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Multivariable predictive control of a pressurized tank using neural networks

Abstract The behavior of a multivariable predictive control scheme based on neural networks applied to a model of a nonlinear multivariable real process, consisting of a pressurized tank is investigated in this paper. The neural scheme consists of three neural networks; the first is meant for the identification of plant parameters (identifier), the second one is for the prediction of future control errors (predictor) and the third one, based on the two previous, compute the control input to be applied to the plant (controller). The weights of the neural networks are updated on-line, using standard and dynamic backpropagation. The model of the nonlinear process is driven to an operation point and it is then controlled with the proposed neural control scheme, analyzing the maximum range over the neural control works properly.

Keywords Predictive neural control · Control of pressurized tank · Multivariable control · Neural control · Adaptive neural control · Adaptive neural network control

1 Introduction

The artificial neural networks (ANN) is a technique which is able to approximate relationships between multiple inputs and multiple outputs of a system [1–3]. The network is trained to approximate these relationships using appropriate input–output data. For this reason the ANN have received considerable attention lately in multivariable control systems [4–6].

The control techniques based on models have been developed to obtain a more precise control. Among them, the control with predictive model has been successfully used in several industrial plants. In most applications of techniques with predictive model, a linear model is used to predict the behavior of the process on the horizon of interest [7, 8]. The majority of the real processes show a nonlinear behavior and some works have extended the techniques of the predictive control incorporating nonlinear models [9–11].

The most difficult part in the realization of a predictive nonlinear control scheme is the derivation of a mathematical model. In many cases, it is even impossible to obtain a satisfactory model of the process physically based, due to its complexity. A promisory way of avoiding these problems is the use a neural network like a nonlinear black-box model of the process behavior [12–14].

During the past decade, several application and theoretically oriented work has been developed in the area of predictive control using neural networks. It is interesting to mention the applications to chemical plants [15–19] and metallurgical processes [20–22] amongst others. Also, it is worth to mention some theoretical developments using multistep models [23], robust predictive control using regional knowledge [24], structured predictive control for constrained models [25], neural predictive control for nonlinear systems [26, 27] and generalized predictive control based on neural networks [28].

Recently, a predictive neural control strategy has been developed [29, 30] by the authors, which is briefly described in Sect. 3 for continuity. In this paper, the behavior of the control strategy proposed in [29, 30] is evaluated on a dynamical model of a multivariable plant consisting of a cylindrical tank containing a water column pressurized by air and compared with control techniques used in [31]. The control objective is to

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maintain the level of the liquid and the pressure of the air contained in the cylinder, in desired reference points. The most relevant dynamics is described through a nonlinear model of the process. First, the model is reduced to its linear equivalent in an operation point and is controlled with the neural control scheme proposed in [29]. Later on, the nonlinear models of the process is directly controlled using the proposed technique.

The paper is organized so that in Sect. 2 the nonlinear model of the pressurized tank is briefly explained. Section 3 is devoted to the description of the multivariable neural predictive control scheme and the characteristics of the neural networks used in the control scheme are presented in Sect. 4. Simulation results under different operating conditions are given in Sect. 5 while in Sect. 6 some conclusions are drawn.

2 Pressurized tank

The process consists of a cylindrical tank containing a water column pressurized by air. Figure 1 shows a simplified diagram of the process. A centrifugal pump *P* feeds water into the tank through the pneumatic valve v_1, and a compressor *C* feeds air through the pneumatic valve v_2. The liquid can drain from the tank through a manual valve v_3 while air can leave the tank through a discharge valve v_4. Measurements of the process outputs; the level of the liquid column y_1 and the gauge pressure y_2 of the inner air, are obtained by means of pressure transducers. The valves v_1 and v_2 are handled through electro-pneumatic transducers by voltage signals u_1 and u_2. The total height of the tank is $L = 1.05$ m and the diameter is $D = 0.075$ m.

