

## NEURAL CONTROL OF A 4<sup>th</sup> ORDER LEVEL PROCESS

**Júlio César Peixoto de Oliveira, juliocpo@uol.com.br**

**Adolfo Bauchspiess, adolfobs@unb.br**

Laboratório de Automação, Visão e Sistemas Inteligentes - LAVSI

Grupo de Robótica, Automação e Visão Computacional – <http://grav.unb.br>

Departamento de Engenharia Elétrica – ENE - Faculdade de Tecnologia - FT

Universidade de Brasília – UnB - 70910-970 Brasília – DF

**Abstract** - This paper presents the applications of a neural network controller for a multivariable system of coupled tanks to evaluate the use of intelligent control techniques. We used a 4<sup>th</sup> order process, where the first three tanks have constant cross section of 60 cm<sup>2</sup> and the fourth tank has a variable section, varying between 60cm<sup>2</sup> and 121.2cm<sup>2</sup>. The maximum allowed level is 49.5cm. Tanks 1 and 3 have water input and output driven by electric pumps, tanks 2 and 4 have 2mm water outlets into a reservoir. Coupling valves between adjacent tanks (a 2mm groove with configurable height) determine the flow parameters of the process. Each tank has is equipped with a pressure level sensor. The contribution of this work consists mainly in the design procedure for intelligent controllers coping with very different configurations of the multivariable system. The controlled variable is the level of tank 4. A dynamic neural network was trained to learn the non linear system characteristics guaranteeing small steady error between the plant output and the reference and almost similar transitory behaviour. The development and implementation of the proposed controller was done using Matlab<sup>®</sup> and Simulink<sup>®</sup>. As some level processes are critical, in the sense that they should operate for months without flaws, it is mandatory to use industrial equipment, in our case a PLC (Programmable Logic Controller). The neural controller was implemented using the Simulink<sup>®</sup> NARMA-L2 block. The control and measurement signals were transferred through the PLC and a PC data server by an OPC interface (via serial interfaces). Neural network control results are presented and compared with a standard PID. Advantages and restrictions of the implemented NARMA-L2 are discussed.

**Keywords** – level control, multivariable systems, artificial neural networks, non linear control, NARMA-L2.

### 1. INTRODUCTION

Artificial Neural Networks are important tools for control of nonlinear plants given their characteristics of universal approximators and due the capacity to learn. Applications involving adaptive control through linearization of SISO systems (Chen & Khalil, 1995) and internal model control (Hunt & Sbarbaro, 1991) are some of the many uses of neural networks in process control.

Nonlinear dynamic systems are of great interest in control engineering. Due to the complexity of such systems it is difficult to develop general control techniques. Some techniques are based on the cancellation of the non linearities (Slotine & Weiping, 1990). They present, however, as main limitation the need of "an accurate" model of the plant and the same must present steady inversible dynamics.

Three main approaches are used to describe non linear systems: 1) Modeling, 2) Identification and 3) Training. Identification is a procedure that, in the simplest case, tries to tune a pre defined structure with measured signals of the process. It is an optimization process that seeks the best parameter values that minimize the error between the process and the model. The disturbance signals of the process also can be identified. If the structure of the process is known, this is the best experimental approach. In the practice it is very difficult to correctly formulate the internal structure of a nonlinear process.

Artificial Neural Network are non linear universal approximators. Nor the internal structure nor the parameter values are necessary in advance. If the training data is rich in information, the number of neurons is enough, and a proper training algorithm is available a reasonable good approximation is expected, at least for some domain extension. Good global solutions are rare for practical problems.

When a wide range of operation is requested it is more difficult and often a single RNA can not cope with the entire operation range. In this article we consider the composition of a set of RNAs trained for complementary operation ranges. A soft transition must occur when a change of operation range takes place.

In this paper we show practical results of a neural control NARMA-L2 for a 4<sup>th</sup> order non linear process - a connected set of four water tanks. The results using training algorithm Conjugate Gradient Backpropagation with Fletcher-Reeves Updates, number of layers and errors using this controller are presented and evaluated.

### 2. THE 4<sup>th</sup> ORDER NON LINEAR LEVEL PROCESS

The process investigated in this work is a multivariable system of interconnected tanks build for the evaluation of control techniques, figures 1 and 2. Three of these tanks possess dimensions of 49.5x10x6 cm and the fourth tank has a non uniform section. The transversal sections of tanks 1, 2 and 3 is 60 cm<sup>2</sup>. The width of tank 4 until 14.7 cm height, representing 29% of the liquid level, has the same value, 60 cm<sup>2</sup>. Then it gets linearly wider up to 20.2 cm (31.65° aperture angle) with a transversal area changing from 60 cm<sup>2</sup> to 121.2 cm<sup>2</sup>.

