Online System Identification of a Compressor Test Stand With Echo State Networks

Guilherme Henrique LUDWIG[1], Bernardo Barancelli SCHWEDERSKY[2], Rodolfo C. C. FLESCH[3*]

[1] Universidade Federal de Santa Catarina, Laboratory for Instrumentation and Automation of Tests, Florianópolis, Santa Catarina, Brazil
guilherme.ludwig@labmetro.ufsc.br

[2] Universidade Federal de Pelotas, Technological Development Center, Pelotas, Rio Grande do Sul, Brazil
bernardo.schwedersky@inf.ufpel.edu.br

[3] Universidade Federal de Santa Catarina, Department of Automation and Systems Engineering, Florianópolis, Santa Catarina, Brazil
rodolfo.flesch@ufsc.br

* Corresponding Author

ABSTRACT

Compressor testing typically requires specialized test stands with several controlled process variables. The use of advanced control methods, which are often model-based, requires a suitable model, either for its synthesis or for its operation. As most compressor test stand dynamics are moderately nonlinear and time-varying, online estimation of nonlinear models is a valuable strategy because it enables the use of advanced model-based controllers that can accurately capture nonlinearities and adapt to changing dynamics. One type of model that has been explored in the literature for online nonlinear estimation is the echo state network, a recurrent artificial neural network architecture that can be trained efficiently. This paper presents an approach which can be used online to identify a nonlinear model of a compressor test stand based on an echo state network, with its output layer weights being estimated using a recursive least squares algorithm. This scheme enables the identification of a nonlinear model without the computational cost typically required to train recurrent neural networks, making it possible to estimate these parameters in an online manner. The evaluation was performed using a real test stand in a scenario in which a multiple-input and multiple-output model was obtained. An adaptive linear model was used as baseline method. The results show that the proposed approach provides significantly better results than the linear baseline, as the linear model was unable to adequately model the nonlinear characteristics of the test stand. The proposed model presented a 34% lower root mean squared error than the baseline.

1. INTRODUCTION

Advances in refrigeration compressor technology are associated with the ability to test compressors to quantify the real benefits of each modification. In several stages of its development, the compressor is tested by subjecting it to various operating conditions that are representative of real-world scenarios. An example is the performance evaluation tests, regulated by standards such as EN 13771-1 (CEN, 2016) and ASHRAE (2005), were several test aspects are specified. One key requirement is to maintain the compressor under specific operating conditions, with variables such as suction and discharge pressures being controlled around certain reference values with low variability. Thus, the improvement of control performance in these tests is important, as the ability to reach the required operating conditions faster results in reduced test duration and fewer hardware and human resources used (Flesch & Normey-Rico, 2010; Chesi et al., 2012).

These performance evaluation tests are performed on dedicated test stands, equipped with the resources needed to reach the test operating conditions and the hardware to measure the desired quantities. Typically, these test stands regulate compressor operating conditions by controlling variables around specific reference values, commonly including the temperature of the refrigerant fluid at the suction inlet, suction pressure, and discharge pressure. Even though the dynamics associated with such test stands present nonlinear dynamics and time delays, they are traditionally controlled by static single-input and single-output linear controllers, such as proportional-integral-derivative (PID) controllers. In this case, the variables of interest may exhibit sluggish or oscillatory responses in closed-loop operation, or it may be necessary to detune the controllers to avoid coupling, thereby prolonging the test duration. Based on that, the use of advanced control strategies, such as nonlinear model predictive control (MPC), is promising, as it can improve control performance and test productivity (Flesch & Normey-Rico, 2010; Flesch et al., 2011, 2012; Dangui et al., 2018; Taheri et al., 2022).

Recent advances in nonlinear MPC have enabled the adaptive control of complex processes using models based on echo state networks (ESNs) (Armenio et al., 2019; Jordanou et al., 2018), with network parameters estimated through recursive least squares (RLS) methods (Schwedersky et al., 2022a,b). With these advances, it is possible to obtain a nonlinear MPC for a process such as a refrigeration compressor test stand without the need to obtain a conventional process model, since the model can be estimated online.

This paper investigates the problem of obtaining a suitable nonlinear model, based on ESNs, to identify the dynamics of a real refrigeration compressor test stand, which is a fundamental step towards the implementation of an adaptive nonlinear MPC. The model is estimated online, using an RLS-based algorithm, with the results being evaluated in a real test stand. An adaptive first-order transfer function also estimated online with an RLS method is used as a baseline model to illustrate the advantages of using the proposed approach.