The nonlinear model describing the plant dynamics has been thoroughly studied in [29, 31, 32] and can be expressed in terms of the following state variables:

– x_1 level of the liquid (m)
– x_2 air pressure (bar gauge)

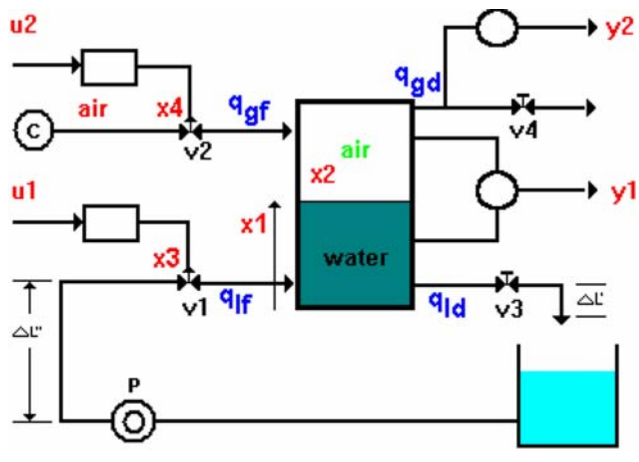


Fig. 1 Pressurized tank system used in the experimental study

– x_3 opening of the water valve 1 (o/1) (v_1)
– x_4 opening of the air valve 2 (o/1) (v_2) The differential equations, describing the dynamic behavior of the system (see Appendix for numerical values) are the following:

$$\frac{dx_1}{dt} = \frac{1}{\rho_l S}(q_{lf} - q_{ld}), \tag{1}$$

$$\frac{dx_2}{dt} = \frac{1}{(L - x_1)}\left\{(1 + x_2)\frac{dx_1}{dt} + \frac{RT\rho_g}{SN_t}(q_{gf} - q_{gd})\right\}, \tag{2}$$

$$\frac{dx_3}{dt} = \frac{1}{\tau_1}(k_l u_1 - x_3), \tag{3}$$

$$\frac{dx_4}{dt} = \frac{1}{\tau_g}(k_g u_2 - x_4). \tag{4}$$

The variables q_{ij} denote the feed ($j = f$) and discharge ($j = d$) flows rates of the liquid ($i = l$) and gas or air ($i = g$) streams. Equations (1) and (2) are obtained from the mass balance principle and the ideal gas law. L and S are the height and surface of the tank, ρ_l and ρ_g are the liquid and air densities respectively, R is the universal gas constant and T is the air temperature. N_t is the conversion constant from (Nw/m^2) to (atm). Equations (3) and (4) result from a first-order dynamics characterization of valves v_1 and v_2 using experimental observations. τ_l and $\tau_g$are the time constants of valves v_1 and v_2, respectively, and k_l and k_g are proper constants of valves v_1 and v_2, respectively.

The liquid flow rates (q_{lf}, q_{ld}) and air flow rates (q_{gf}, q_{gd}) are modeled according to the square root of the differential pressure across the valves and they are given by

$$q_{lf} = x_3 K_{lf}\left(\sqrt{P_{lf} - x_2 - \frac{\rho_l G}{N_t}(X_1 + \Delta L')}\right)\sqrt{N_t}, \tag{5}$$

$$q_{ld} = x_{ld} K_{ld}\left(\sqrt{x_2 + \frac{\rho_l G}{N_t}(X_1 + \Delta L'')}\right)\sqrt{N_t}, \tag{6}$$

$$q_{gf} = x_4 K_{gf}(P_{gf} - x_2)^{0.65}, \tag{7}$$

$$q_{gd} = x_{gd} K_{gd}\sqrt{x_2}, \tag{8}$$

where x_{ld} and x_{gd} are the valves openings for valves v_3 and v_4 respectively, and K_{ij} are proper constants of valves v_1, v_2, v_3 and v_4.

The numerical values of all parameters and constants of the model are given in the Appendix. The states and inputs satisfy the following constraints:

$$\begin{array}{ll} 0 \le x_1 \le \bar{x}_1, & 0 \le x_2 \le \bar{x}_2, \\ 0 \le x_3 \le 1, & 0 \le x_4 \le 1, \\ 0 \le u_1 \le \bar{u}_1, & 0 \le u_2 \le \bar{u}_2, \end{array} \tag{9}$$

where $\bar{u_1} = \bar{u_2} = 1(V)$ (maximum voltage signal) and $\bar{x_1}, y\bar{x_2}$ are bounds established by the designer. The bounds on the components of the output vector are identical to the states x_1 and x_2 since $y_1 = x_1$ and $y_2 = x_2$.