Tank 1, has a water input, pumped from reservoir by means of a pump  $u_1$ , and also has a water output,  $q_{o1}$ . A second pump  $u_2$  drives water from 1 to the reservoir. Tank 2, has a water output,  $q_{o2}$ , passing through a puncture of 2mm, situated in the bottom of this tank to the reservoir. Tank 3, has water input, that is pumped from the reservoir by means of pump  $u_3$ , Tank 3 also has a water exit,  $q_{o3}$ . Tank 3 has also the possibility to pump water out using pump  $u_4$ . The contents of tank 4 reaches the reservoir through  $q_{o4}$ , a puncture of 2mm, situated in the bottom of this tank.

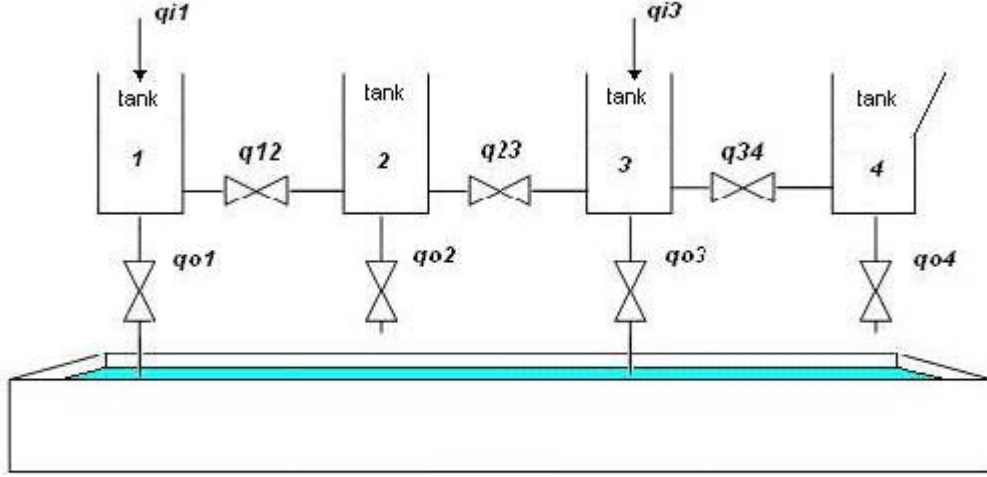


Figure 1. Schematic representation of the 4<sup>th</sup> order liquid level process.

Between the tanks a groove with approximately 2mm width and configurable height is used, that determines the interconnecting flow parameter. The pumps are driven by means of a power system commanded by a voltage between 0 and 10 VCC. Each tank is endowed with a pressure level sensor, able to measurement with good precision inclusive the maximum water column of 49.5 cm.

The complete dynamic model of the interconnected tanks process at LAVSI is given by equations 1 (Melo, G.A.F and Bernardes, M. C., 2006):

$$\begin{aligned}
 A_1 \frac{dh_1}{dt} &= q_{i1} - k_{o1} \sqrt{h_1} - \text{signal}(h_1 - h_2) k_{12} \sqrt{|h_1 - h_2|} \\
 A_2 \frac{dh_2}{dt} &= \text{signal}(h_1 - h_2) k_{12} \sqrt{|h_1 - h_2|} - k_{o2} \sqrt{h_2} \\
 &\quad - \text{signal}(h_2 - h_3) k_{23} \sqrt{|h_2 - h_3|} \\
 A_3 \frac{dh_3}{dt} &= q_{i3} + \text{signal}(h_2 - h_3) k_{23} \sqrt{|h_2 - h_3|} - k_{o3} \sqrt{h_3} \\
 &\quad - \text{signal}(h_3 - h_4) k_{34} \sqrt{|h_3 - h_4|} \\
 A_4(h_4) \frac{dh_4}{dt} &= \text{signal}(h_3 - h_4) k_{34} \sqrt{|h_3 - h_4|} - k_{o4} \sqrt{h_4}
 \end{aligned} \tag{1}$$

The valve  $k_{12}$  allow water to flow between tank 1 and tank 2. In the same way  $k_{23}$  and  $k_{34}$  shape the flow between tanks 2 and 3, and 3 and 4, respectively. The problem focused in this work is the height control of level 4 ( $h_4$ ). The outflows and the heights are thus defined as follows:

- $q_{i1}$  and  $q_{i3}$  = inputs flows into tanks 1 and 3, [cm<sup>3</sup>/s];
- $q_{o1}$  and  $q_{o3}$  = output flows from tanks 1 and 3, [cm<sup>3</sup>/s];
- $q_{12}$ ,  $q_{23}$  and  $q_{34}$  = interconnected flows between tanks 1-2, 2-3 and 3-4, [cm<sup>3</sup>/s];
- $q_{o2}$  and  $q_{o4}$  = output flows from tanks 2 and 4, through 2mm punctures [cm<sup>3</sup>/s];
- $h_1$ ,  $h_2$ ,  $h_3$  and  $h_4$  = water column height in tanks 1, 2, 3 and 4, [cm].
- $A$  it is the area of the transversal section of tanks
- $k$  is the valve parameter between tanks  $k_{12}$ ,  $k_{23}$ , and  $k_{34}$  [cm<sup>2,5</sup>/s]



Figure 2 - The 4<sup>rd</sup> order Liquid Level Process.