The paper is organized as follows. Section 2 presents the ESN model and its online estimation algorithm. Section 3 introduces the refrigeration test stand used in the experimental evaluation. Section 4 presents the model estimation procedure and the estimation results. Section 5 presents the conclusions of the paper.

2. ONLINE ECHO STATE NETWORK FOR SYSTEM IDENTIFICATION

An alternative for identification of nonlinear models is employing the echo state network, which constitutes an artificial recurrent neural network (RNN) based on reservoir computing principles. In this learning framework, a static RNN, referred to as the reservoir, generates a series of dynamics that can be harnessed in a readout layer to construct the model output, typically via a linear combination (Jaeger, 2003; Lukoševičius & Jaeger, 2009). With this fixed RNN, solely the ESN readout layer is subject to training, facilitating the execution of the learning task in an online manner, which includes the case in which the RLS algorithm is used for this purpose (Schwedersky et al., 2022b).

There are various conceivable ESN configurations and the focus of this study is on a specific structure with an input layer connected to a reservoir and a linear readout layer connected to both the model input and the reservoir output. The weights of both the input layer and the reservoir are defined before the training phase and remain constant during the whole process. The only trainable portion of the model is the weights of the readout layer. This ESN model can be represented by a pair of equations, namely the state and output equations. The state equation delineates the transition of the reservoir state as follows: for a reservoir of dimension s, the state $\mathbf{x}$ of the reservoir at time k is:

$$\mathbf{x}(k) = \tanh\left(\mathbf{W}_{\text{in}}\begin{bmatrix}1\\ \mathbf{u}(k)\end{bmatrix} + \mathbf{W}^{\text{res}}\mathbf{x}(k-1)\right), \tag{1}$$

where $\mathbf{u} \in \Re^{n}$ represents the input and $\mathbf{x} \in \Re^{r}$ is the signal of the reservoir state. Additionally, $\mathbf{W}_{\text{in}} \in \Re^{r\times(n+1)}$ is the matrix for input weighting; $\mathbf{W}^{\text{res}} \in \Re^{r\times r}$ is the matrix with the recurrent weights of the reservoir; and $\tanh(\cdot)$ corresponds to the hyperbolic tangent function, which is defined as:

$$\tanh(q) = \frac{1-\mathrm{e}^{-2q}}{1+\mathrm{e}^{2q}}. \tag{2}$$

The readout equation is given by:

$$\hat{\mathbf{y}}(k) = \mathbf{W}^{\text{out}}\begin{bmatrix}1 & \mathbf{x}(k)^{T} & \mathbf{u}(k)^{T}\end{bmatrix}^{T}, \tag{3}$$

where $\hat{\mathbf{y}} \in \Re^{m}$ represents a vector containing the estimated outputs, while matrix $\mathbf{W}^{\text{out}} \in \Re^{m\times 1+r+m}$ is a matrix with the weights connecting the input and the reservoir to the readout layer. Since (3) defines a linear readout, the weights $\mathbf{W}^{\text{out}}$ can be estimated online using an RLS method, which is the estimation approach used in this study. The online estimation framework used in this paper is shown in the block diagram in Figure 1.

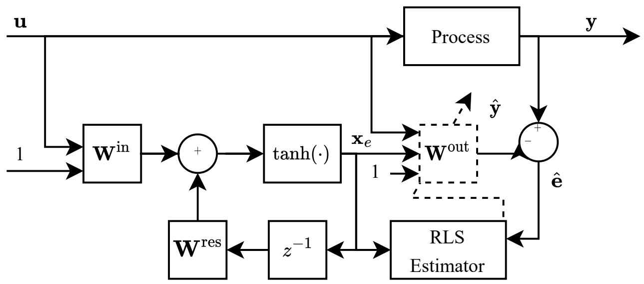


Figure 1: Block diagram for the ESN estimation task. Only the reservoir readout connections, represented by matrix $\mathbf{W}^{\text{out}}$, are estimated online, because matrices $\mathbf{W}^{\text{in}}$ and $\mathbf{W}^{\text{res}}$ are static, generated before training.