The dynamics of the air pressure x_2 and air valve x_4 are much faster than the dynamics of the liquid level x_1 and water valve x_3. Indeed, open-loop step-response experiments with the liquid level, under zero air gauge pressure, reveal a time constant between 50 and 70 s for x_1, depending on the operation point, whereas, the time constant for the air pressure x_2 is approximately 1.3 s. A sample period of $h=0.1$ s. was chosen to adequately sample the pressure signals.

3 Multivariable control schemes

The configuration of multivariable control used in this study corresponds to the neural scheme based on model with and without prediction of the control error described in references [29, 30]. Figure 2 shows both MIMO schemes adapted to the process variables of the plant described in Sect. 2.

The central idea is to improve the direct control approach with model (Fig. 2a), by optimizing the neural network controller with respect to the present as well as the future control errors. In order to obtain the future errors, a predictive network with d step ahead is proposed (Fig. 2b).

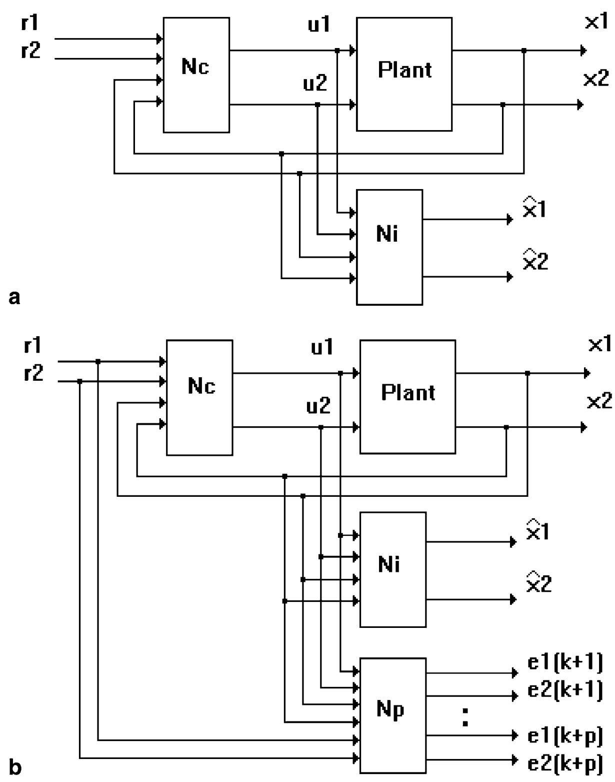


Fig. 2 Configuration of control scheme using a neural scheme based on model. **a** Without prediction network. **b** With prediction network. (*Nc* Controller network *Ni* Identifier network. *Np* Predictor network)

The predictive neural control scheme is designed for a MIMO plant, where $u(t)$ $\Re^{\mathrm{p}}$ and $y(t)\in\Re^{\mathrm{m}}$ are the input and output variables, respectively. The NN denoted as N_{I} corresponds to the identifier which gives us an estimation $\hat{y}(t)$of output variable $y(t)$. This is based on a series-parallel identification scheme using as input data the plant input and the plant output collected on-line at time k and some delayed instants of time. The identifier parameters (weights) are adjusted using static backpropagation of the identification error $e_{\mathrm{i}}(t)=y(t)-\hat{y}(t)\in\Re^{\mathrm{m}}$, with the aim of minimizing some criteria function of the identification error.