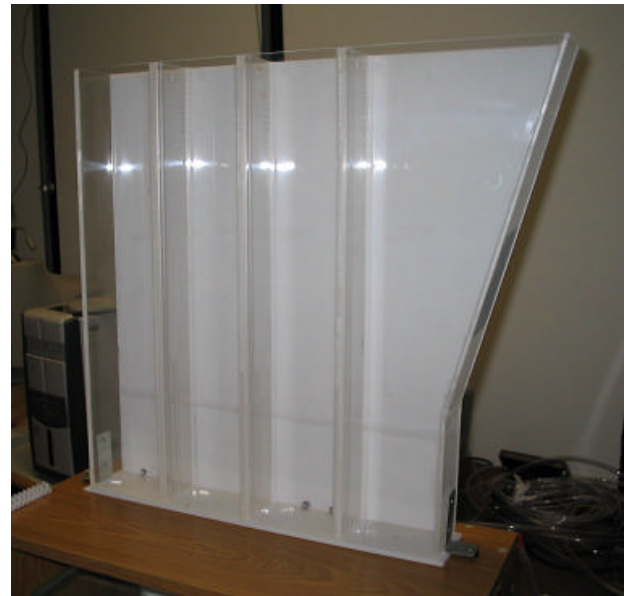


Figure 3. PLC Ref 1770 Metal Leve

### 3. PROGRAMMABLE LOGIC CONTROLLER (PLC)

A Programmable Logic Controller is an electronic equipment aimed to substitute burst systems and electromechanical devices and to interface Numerical Commands with operating machines. This equipment substitutes the electric diagram, the relays and its interconnections by programs that simulate these components. The Supervisory Control aims the global control of a process, instead of partial, as the Programmable Controller.

PLC's control with precision and robustness mechanical, pneumatical, hydraulical and electrical processes. So they are the first choice when controlling industrial processes.

In this work the PCL Ref. 1770 from Metal Leve (1987), shown in Figure 3, was used. In ladder logic the PLC executes control algorithm accordingly to the stored instructions in memory.

The implementation of ladder logic control in CLP, they were based on "Controlador Programável" (Oliveira, Júlio César Peixoto, 1993).

### 4. NARMA-L2® (FEEDBACK LINEARIZATION) CONTROL

The NARMA-L2 model was proposed by Narendra and Mukhopadhyay (1997). It can be used to model the plant previously cited, using two distinct neural networks. One net implements a controller and the another simulates a model of the plant. In this model the number delays is the discrete model order. The NARMA-L2 – use an non linear identification tool. The identified model is used in a neural network controller that transforms the not linear system into a linear system through the additive and multiplicative cancellation of non linearities.

Diverse nonlinear approximative models have been developed. An excellent examination can be found in the works of Billings (1985a and 1985b). The standard model that is used to represent non linear general systems in the discrete time NARMA (Nonlinear Autoregressive-Moving Average) model.

The Narma-L2 controller, trained off-line, is a rearrangement of the standard neural network using the plant model. The controller transforms the nonlinear dynamics of the system into linear dynamics canceling non linearities. Many stages must be followed to obtain a Narma-L2 controller. The first stage is to identify a neural net that represents the system dynamics. A NARMA model is represented by:

$$\hat{y}(k+d) = f[y(k), y(k-1), \dots, y(k-n+1), \dots, u(k-m+1)] + g[y(k), y(k-1), \dots, y(k-n+1), u(k-1), \dots, u(k-m+1)]u(k)$$

Where  $d \leq 2$ , using controlling model NARMA-L2, gets it form forms:

$$u(k+1) = \frac{y_r(k+d) - f[Y, U]}{g[Y, U]} \quad \text{where} \quad \begin{cases} Y = [y(k), \dots, y(k-n+1)] \\ U = [u(k), u(k-1), \dots, u(k-n+1)] \end{cases}$$

The performance of Narma-L2 controller depends essentially on the identification of the system with a neural network. A good model of a neural net for the system supplies good results in the desired points of operation. A NARMA-L2 controller is shown in figure 3, where TDL (Time Delay Lines) blocks are lines of fast delays that store preceding values of the input signal and the transfer functions are: sigmoidal and linear, respectively.

NARMA-L2 is include in the MATLAB® Software and uses the theory of neural networks and parameter identification to carry out the identification and the control, as shown in figure 4.