As mentioned before, in this model both $\mathbf{W}^{\text{res}}$ and $\mathbf{W}^{\text{in}}$ are predetermined and not subject to training. A common practice is to generate those values using a uniform distribution. The input matrix is constructed with sparse weights and is appropriately scaled to prevent initial saturation of the reservoir states. Of particular significance is matrix $\mathbf{W}^{\text{res}}$, as it governs the recurrent connections among reservoir units. The pivotal parameter is the matrix spectral radius $\rho(\mathbf{W}^{\text{res}})$, which is associated with its largest eigenvalue, directly influencing the stability of the model. A prevalent approach involves constructing a reservoir with a predefined sparsity and adjusting it to achieve the desired spectral radius. If the reservoir is stable and its states converge asymptotically under the influence of an input signal, it possesses the echo state property. For the ESN model used in this study, a prerequisite for the echo state property is $\rho(|\mathbf{W}^{\text{res}}_{\text{res}}|) < 1$, where $|\mathbf{W}^{\text{res}}|$ denotes the absolute value of each element. A comprehensive exploration of the echo state property and the criteria for achieving it can be found in Yildiz et al. (2012).

The sole trainable matrix in this context is $\mathbf{W}^{\text{out}}$, which determines a linear combination of both inputs and reservoir states, supplemented by a bias term. To simplify the notation, an augmented variable:

$$\bar{\mathbf{x}}(k) = \begin{bmatrix} 1 & \mathbf{x}(k)^T & \mathbf{y}(k-1)^T \end{bmatrix}^T \tag{4}$$

can be defined and the network output can be expressed as:

$$\hat{\mathbf{y}}(k) = \mathbf{W}^{\text{out}}(k)\bar{\mathbf{x}}(k). \tag{5}$$

The identification process is accomplished using the data collected during the plant operation. This task generally involves determining the model parameters that minimize a cost function, such as the one-step ahead prediction (OSAP) error, which is defined as Ljung (1999):

$$J = \frac{1}{Am} \sum_{i=1}^{m} \sum_{j=1}^{T} \| y_i(j) - \hat{y}_i(j \mid j-1) \|^2 , \tag{6}$$

where m denotes the number of outputs; $y_i(j)$ is the measured value for i-th output at the instant of time j; $\hat{y}_i(j \mid j-1)$ is the predicted value for i-th output at the instant of time j defined with information up to the instant of time $j-1$; and A is the number of output observations.

To determine the optimal value of $\mathbf{W}^{\text{out}}(k)$ that minimizes the estimation error, according to the cost function in (6), an RLS method with an adaptive forgetting factor is considered in this study. When new data is available, $\mathbf{W}^{\text{out}}(k)$ is updated with

$$\mathbf{W}^{\text{out}}(k) = \mathbf{W}^{\text{out}}(k-1) + \frac{\mathbf{P}(k)\mathbf{x}(k-1)}{1+\xi(k)}\hat{e}(k), \tag{7}$$

where

$$\xi(k) = \mathbf{x}(k-1)^T \mathbf{P}(k)\mathbf{x}(k-1), \tag{8}$$

$$\hat{e}(k) = \mathbf{y}(k) - \mathbf{W}^{\text{out}}(k-1)\mathbf{x}(k-1). \tag{9}$$

In the RLS algorithm, $\mathbf{P}(k)$ denotes the covariance matrix, which is continuously updated as (Bobál et al., 2006)

$$\mathbf{P}(k) = \mathbf{P}(k-1) - \frac{\mathbf{P}(k-1)\mathbf{x}(k)\mathbf{x}^T(k)\mathbf{P}(k-1)}{\varepsilon^{-1}(k) + \xi(k)}, \tag{10}$$

$$\varepsilon(k) = \varphi - \frac{1-\varphi}{\xi(k-1)}, \tag{11}$$

when $\xi(k) > 0$, or kept constant otherwise, i.e.

$$\mathbf{P}(k) = \mathbf{P}(k-1) \quad \text{if} \quad \xi(\mathrm{k}) \leq 0. \tag{12}$$