The NN denoted as N_{C} represents the controller and provides the control variable $u(t)\in\Re^{\mathrm{m}}$ to be applied to the plant. This is done using as input data the reference signal and the plant output at time k and at some delayed instants of time. The controller parameters (weights) are adjusted using dynamic backpropagation [29, 30] of the control error $e_{\mathrm{c}}(t) = y(t) - r(t) \in\Re^{\mathrm{m}}$, through the identified model (since the plant is unknown) and with the objective of minimizing some criteria function of the control error at time k and up to d step ahead, $e_{\mathrm{c}}(k)$, $e_{\mathrm{c}}(k+1)$, …, $e_{\mathrm{c}}(k+d)$, such that the following criterion function is minimized:

$$J(t)=\frac{1}{2}\sum_{i=0}^{i=d}\lambda_i e_c^2(t+i),\quad \text{with } \lambda_i=\frac{1}{1+d}$$

Finally, the NN denoted by N_{P} provides a prediction of the future control errors (prediction errors) using as input data the reference signal, the plant input and the plant output at time k and at some delayed instants of time. Notice that the reference input is not needed in advance. The parameters (weights) of the prediction NN are updated in two stages; during the training phase the weights of the N_{P} are updated using past information with the objective of minimizing a criterion function depending on past known predicted errors, and then based on these weights, the future values of the control errors are computed (prediction phase).

4 Neural networks characteristics

In this section the main characteristics of the neural networks used in the control scheme are described. After a series of previous tests the signals, delays and structures of the neural networks considered to control the model of the nonlinear process described in Sect. 2 were chosen as follows:

(a) Controller network

- Four layers (Input, two hidden and output)
- Input layer is conformed by:
  - Two references with four delays each. [$r_1(k-1)$, $r_1(k-2)$, $r_1(k-3)$, $r_1(k-4)$, $r_2(k-1)$, $r_2(k-2)$, $r_2(k-3)$, $r_2(k-4)$]

– Two feedback outputs with four delays each. $[x_1(k-1),\ x_1(k-2),\ x_1(k-3),\ x_1(k-4),\ x_2(k-1),\ x_2(k-2),\ x_2(k-3),\ x_2(k-4)]$

- First hidden layer with 10 neurons and activation function tanh.
- Second hidden layer with 5 neurons and activation function tanh.
- Output layer with 2 neurons and activation function tanh (output $u_1(k)$ and $u_2(k)$).
- Sample period 0.2 s

(b) Identifier network

- Four layers (Input, two hidden and output)
- Input layer is conformed by:
  - Two inputs with four delays each. $[u_1(k-1),\ u_1(k-2),\ u_1(k-3),\ u_1(k-4),\ u_2(k-1),\ u_2(k-2),\ u_2(k-3),\ u_2(k-4)]$
  - Two feedback outputs with four delays each. $[x_1(k-1),\ x_1(k-2),\ x_1(k-3),\ x_1(k-4),\ x_2(k-1),\ x_2(k-2),\ x_2(k-3),\ x_2(k-4)]$
- First hidden layer with 10 neurons and activation function tanh.
- Second hidden layer with 5 neurons and activation function tanh.
- Output layer with 2 neurons and linear activation function. (output $\hat{y}_1(k)$ and $\hat{y}_2(k)$)
- Sample period 0.2 s

(c) Predictor network

- Four layers (Input, two hidden and output)
- Input layer is conformed by:
  - Two inputs with four delays each. $[u_1(k-1),\ u_1(k-2),\ u_1(k-3),\ u_1(k-4),\ u_2(k-1),\ u_2(k-2),\ u_2(k-3),\ u_2(k-4)]$
  - Two outputs with four delays each. $[x_1(k-1),\ x_1(k-2),\ x_1(k-3),\ x_1(k-4),\ x_2(k-1),\ x_2(k-2),\ x_2(k-3),\ x_2(k-4)]$
  - Two references with four delays each. $[r_1(k-1),\ r_1(k-2),\ r_1(k-3),\ r_1(k-4),\ r_2(k-1),\ r_2(k-2), r_2(k-3),\ r_2(k-4)]$
- First hidden layer with 10 neurons and activation function tanh.
- Second hidden layer with 5 neurons and activation function tanh.
- Output layer with 6 neurons and linear activation function. (output three prediction periods $[e_1(k+1),\ e_1(k+2),\ e_1(k+3),\ e_2(k+1),\ e_2(k+2),\ e_2(k+3)]$)
- Sample period 0.2 s

5 Simulation results

In this section the simulation results of the control strategy applied to the nonlinear model of the plant are presented. When the control of the nonlinear model was done using neural networks with linear activation functions it was impossible to achieve a stable control. Therefore, only results with nonlinear activation functions are shown.