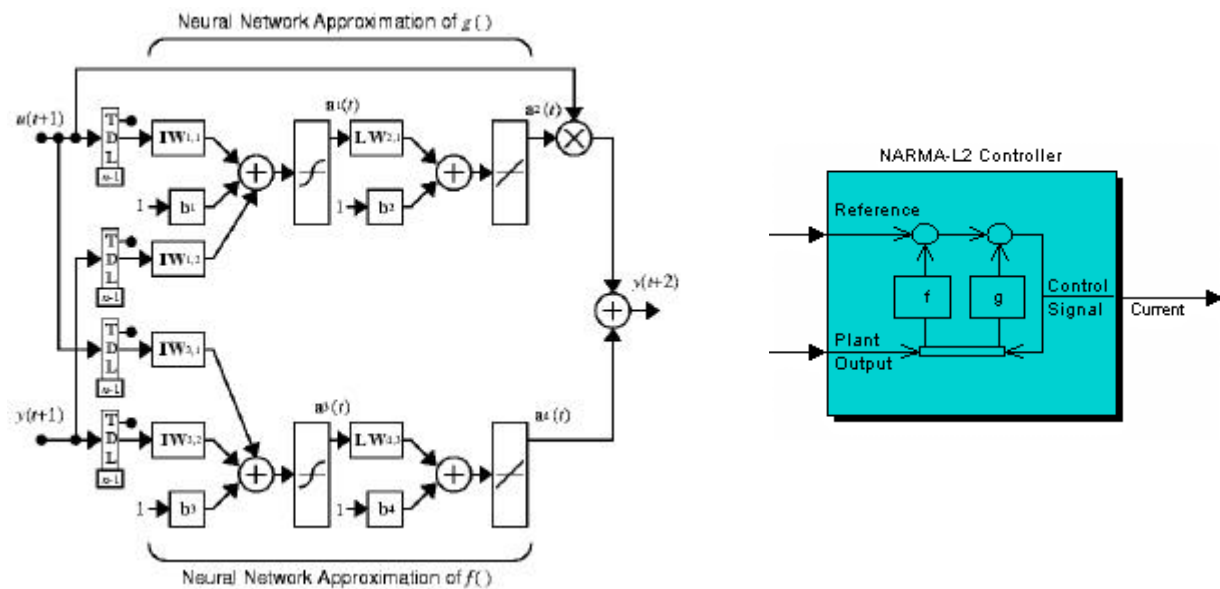


Figure 4. NARMA-L2 control

The user interface has three panels: architecture of the net, training parameters and training. The identification is initiated using the training data that can be generated by a convenient tool (Generate training data) or imported from some archive (Import data). A topology for the net is defined (Network Architecture). The choice of the number of layers, delays and interval of sampling is made based in the nonlinear system to be controlled. In the identification stage it is necessary to choose the training parameters (Training parameters), which depends on the complexity of the studied system and in the computational capacity. After the three fields are defined, the training can be started. The quadratic average error of the data serves as stopping criterion for the training. At the end of the training, the following answers are supplied in graphical form the three types of data: quadratic average error, quadratic error, input signal, output signal of the plant and the output signal of the net.

Finally, the obtained neural net is applied to the block of control NARMA-L2® (figure 4). In this tool the controller will be the proper neural net, or either, the proper net will be inserted in the mesh of the system. The training gets, approximatively, the inverse model of the non linear dynamic system.

## 5. METHODOLOGY

The plant was identified by the training data generated by the Generate Training Data tool NARMA-L2. After this, we defined the topology of the net in Network Architecture, choosing the number of layers, delays and sampling interval.

The complete joined network was applied the controller. To verify the response of the controller the configuration in figure 5 was used. This procedure was repeated for some configurations of the neural net, as training algorithm, number of layers and delays. During the tests it was verified that the output signal of the net follows the input signal adequately and, it satisfactorily reflects the behavior shown at the output of the plant. Observing, still, that the output signal of the plant and that of the net always reach the steady state for inputs of amplitude  $qi1 = 0$  to  $66$  [  $cm^3/s$  ].

All the simulations have been carried out in the SIMULINK® of MATLAB® software.

As described, answers for some configurations of the interconnected water tanks had been obtained. For the presentation of the graphical results the model shown in Figure 6 was used. The following parameters were used:

$$qi1 = 0 \text{ a } 66 \text{ [cm}^3\text{/s]}; qi3 = 0 \text{ [cm}^3\text{/s]}; h4 = 0 \text{ a } 46 \text{ [cm]};$$

$$k1=0, k2=5, k3=0 \text{ e } k5=5 \text{ [cm}^2\text{/s]}; k12 = 12, k23 = 2.5, \text{ e } k34 = 6 \text{ [cm}^2\text{/s]}$$