The purpose of the forgetting factor is to enhance the representation of the ESN output weights, $\mathbf{W}^{\text{out}}(k)$, with respect to the current system measurements, by adjusting the importance of previous measured values. In the proposed ESN readout estimation algorithm, an adaptive forgetting factor $\varphi(k)$ is used instead of a constant value φ, as typically assumed in conventional RLS algorithms (Jaeger, 2003). The parameter $\varphi(k)$ serves as a dynamic forgetting factor, capable of assuming varying values throughout the estimation process within the range $0 < \varphi(k) \leq 1$. Due to its adaptability, the algorithm can effectively monitor changes in the process parameters, thereby updating the estimated ESN parameters according to the direction in which new process data are measured. This directional forgetting approach is defined as (Kulhavý, 1987):

$$\begin{aligned}\varphi(k)^{-1} = 1 &+ (1+\rho)[\ln(1+\xi(\mathrm{k}))] \\ &+ \left(\frac{(\upsilon(k)+1)\eta(k)}{1+\xi(k)+\eta(k)} - 1\right)\frac{\xi(k)}{1+\xi(k)},\end{aligned} \tag{13}$$

where

$$\eta(k) = \frac{\hat{e}(k)^2}{\lambda(k)}, \tag{14}$$

$$\upsilon(k) = \varphi(k)[(\upsilon(k-1)+1)], \tag{15}$$

$$\lambda(k) = \varphi(k)\left(\lambda(k-1) + \frac{\hat{e}(k)^2}{1+\xi(k)}\right). \tag{16}$$

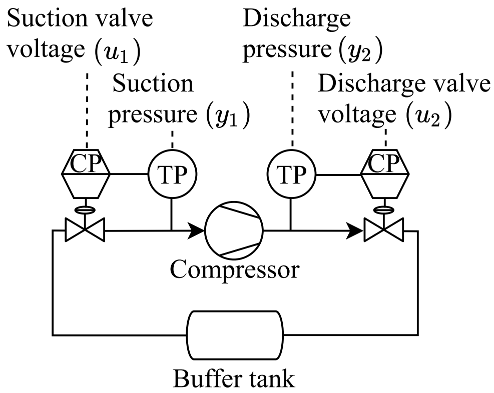
The parameter $\rho \in [0, 1]$ is used to specify the extent of the prior information retained in each iteration, where smaller values indicate that less information is discarded (Bobál et al., 2006). The proposed online ESN estimation, incorporating the directional forgetting factor, is detailed in Algorithm 1.

Algorithm 1 Online ESN estimation using recursive least squares with adaptive directional forgetting.

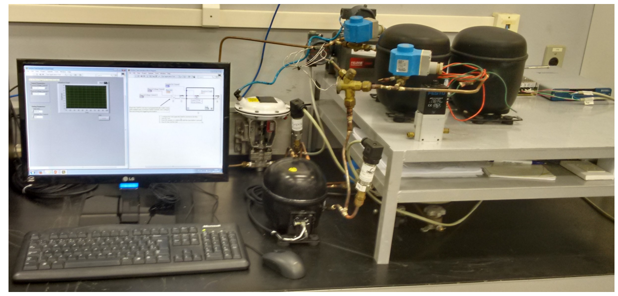
1: Measure the current process outputs;
2: Obtain the directional forgetting factor $\varphi(k)^{-1}$ using (13);
3: Update the covariance matrix $\mathbf{P}(k)$ using (10);
4: Obtain $\mathbf{W}^{\text{out}}(k)$ using (7);
5: Return to step 1.

3. REFRIGERATION COMPRESSOR TEST STAND

The refrigeration compressor test stand investigated in this study serves the purpose of performing tests on refrigeration compressor samples in industry. These tests involve subjecting the sample to various operating conditions, simulating its performance in several types of refrigeration systems. The test stand incorporates valves connected to the compressor suction and discharge lines, enabling the manipulation of the pressures within these lines. These valves are interconnected with a buffer tank, which partially decouples suction and discharge pressures. The circuit is based on a superheated gas cycle, so there is no phase change. Figure 2 presents a simplified piping and instrumentation diagram of the process alongside a picture of the experimental test stand.



(a)



(b)

Figure 2: Refrigeration compressor test stand: (a) simplified piping and instrumentation diagram; (b) picture of the experimental setup

The valve in the suction line is normally closed, resulting in the suction pressure being directly proportional to the applied voltage. Conversely, the valve connected to the discharge line is normally open, causing the discharge pressure to also be directly proportional to the applied voltage. Due to the inherent characteristics of the process, there is coupling between the suction and discharge pressures, such that changes in the suction valve position affect not only the suction pressure but also the discharge pressure. However, the interaction between the discharge valve and the suction pressure is minimal, as it is nearly entirely offset by the buffer tank.