The control scheme used in this case is shown in Fig. 2. In this scheme the nonlinear model of the pressurized tank, described by (1) to (8) and the nonlinear networks in the controller, identifier and predictor units described in Sect. 4 were used. In the simulations, two kinds of control schemes were considered; with and without prediction network.

Figures 3 and 4 illustrate the behavior of the system when it is carried out the transference from manual control to the neural automatic control at $t=0$. It is observed a transient of adaptation during a short period of time, so that the neural networks are adjusted to the new operation point. In Fig. 4 the evolution of control variables can be observed for this case.

Figures 5 and 6 show the system response when the neural control without prediction is used. In Fig. 5a and b the responses of x_1 and x_2 for changes in their references are illustrated. In Fig. 5b, when changing the reference of x_2 at the instant 800 s, from 0.1 to 0.2 (bar) and at instant 1,100 s, from 0.2 at 0.1 (bar), a low degree of interaction between x_2 and x_1 is appreciated, both in stationary and in transient regimes. An oscillatory effect in the transient stage appears in the output x_2. Also, from Fig. 5a when varying the level reference at instant 200 s, from 0.4 to 0.6 (m) and at instant 500 s, from 0.6 to 0.4 (m), a small interaction between the level x_1 and the pressure x_2 is observed.

In Fig. 6 the evolution of control variables u_1 and u_2 are shown, which have a suitable behavior.

Figures 7 and 8 show the response of the neural control system with predictive effects. The responses for changes in references of x_1 and x_2 are illustrated in Fig. 7. From this, a small interaction of x_2 with x_1 is appreciated, both in stationary and in transient regime. This is because the predictor network needs more training time due to the large number of weights to adjust. Increasing the learning ratio in the predictive scheme can increase the adjustment speed. The oscillatory effects of the transient stage observed in the case without predictor network, are minimized; because the predictive effect makes more stable the system.

In Fig. 8 the evolution of control variables u_1 and u_2 is shown in this control scheme using predictive effect.

6 Conclusions

A new strategy of neural control with predictive effects has been presented and applied at simulation level to a process consistent in a pressurized tank. This control

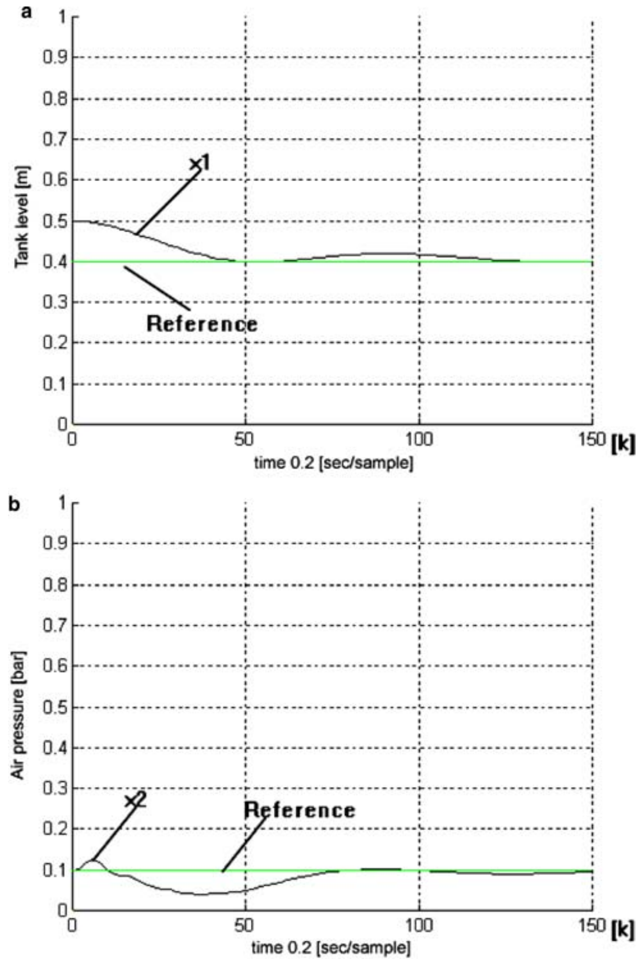


Fig. 3 Variations of the output variables when the control is passed from manual to neural automatic. **a** Tank level **b** Air pressure