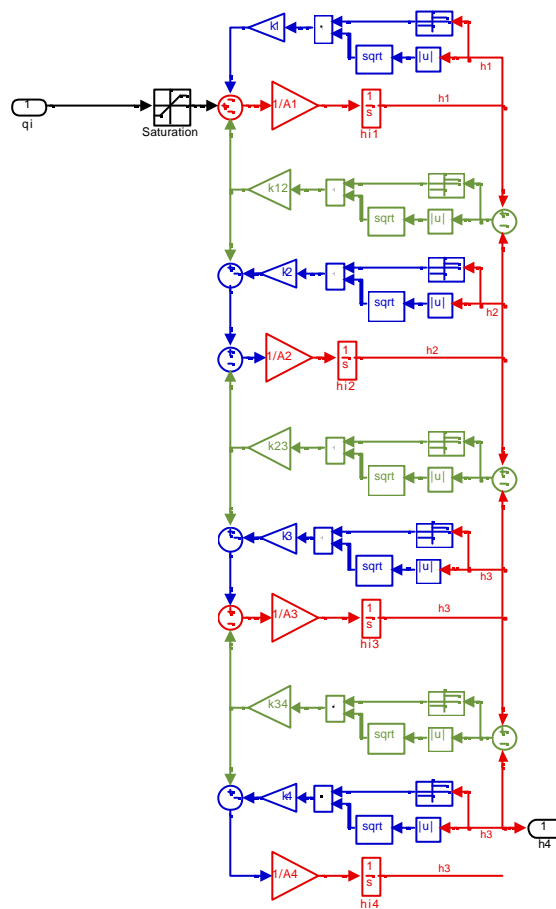


Figure 5. Diagram of blocks of the tanks

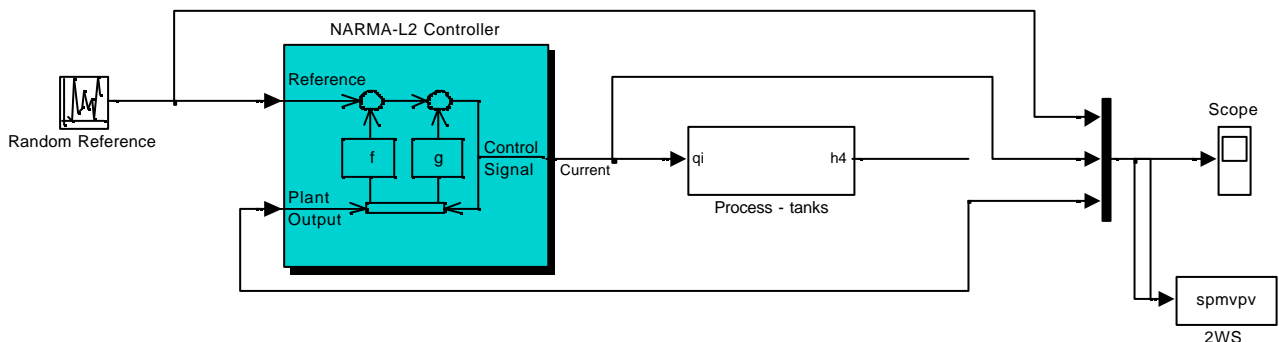


Figure 6 – Simulink model of the controlled process.

In the figure 7 we show the NARMA-L2. SP: setpoint, PV: process variable  $y(k)$  e MV: manipulated variable  $u(k)$   
 Algorithm of training *traincgf* in model of the plant of four coupled to water reservoirs.

The results for the algorithm of training Conjugate Gradient Backpropagation With Fletcher-Reeves Updates (*traincgf*), network architecture, training date and training epochs using this controller are presented. More information on the Fletcher-Reeves Update (*traincgf*) are gotten in the Neural Network Toolbox.

The plant was identified by Plant Identification - NARMA-L2: Network Architecture: Size of hidden layer: 5, Delayed plant inputs: 4, Delayed Plant Outputs: 4, Sampling Interval(sec): 8. Training Data: Training Samples: 5000, Maximum Plant Input: 66, Minimum Plant Input: 0, Maximum Interval: 500, Minimum Interval Value: 50. Training Epochs: 5000. Training parameters: testing data, validation data, training data and Training with *traincgf*. In the Table n° 1, we show the answers for the used configuration in the connected water tanks.

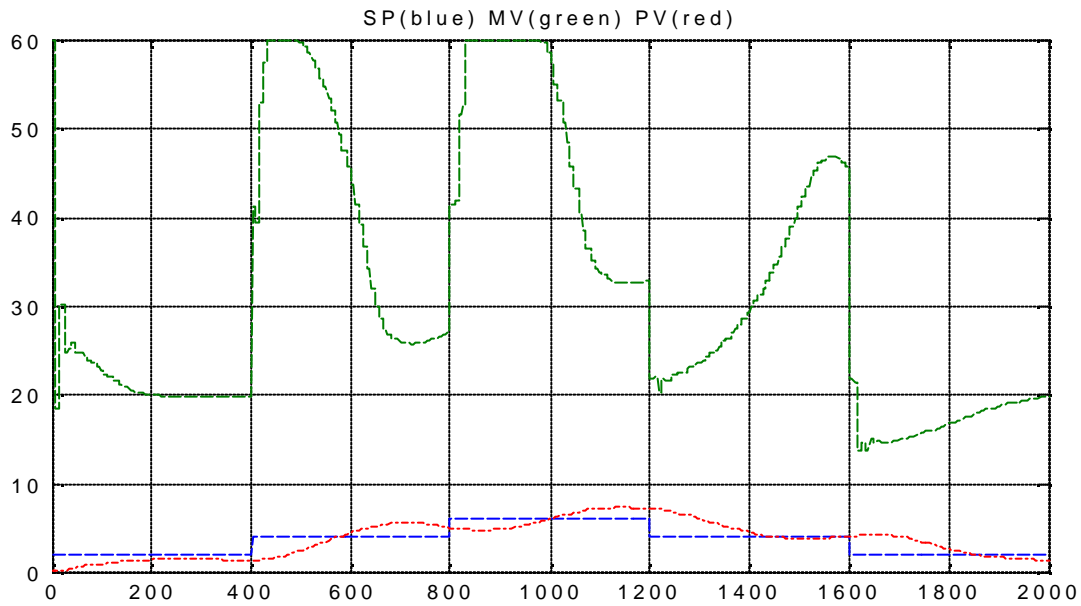


Figure 7 – NARMA-L2 - SP: setpoint, PV: process variable  $y(k)$  e MV: manipulated variable  $u(k)$   
 Algorithm of training *traincgf* in model of the plant of four coupled to water reservoirs