4. EXPERIMENTAL RESULTS

In this section, the results of the dynamic identification of the refrigeration test stand are presented. For the sake of brevity, only the discharge pressure dynamics are discussed. The discharge pressure was selected as it presented a more nonlinear behavior than the suction pressure, making the use of a nonlinear model more suitable. The procedure for estimating the model online is presented in Section 4.1 and the results and comparison with a baseline model are presented in Section 4.2.

4.1 Model Estimation

To estimate the ESN model, a scenario in which the test stand was manually controlled was considered. In this scenario, the discharge valve voltage was changed randomly, with the suction valve voltage kept constant throughout the estimation and model testing phases. These random changes were designed using an amplitude-modulated pseudorandom binary sequence (APRBS), as described in Nelles (2001), to cover all possible test stand operating conditions.

The ESN model was created considering a 300 unit reservoir matrix, $\mathbf{W}_{\text{res}}^{\text{res}}$, with a sparse connection rate of 1% between reservoir units. The non-zero weights in $\mathbf{W}_{\text{res}}^{\text{res}}$ are sampled from a uniform distribution in the interval $[-1, +1]$. The selected spectral radius was $\rho(\mathbf{W}_{\text{res}}^{\text{res}}) = 0.99$, so the reservoir matrix was re-scaled to set its largest eigenvalue as 0.99. The input matrix, $\mathbf{W}_{\text{in}}^{\text{res}}$, was created dense, with all weights equal to $+1$ or -1 (50% of each case), and further re-scaled considering an scale factor of 0.1, to avoid initial saturation of the reservoir connections. The RLS estimator was initialized considering the main diagonal elements of the covariance matrix as $\mathbf{P}(0) = 10$; $\varphi(0) = 1$; $\lambda(0) = 0.1$; $\rho = 0.6$; and $\upsilon(0) = 10^{-6}$.

The estimation of the ESN model is presented in Figure 3, which contains the discharge pressure, the discharge valve voltage, and a subset of weights $\mathbf{W}^{\text{out}}$ during the estimation phase. The ESN weights $\mathbf{W}^{\text{out}}$ were updated using the RLS algorithm, with all parameters being initialized as 0 in the beginning of the estimation process. As the ESN model evolves during the estimation, the weights in $\mathbf{W}^{\text{out}}$ are updated, with most changes occurring when the discharge pressure reaches previously unseen operating conditions, for example, between 1100 s and 1250 s. As this estimation was conducted on a real test stand, which presents nonlinearities and time-varying behaviors associated with non-measured variables, the model parameters were updated during the entire estimation scenario, with the final model, obtained at time 2500 s.