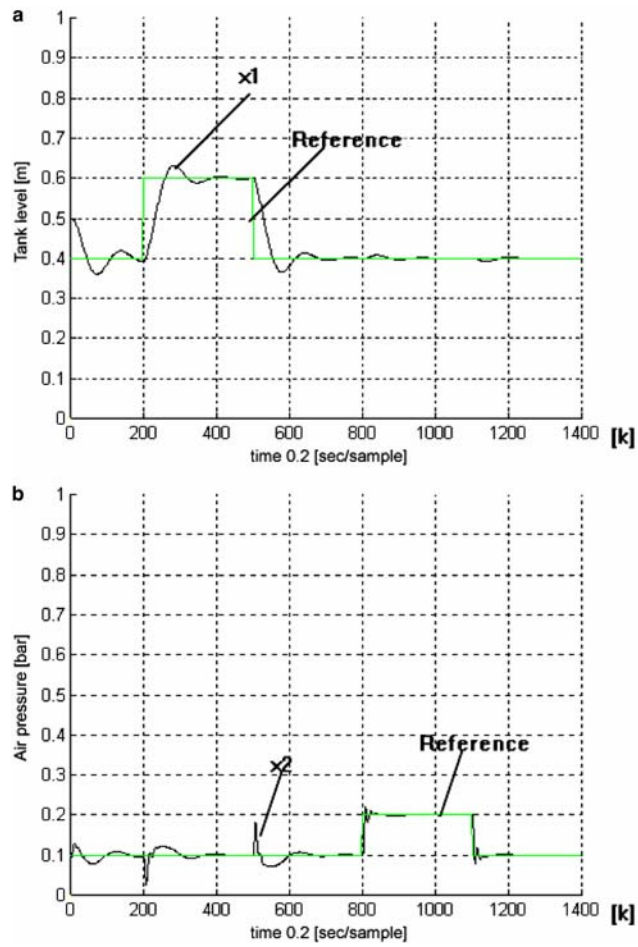


Fig. 5 Tank control applying neural control without predictive effects, nonlinear model and nonlinear NN case. **a** Tank level x_1 **b** Air pressure x_2

strategy offers a simple control method since only a reduced number of parameters should be initially chosen. The weights of the networks can be initially trained off-line using process data or can be trained on-line if the process is brought to an operation point.

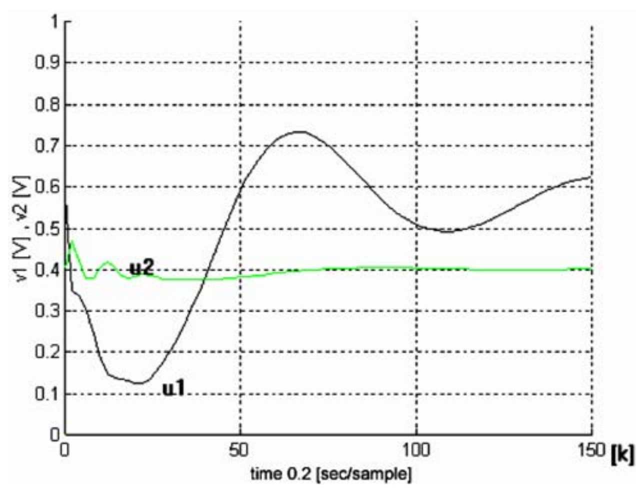


Fig. 4 Variations of the input variables when the control is passed from manual to neural automatic