Table 1 - Answers for the used configuration in the connected water tanks

Algorithm train	Size hidden	Delay In	Delay out	Error Goal	Error Train	Error Validation	Error Testing
<i>traincgf</i>	5	4	4	0.4877	$-5 a +15 \times 10^{-4}$	$-5 a +15 \times 10^{-4}$	$-5 a +10 \times 10^{-4}$

In the Table n° 2, we show the Time of Reply in the experiments for Controller NARMA-L2, carried through in environment Matlab and Simulink, in the model plant. In this table we show: setpoint change, theoretical rise time, rise time, peak time and the overshoot for the algorithm Conjugate Gradient Backpropagation With Fletcher-Reeves Updates - *traincgf*, that got a smaller error and one better excursion of the variable manipulated for the level process.

Table 2 – Time of Reply in the experiments for Controller NARMA-L2- Model Plant

NARMA_L2 control	Setpoint change (cm)	Rise time Theoretical (%)	Rise time (seg) *	Peak time (seg)	Overshoot (%)
RNA - CGF	2 cm	0 cm a 2,0 cm	no	no	no
RNA - CGF	4 cm	2,0 cm a 4,0 cm	176	312	38,6
RNA - CGF	6 cm	4,0 cm a 6,0 cm	199	347	23,1

\* the continuity of the signal in the exchange of the SP was considered



## 6. EXPERIMENTAL AND SIMULATION RESULTS

So, as described, measurements for some configurations of the interconnected water tanks have been obtained. For the presentation, after properly trained the neural network is used to control the real plant, as shown in figure 8. The neural controller with NARMA-L2, used the following parameters:

$$q_{i1} = 0 \text{ a } 66 \text{ [cm}^3\text{/s]}; q_{i3} = 0 \text{ [cm}^3\text{/s]}; h_4 = 0 \text{ a } 46 \text{ [cm]};$$

$$k_{12}=0, k_{25}=5, k_{30} e k_{55} \text{ [cm}^2\text{/5/s]}; k_{12} = 12, k_{23} = 2.5, e k_{34} = 6 \text{ [cm}^2\text{/5/s]}$$

The experimental data was recorded using a OPC server connection (refer to figure 9). The data was acquired from the level sensors located in the tanks. The data acquisition rate was half second. At present, two signals are recorded and transmitted to the MATLAB software in real time. The data transmission from the Allen Bradley PLC-5 is one way so that the 4rd order level process is not interrupted. The data acquisition process is initiated by executing the initializing code which includes specifying the signals to be recorded and the time for the data to be acquired.

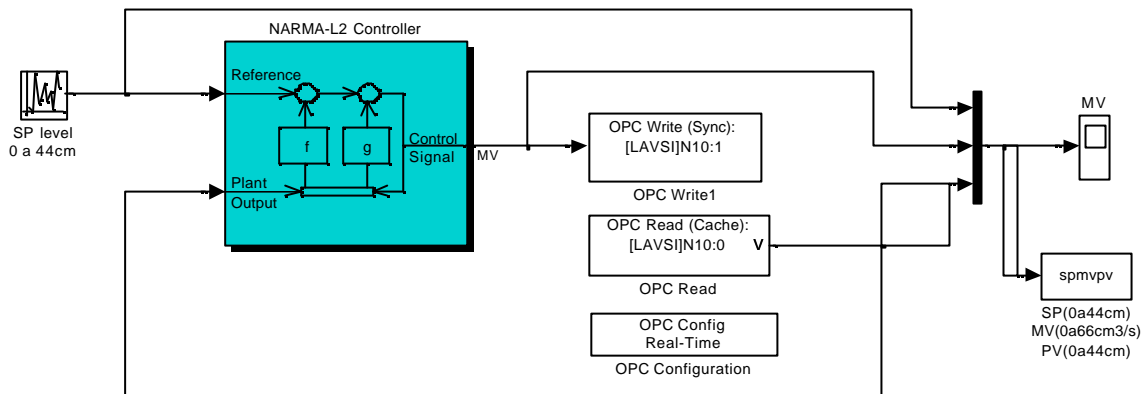


Figure 8 –. Model of the controlled system implementation on a real plant

The subsystems have been interconnected in Matlab and Simulink to create a simulation tool set that uses the OPC Toolbox. A variety of model input and output signals have been considered including the input electric pumps and output level sensor.