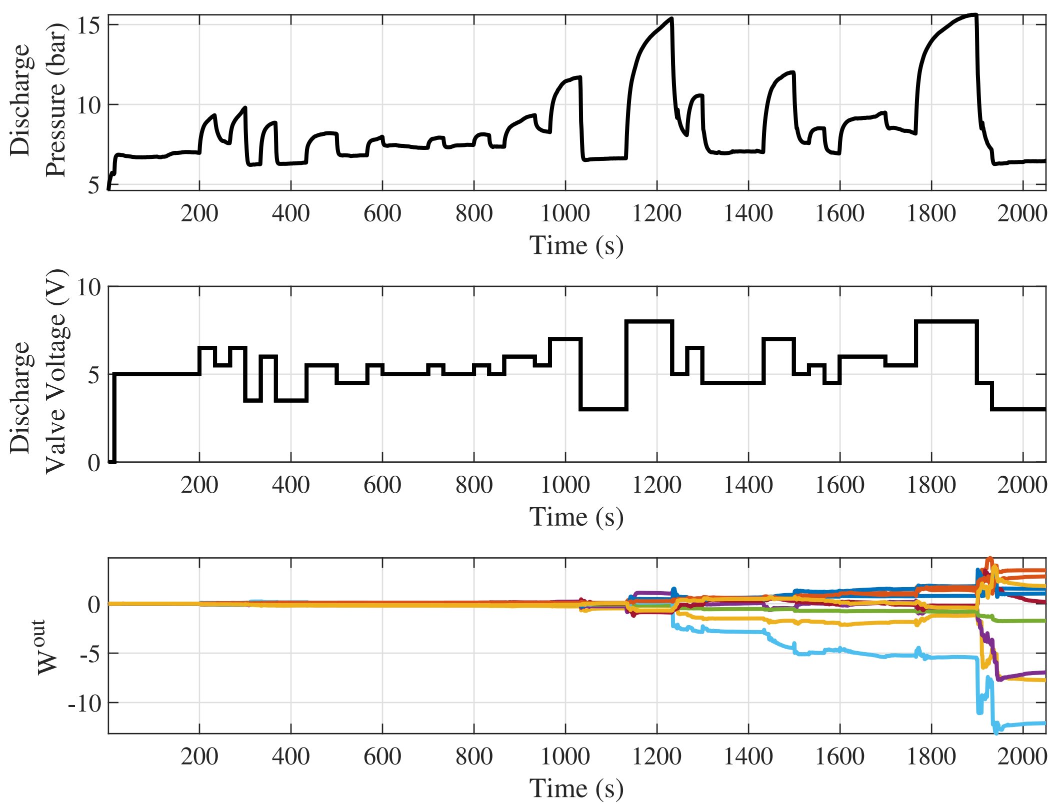


Figure 3: ESN online estimation results.

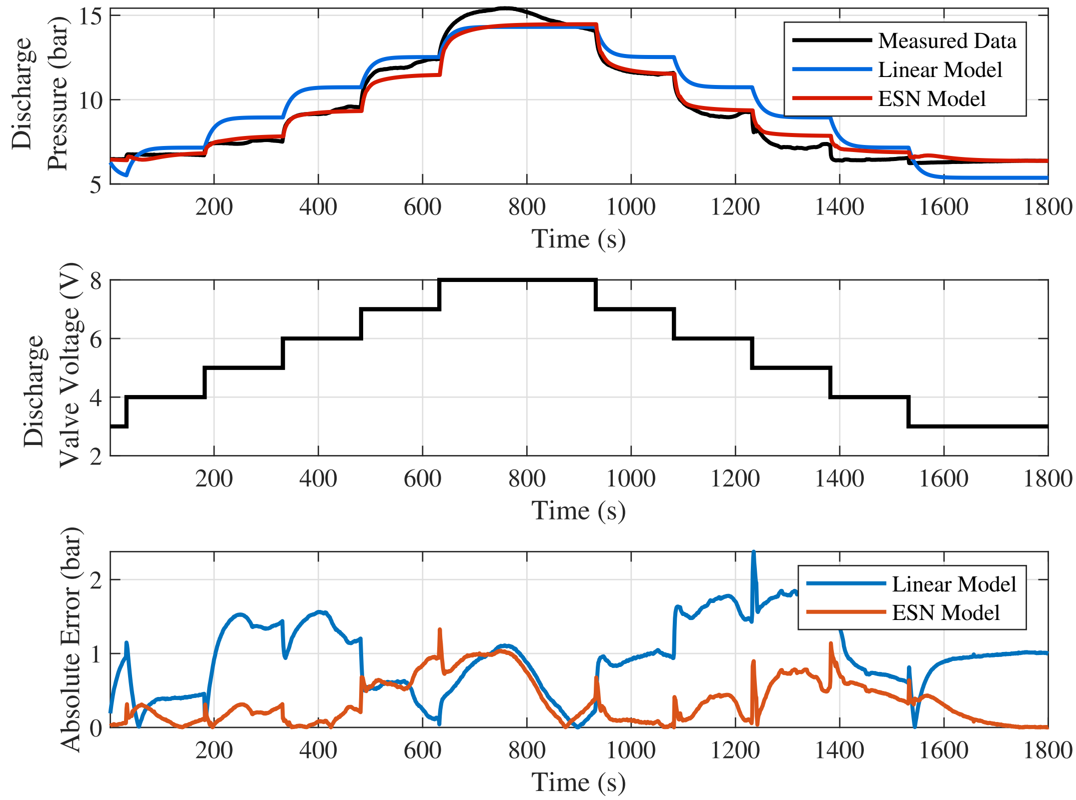


Figure 4: Model performance evaluation for a test scenario.