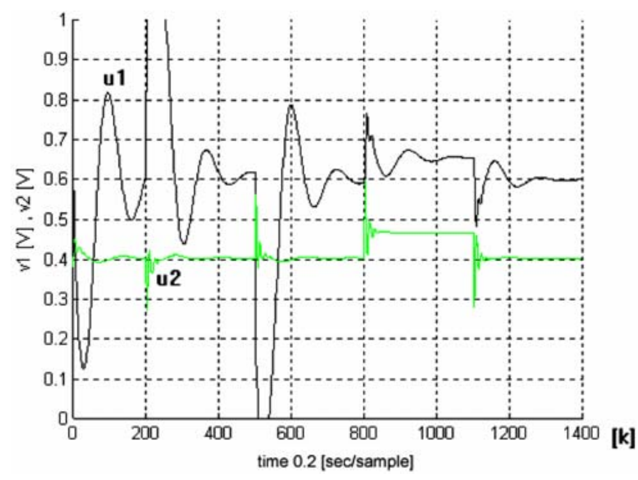
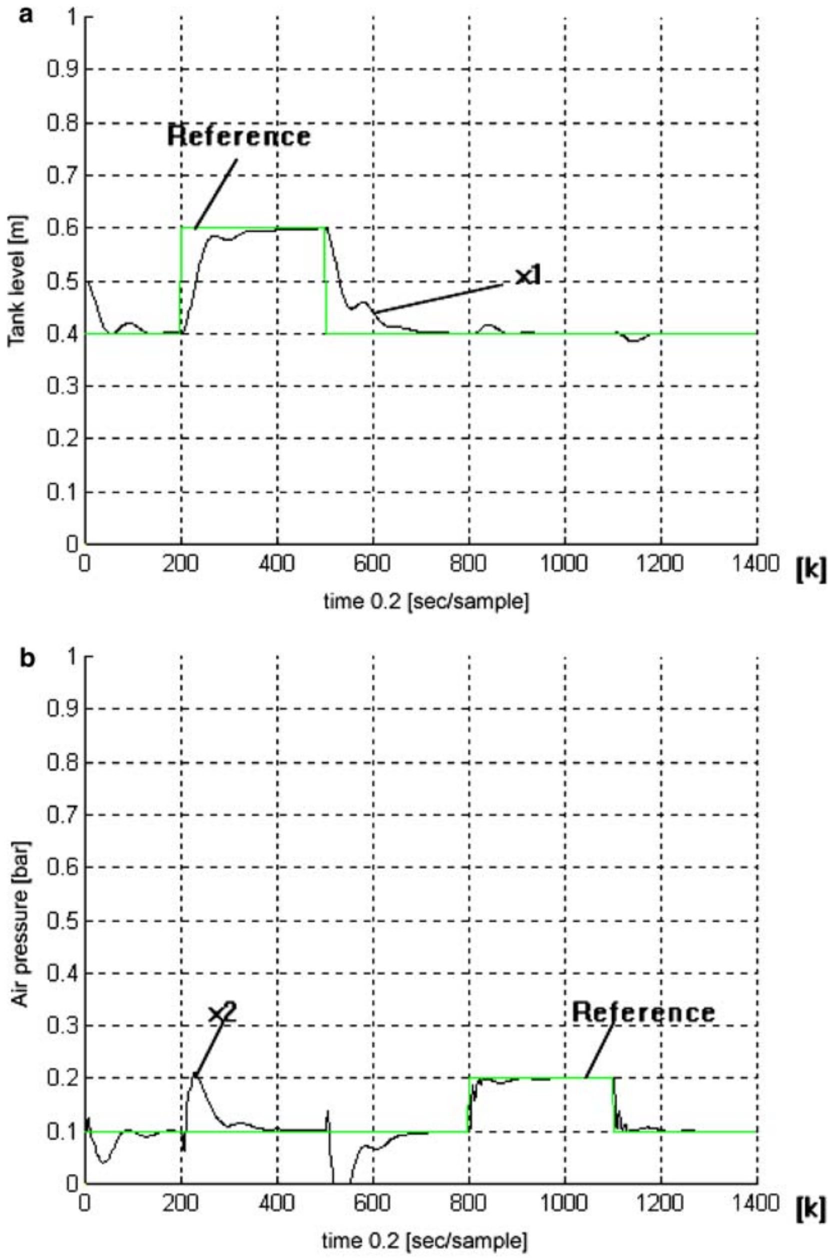


Fig. 6 Tank control applying neural control without predictive effects, nonlinear model and nonlinear NN case. Control variables of the valves v_1 and v_2

Fig. 7 Tank control applying neural control with predictive effects, nonlinear model and nonlinear NN case. **a** Tank level x_1 **b** Air pressure x_2



Comparing the results obtained in this study with those of the work [31] (although in this reference the tests are carried out in a real process) it can be observed that the controlled variables are properly decoupling and quick and stable response is gotten.