**DATA LOGGING SCHEME:** As shown in figure 9, the system handles most of the data transfer from the Programmable Logic Controllers through a server data and the Matlab OPC Toolbox, connected to the PLC are logged through RS-232 communications. There is a configuration table which serves as an index for data retrieval. Other information is also stored in this table, for instance, description of the logged parameter, upper and lower limits, interface type, etc. The logged data is stored in a separate table. The computer retrieves the information on the data to PLC tag name, from the configuration table [LAVSI] in the server database. Then the logging process will be executed at the specified time interval.

OPC Toolbox (Open Process Control) is a collection of functions that extend the capability of the MATLAB® numeric computing environment, and blocks that extend the Simulink® dynamic system simulation environment. Using OPC Toolbox, you can acquire live OPC data directly into MATLAB and Simulink, and write data directly to the OPC server from MATLAB and Simulink.

In this work, controller NARMA-L2, through the computer (a) processes the neural network and sends the control signal  $u(k)$  for the PLC (b) which sets in motion the pump  $q_{o1}$  of tank 1 (c) and carries through the reading of level of 4 tank  $h_4$ , through the server data collection and OPC Toolbox Read/Write (figure 9).

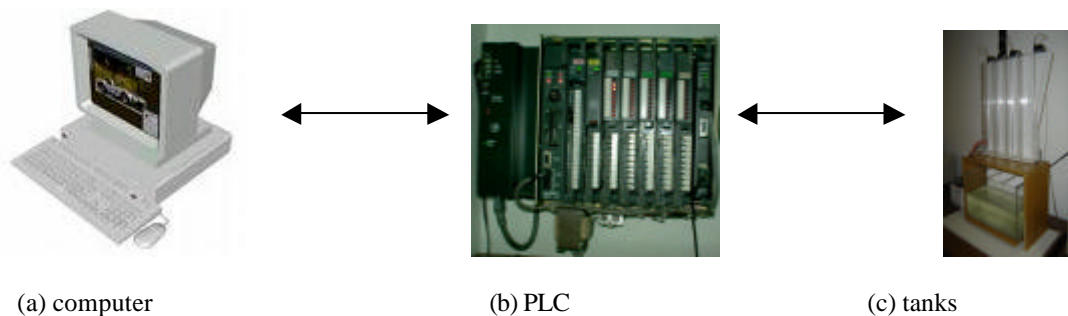


Figure 9 - Diagram of the communication system by Data Logging Scheme

In the figure 10 we show the NARMA-L2 - SP: setpoint, PV: process variable  $y(k)$  e MV: manipulated variable  $u(k)$  Algorithm of training *traincgf* in real plant of four coupled to water reservoirs.

In the Table n° 3, we show the Time of Reply in the experiments for Controller NARMA-L2, carried through in environment Matlab and Simulink, in the real plant of four coupled to water reservoirs. In this table we show: setpoint change, theoretical rise time, rise time, peak time and the overshoot for the algorithm Conjugate Gradient Backpropagation With Fletcher-Reeves Updates - *traincgf*, that it got a lesser error and one better excursion of the variable manipulated for the process of level of liquids of 4<sup>a</sup> order.

In the figure 11 we show the SP: setpoint, PV: process variable  $y(k)$  e MV: manipulated variable  $u(k)$  The PID Controller in real plant of four coupled to water reservoirs. The project of controller PID was carried through by manual tuning (trial and error) which had the difficulties in the operation band proposal.

In the Table n° 2, we show the Time of Reply in the experiments for PID Controller, carried through in environment Matlab and Simulink, in the real plant of four coupled to water reservoirs. In this table we show: setpoint change, theoretical rise time, rise time, peak time and the overshoot for the algorithm PID Controller.

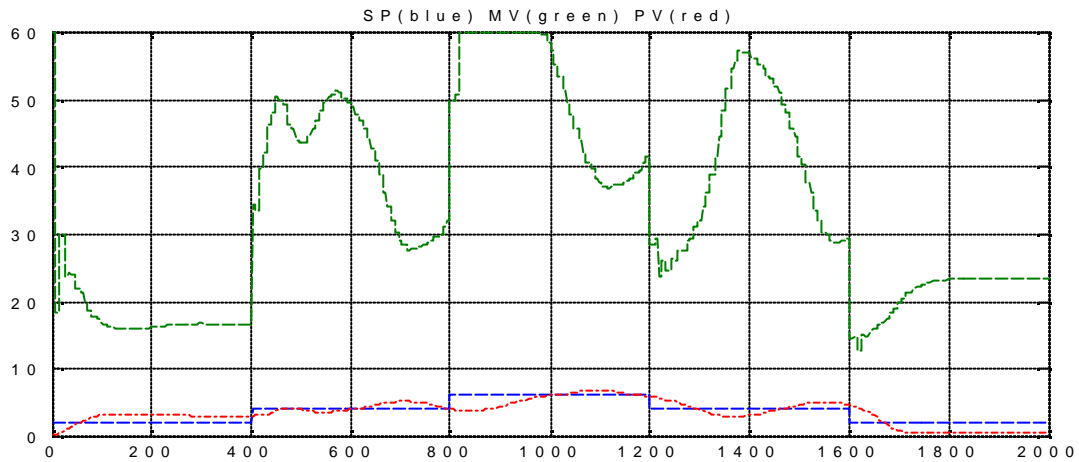


Figure 10 – NARMA-L2 - SP: setpoint, PV: process variable  $y(k)$  e MV: manipulated variable  $u(k)$  Algorithm of training *traincgf* in real plant of four coupled to water reservoirs

