proposed method consists in an intuitive interpretation of the tuning process, based on the knowledge of the process dynamics and the real operation of the test rig.

The tuning method was used in a real test rig and obtained promising results. It is shown that from the proposed tuning method it is possible to easily establish a compromise between the tracking performance of the references and the attenuation of the effect of the dynamic coupling between the outputs, resulting in faster compressor evaluation tests. These results show that the proposed tuning method can be used as a starting point for the tuning of MPC controllers in this kind of test rigs. Thus, the practical approach for parameters tuning developed in this work contributes to making the tuning complexity of MPC controllers simpler and more intuitive because it uses concepts that can be easily understood by people without much experience in controller design.

In addition, this work shows that GPC is an alternative to the typically used PID controllers for the regulation of pressures in test rigs, since it improves the dynamic performance of the responses, especially by reducing the coupling between both variables, which results in faster tests. However, its implementation is not as straightforward as the implementation of PID controllers.

It is suggested in future work to study and develop tuning techniques for MPC that consider the parametric variations of the process models over the test rig operating range in order to make the pressure regulation more robust, which may contribute to the increase in the accuracy of compressor evaluation tests.

NOMENCLATURE

$\boldsymbol{A}$	matrix of constraints	(–)
$\boldsymbol{b}$	vector of constraints	(–)
e	setpoint-tracking error	(–)
$\boldsymbol{f}$	free trajectory vector	(–)
$\boldsymbol{G}$	dynamic matrix	(–)
m	number of outputs	(–)
n	number of inputs	(–)
N	prediction horizon	(–)
N_1	minimum prediction horizon	(–)
N_2	maximum prediction horizon	(–)
M	control horizon	(–)
u	control signal	(–)
$\Delta\boldsymbol{u}$	array of control increments	(–)
T	sampling period	(–)
y	system output	(–)
$\hat{\boldsymbol{y}}$	array of output predictions	(–)
$\boldsymbol{w}$	setpoint	(–)
α	suction-pressure setpoint-tracking tuning parameter	(–)
β	control-smoothness tuning parameter	(–)
δ	setpoint-tracking weighting	(–)
λ	control effort weighting	(–)
θ	time delay	(–)

Subscript

s	suction
d	discharge

REFERENCES

ASHRAE, 2005. *ANSI/ASHRAE Standard 23*: Methods of testing for rating positive displacement refrigerant compressors and condensing units, 11 p.
CEN, 2016, *EN Standard 12900-1*: Compressor and condensing units for refrigeration – Performance testing and test methods. Refrigerant compressors, 42 p.
Camacho, E. F. and Bordons, C., 2007, *Model Predictive Control*, Springer Verlag, London.
Clarke, D., Mohtadi, C. and Tuffs, P., 1987, Generalized predictive control - Part i. The basic algorithm, *Automatica* **23**(2): 137-148.

Fallahsohi, H., Changenet, C., Placé, S., Ligeret, C. and Lin-Shi, X., 2010, Predicive functional control of an expansion valve for minimizing the superheat of an evaporator, *International Journal of Refrigeration* **33,** 409-418.
Flesch, R.C.C., Normey-Rico, J.E., 2010, Modelling, identification and control of a calorimeter used for performance evaluation of refrigerant compressors, *Control Eng. Pract.*, vol. 18, no. 3, p. 254-261.
Flesch, R.C.C., Torrico, B.C., Normey-Rico, J.E., Cavalcante, M.U., 2011, Unified approach for minimal output dead time compensation in MIMO processes, *J. Process Control*, vol. 21, no. 7, p. 1080-1091.
Flesch, R.C.C., Normey-Rico, J.E., Carlos, A.F., Rosa, A.P., 2012, Multivariable Identification and Control of a Calorimeter Used for Performance Evaluation of Refrigerant Compressor, *International Compressor Engineering Conference*, Paper 2118.
Garriga, J. L. and Soroush, M., 2010, Model Predictive Control Tuning Methods: A Review, *Ind. Eng. Chem. Res*, 49, 3505-3515.
Ma, Y., Borrelli, F., Hencey, B., Coffey, B., Bengea, S. and Haves, P., 2010, Model Predictive Control for the Operation of Building Cooling Systems, *2010 American Control Conference*, **IEEE**, 5106-5011.
Naidu, D. S. and Rieger, C., 2011, Advanced control strategies for heating, ventilation, air conditioning, and refrigeration systems - an overview: Part i: Hard control, *HVAC&R Research* **17**(1): 2-21.
Ng, B. C., Darus, I. Z. M., Jamaluddin, H. and Kamar, H. M., 2014, Application of adaptive neural predictive control for an automotive air conditioning system, *Applied Thermal Engineering* **73**, 1244-1254.
Pedersen, T. S., Nielsen, K. M., Hindsborg, J., Reichwald, P., Vinther, K. and Izadi-Zamanabadi, R., 2017, Predictive functional control of superheat in a refrigeration system using a neural network model. *IFAC-PapersOnLine*, ***50*** (1), 43–48.
Pollock, D. T., Yang, Z., Wen, J. T., Peles, Y., Jensen, M. K., 2014, Model-based control of vapor compression cycles for transient heat-flux removal, 2014, *International Journal of Heat and Mass Transfer* **77**, 662-683.
Schalbart, P., Leducq, D. and Alvarez, G., 2015, Ice-cream storage energy efficiency with model predictive control of a refrigeration system coupled to a PCM tank, *International Journal of Refrigeration* **52**: 140-150.
Shafiei, S. E. and Alleyne, A., 2015, Model predictive control of hybrid thermal energy systems in transport refrigeration, *Applied Thermal Engineering* **82**, 264-280.
Shafiei, S. E., Stoustrup, J. and Rasmussen, H., 2014, Model predictive control for flexible power consumption of large-scale refrigeration systems, *2014 American Control Conference*, **IEEE**.
Shah, G. and Engell, S., 2011, Tuning MPC for Desired Closed-Loop Performance for MIMO System, *2011 American Control Conference*, **IEEE**.
Thiem, S., Born, A., Danov, V., Vandersickel, A., Schäfer, J. and Hamacher, T., 2017, *Applied Thermal Engineering* **121**, 922-940.
Trierweiler, J. O. and Farina, L. A., 2003, RPN tuning strategy for model predictive control, *Journal of Process Control* **13**, 591-598.
Yang, Z., Pollock, D. T. and Wen, T. W., 2017, Optimization and predictive control of a vapor compression cycle under transient pulse heat load, *International Journal of Refrigeration* **75**, 14-25.

ACKNOWLEDGEMENT

This work was supported by the Brazilian National Council for Scientific and Technological Development (CNPq) under Grants 140283/2018-8 and 311024/2015-7, and by Coordination for the Improvement of Higher Education Personnel (CAPES), and by the Brazilian National Agency of Petroleum, Natural Gas and Biofuels (ANP), Brazilian Innovation Agency (FINEP) and the Ministry of Science, Technology, Innovation and Communication of Brazil (MCTI) through the ANP Human Resources Program for the Petroleum and Gas Sector (PRH-ANP/MCTI).