A comparison of the control strategies with and without predictive effects, maintaining the rest of the parameters without changes, was analyzed. The predictive effect makes the control more stable. However, the transient stage is slower, which can be improved by increasing the learning ratio of the networks.

Considering the linear model of the tank in an operation point it is possible to conclude that the control using nonlinear networks is more effective in decoupling the variables then that using linear networks. The simulations using linear neural networks was not presented in this work for the sake of space, but from the simulations carried out it was concluded that it is very difficult to satisfy the control objectives under those conditions.

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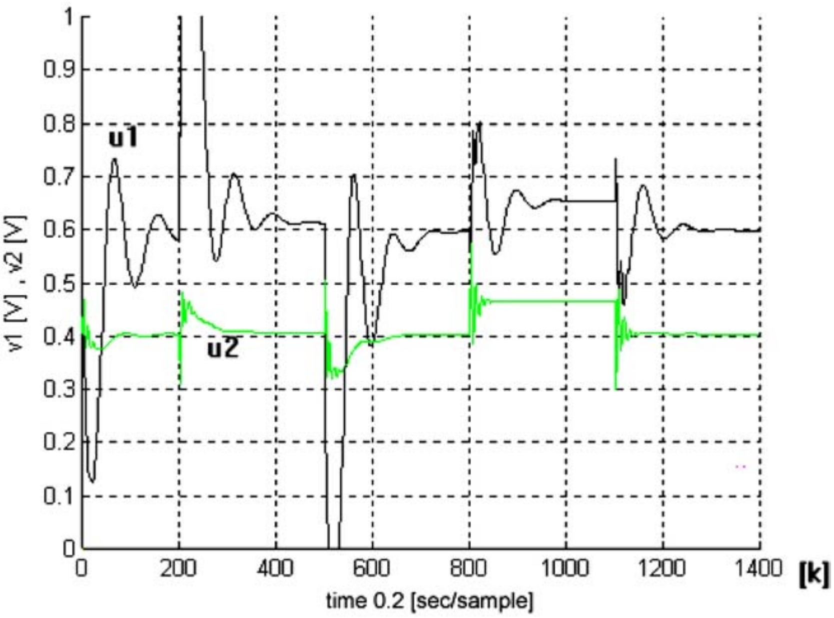

Fig. 8 Tank control applying neural control with predictive effects, nonlinear model and nonlinear NN case. Control variables of the valves v_1 and v_2

7 Appendix

Table 1 The following are the numerical values of the model parameters used in all simulations

Parameter/Constant	Notation	Value
Water density	ρ_l	1,000 (Kg/m^3)
Tank base surface	S	0.00442 (m^2)
Tank total height	L	1.05 (m)
Tank base diameter	D	0.075 (m)
Tank volume	V	0.00464 (m^3)
Air density	ρ_g	2.41 (Kg/m^3)
Boltzman's constant	K	1.3803×10^{-23} (Nw m/mol°K)
Conversion factor	N_t	9.869×10^{-6} (Nw/m^2) to (atm)
Air temperature	T	20 (°C) = 293.2 (°K)
Liquid time constant	τ_l	60 s
Air pressure time constant.	τ_g	1.3 s
Gravity acceleration	G	9.81 (m/s^2)
Level difference	$\Delta L'$	0.2 (m)
Valve constant (liquid)	K_{lf}	$21.86\times10^{-6}\sqrt{\text{Kg/m}}$
Level difference	$\Delta L''$	0.1 (m)
Valve constant (liquid)	K_{ld}	$29.49\times10^{-6}\sqrt{\text{Kg/m}}$
Valve constant (gas	K_{gf}	$0.382\times10^{-6}\sqrt{\text{Kg/m}}$
Valve constant (gas)	K_{gd}	$3.38\times10^{-6}\sqrt{\text{Kg/m}}$
Manometric pressure (liquid)	P_{lf}	303975 (N/m^2) = 3 (atm)
Manometric pressure (gas)	P_{gf}	303975 (N/m^2) = 3 (atm)
Sample period	H	0.2 s

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