4.2 Model Performance

After the online training, the final ESN model parameters were kept constant for performance evaluation. For this purpose, a test scenario was designed to evaluate the model performance for all possible operating conditions of the test stand. This scenario consisted of changes in the discharge valve voltage between 2 V and 8 V, which are the voltage values that represent the maximum and minimum operating values.

The proposed model was compared with a discrete-time model, linear in its parameters, described as

$$y_l(k) = -a_1 y_l(k-1) + b_1 u(k-1), \tag{17}$$

with a_1 and b_1 estimated using an RLS with directional forgetting factor. This baseline was estimated simultaneously with the proposed model, and the results for the evaluation using the test scenario are presented in Figure 4.

The proposed ESN model clearly outperformed the baseline linear model, being able to model the nonlinear characteristics of discharge pressure dynamics with better precision. The linear model presented results closer to the measured data when the discharge pressure was close to its maximum and minimum values. However, when the pressure reached intermediate values, the linear model presented larger errors, due to nonlinear behavior of the discharge pressure dynamics. However, the proposed ESN model was able to adequately model this nonlinear behavior, presenting lower error during almost the entire test scenario.

The proposed model presented the largest errors between 500 s and 900 s, but in this interval the performance of both models is quite similar. The main reason of this modeling error is the occurrence of a non measured disturbance, which can be quite common in this type of process, due to the complexity of the phenomena associated with refrigeration systems.

The overall performance of the model was also evaluated using the root mean-squared error (RMSE) and the determination coefficient (R^2) performance metrics, with the values obtained during the test scenario presented in Table 1. The

Table 1: Performance metrics of the proposed ESN model and the baseline for the test scenario.

Model	**RMSE** (bar)	$\mathbf{R}^2$
Linear	1.04	0.90
ESN	0.68	0.95

proposed ESN model presented a 34% lower RMSE and a 5% closer to unity R^2, showing that the choice of a nonlinear model results in significant improvements for the nonlinear estimation of a discharge pressure model on refrigeration compressor test stands.

5. CONCLUSIONS

In this paper a nonlinear ESN network model, with its parameters estimated online using the recursive least squares method, was proposed to identify the discharge pressure dynamics in a refrigeration compressor test stand. The proposed model comprises an ESN network, characterized by an architecture in which only its reservoir readout layer weights are adjusted. This structure can be exploited to identify nonlinear systems in an online manner, as the network can be efficiently trained using the least squares method.

The proposed nonlinear ESN model was evaluated considering a real refrigeration compressor test stand and it was used to identify the discharge pressure dynamics. The ESN model was estimated online during the test stand operation, considering a scenario in which random changes in the discharge valve voltage were made. A model linear in its parameters was used as the baseline, with its parameters estimated with a similar recursive least squares method. In both cases, no prior information regarding the system dynamics is necessary.

The evaluation was conducted using a test scenario in which the model that was obtained in the last estimation scenario time instant was tested under all typical test stand operating conditions. The results showed that the proposed approach outperformed the baseline, with a 34% lower RSME. Graphical inspection showed that the proposed ESN was able to better model the nonlinear gain of the discharge pressure, presenting less error than the linear baseline. These results show that the use of nonlinear models to identify refrigeration compressor test stands brings improvements in the modeling precision, and have potential to improve control performance when applying model based control solutions, such as nonlinear model based predictive controllers.

NOMENCLATURE

A	total number of samples	(–)
$e(k)$	estimation error	(–)
$\mathbf{P}(k)$	covariance matrix	(–)
$u_1(t)$	suction valve voltage	(V)
$u_2(t)$	discharge valve voltage	(V)
$\mathbf{u}(k)$	ESN input array	(–)
$\mathbf{x}(k)$	reservoir state array	(–)
$y_1(t)$	suction pressure	(bar)
$y_2(t)$	discharge pressure	(bar)
$\mathbf{y}(k)$	ESN output array	(–)
$\mathbf{W}$	weight matrix	(–)
ρ	spectral radius	(–)
$\varphi(k)$	adaptive forgetting factor	(–)
Subscript		
in	input	
l	linear	
m	number of outputs	
n	number of inputs	
out	output	
r	reservoir size	
res	reservoir	

REFERENCES

Armenio, L. B., Terzi, E., Farina, M., & Scattolini, R. (2019). Model predictive control design for dynamical systems learned by echo state networks. *IEEE Control Systems Letters*, *3*(4), 1044-1049. doi: 10.1109/LCSYS.2019.2920720

ASHRAE. (2005). *ANSI/ASHRAE 23 – Methods of testing for rating positive displacement refrigerant compressors and condensing units* (Standard). Atlanta: ANSI/ASHRAE.