Table 3 – Time of Reply in the experiments for Controller NARMA-L2 – Real Plant

NARMA_L2 control	Setpoint change (cm)	Rise time Theoretical (%)	Rise time (seg) *	Peak time (seg)	Overshoot (%)
RNA - CGF	2 cm	0 cm a 2,0 cm	60	118	65
RNA - CGF	4 cm	2,0 cm a 4,0 cm	60	294	27
RNA - CGF	6 cm	4,0 cm a 6,0 cm	203	280	10

\* the continuity of the signal in the exchange of the SP was considered

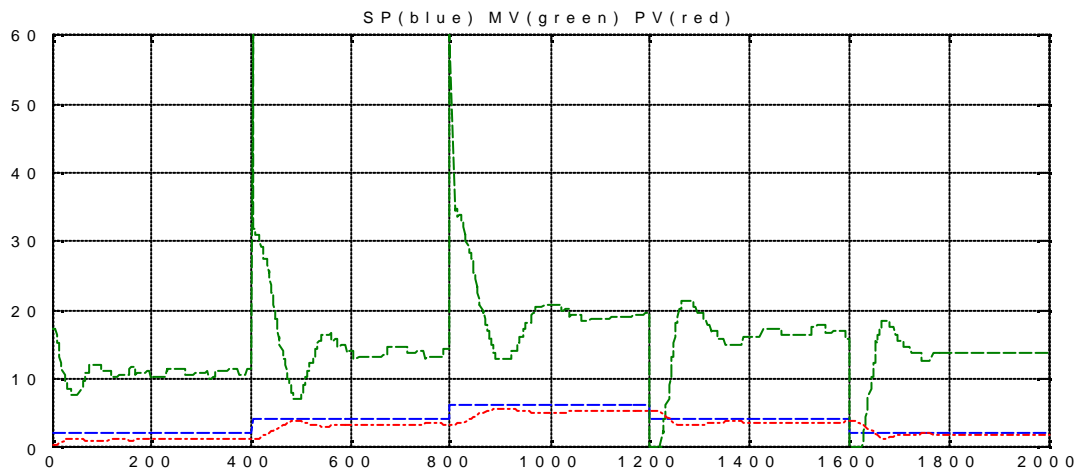


Figure 11 – SP: setpoint, PV: process variable  $y(k)$  e MV: manipulated variable  $u(k)$  The PID Controller in real plant of four coupled to water reservoirs



Table 4 – Time of Reply in the experiments for Controller NARMA-L2 – Real Plant

NARMA_L2 control	Setpoint change (cm)	Rise time Theoretical (%)	Rise time (seg)*	Peak time (seg)	Overshoot (%)
RNA - CGF	2 cm	0 cm a 2,0 cm	no	no	no
RNA - CGF	4 cm	2,0 cm a 4,0 cm	no	no	no
RNA - CGF	6 cm	4,0 cm a 6,0 cm	no	no	no

\* the continuity of the signal in the exchange of the SP was considered

## 7. CONCLUSIONS

We presented in this paper a NARMA-L2 controller, for the control of a 4<sup>th</sup> order liquid level process, that was identified and controlled with SIMULINK®. We presented measured signals for the controllers, trained using Conjugate Gradient Backpropagation with Fletcher-Reeves Updates (model and real plant) and PID Controller (real plant).

The main purpose of the experiment was to have a single neural network that learn the whole process behaviour, that means, a neural controller that works properly (linear behaviour) in every operating point of the 4<sup>th</sup> order non linear liquid level process.

The experimental data was recorded using an OPC server connection. The data was acquired from the level sensors located in each tank. The data transmission from the Allen Bradley PLC-5 is one way so that the 4<sup>th</sup> order level process is not interrupted. A diversity of model input e output signals have been considered including the input electric pumps and output level sensor. The system handles most of the data transfer from the Programmable Logic Controllers through a data server and the Matlab OPC Toolbox, connected to the PLC through RS-232 communications.

The obtained results show the viability of the neural approach for the control of real non linear plants. The behavior of the manipulated variable for the neural controller is softer, still reaching the desired value, in relation to a PID controller, preserving the pumps during operation. Careful attention was needed to not saturate the control variable. A good controller must follow the reference in the steady state ( $t \rightarrow \infty$ ), while keeping the control signal in the operation band of the actuator.

A future enhancement would be to actively treat the saturation, an important issue for every real system.

The common computer does not have robustness and compatibility with the electric standards and electromechanical specifications used in the industry. This work investigated the implementation of the theory of artificial neural nets in NARMA-L2 in commercial computer associated with PLCs.

Further studies and experiments are in progress at the Group of Robotics, Automation and Computational Vision - GRAV, University of Brasilia, so that the NARMA-L2 controller would be a feasible approach for the process industry.

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