Bobál, V., Böhm, J., Fessl, J., & Machácek, J. (2006). *Digital self-tuning controllers: algorithms, implementation and applications*. London: Springer Science & Business Media.

CEN. (2016). *EN standard 12900-1:2016 - Compressor and condensing units for refrigeration – Performance testing and test methods. Refrigerant compressors.* 42 p.

Chesi, A., Ferrara, G., Ferrari, L., & Tarani, F. (2012, November). Setup and characterisation of a multi-purpose test rig for r744 refrigerating cycles and equipment. *International Journal of Refrigeration*, *35*(7), 1848–1859. doi: 10.1016/j.ijrefrig.2012.06.005

Dangui, H. A. S., Flesch, R. C. C., & Schwedersky, B. B. (2018). Practical guidelines for tuning model-based predictive controllers for refrigeration compressor test rigs. In *International Compressor Engineering Conference.*

Flesch, R., & Normey-Rico, J. (2010). Modelling, identification and control of a calorimeter used for performance evaluation of refrigerant compressors. *Control Eng. Pract.*, *18*(3), 254–261.

Flesch, R., Normey-Rico, J., Carlos, A., & Rosa, A. (2012). Multivariable identification and control of a calorimeter used for performance evaluation of refrigerant compressor. In *International Compressor Engineering Conference.*

Flesch, R., Torrico, B., Normey-Rico, J., & Cavalcante, M. (2011). Unified approach for minimal output dead time compensation in MIMO processes. *J. Process Control*, *21*(7), 1080–1091.

Jaeger, H. (2003). Adaptive nonlinear system identification with echo state networks. In *Advances in neural information processing systems (nips 2003)* (p. 609-616).

Jordanou, J. P., Camponogara, E., Antonelo, E. A., & Schmitz Aguiar, M. A. (2018). Nonlinear model predictive control of an oil well with echo state networks. *IFAC-PapersOnLine*, *51*(8), 13-18. (3rd IFAC Workshop on Automatic Control in Offshore Oil and Gas Production OOGP 2018) doi: 10.1016/j.ifacol.2018.06.348

Kulhavý, R. (1987). Restricted exponential forgetting in real-time identification. *Automatica*, *23*(5), 589-600. doi: 10.1016/0005-1098(87)90054-9

Ljung, L. (1999). *System identification* (2nd ed.). Englewood Cliffs, New Jersey: Prentice Hall.

Lukoševičius, M., & Jaeger, H. (2009, aug). Reservoir computing approaches to recurrent neural network training. *Computer Science Review*, *3*(3), 127-149. doi: 10.1016/j.cosrev.2009.03.005

Nelles, O. (2001). *Nonlinear system identification*. London: Springer.

Schwedersky, B. B., Flesch, R. C., & Rovea, S. B. (2022b, February). Echo state networks for online, multi-step mpc relevant identification. *Engineering Applications of Artificial Intelligence*, *108*, 104596. doi: 10.1016/j.engappai.2021.104596

Schwedersky, B. B., Flesch, R. C. C., & Rovea, S. B. (2022a). Adaptive practical nonlinear model predictive control for echo state network models. *IEEE Transactions on Neural Networks and Learning Systems*, *33*(6), 2605-2614. doi: 10.1109/TNNLS.2021.3109821

Taheri, S., Hosseini, P., & Razban, A. (2022). Model predictive control of heating, ventilation, and air conditioning (HVAC) systems: A state-of-the-art review. *Journal of Building Engineering*, *60*, 105067. doi: 10.1016/j.jobe.2022.105067

Yildiz, I. B., Jaeger, H., & Kiebel, S. J. (2012, nov). Re-visiting the echo state property. *Neural Networks*, *35*, 1-9. doi: 10.1016/j.neunet.2012.07.005

ACKNOWLEDGMENT

This work was supported in part by the Brazilian National Agency of Petroleum, Natural Gas and Biofuels (ANP) under the Human Resource Training Program (PRH), in part by the Brazilian National Council for Scientific and Technological Development (CNPq) under Grant 315546/2021-2, in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) – Finance Code 001, and in part by Nidec Global Appliance.