

IDENTIFICATION OF A NONLINEAR PNEUMATIC SERVO SYSTEM USING MODULAR NEURAL NETWORKS

Codreş Bogdan, Gheorghe Puşcaşu, Gabriel Murariu, Zanoschi Aurelian

*"Dunărea de Jos" University Galaţi, Automatic Control, Computers, Electrical and
Electronics Engineering, Romania*

Abstract: Sometimes, in the case of highly nonlinear systems the traditional approaches of identification and control could be difficult to implement. In this case, a good alternative are the neural networks. In this paper a modular neural network for the identification of a pneumatic servo system is proposed. This approach is based on the partitioning of static characteristic of the pneumatic system. The neural modules are implemented with multilayer neural networks.

Keywords: modular neural networks, nonlinear system, identification, characteristic partitioning, pneumatic servo system.

1. INTRODUCTION

Considerable research has been conducted on the control of pneumatic systems (Bone and Ning 2007); Chillari, 2001) due to their potential as a low-cost, clean, high speed, high flexibility, high power-to-weight ratio actuators (van Varseveld and Bone, 1997). However, nonlinearities such as those due to compressibility of air continue to limit their accuracy. Among the nonlinearities in a pneumatic system, friction (Ning and Bone, 2002) can have a significant effect on tracking performance, especially in applications that use rodless cylinders which have higher Coulomb friction than rodded cylinders.

Compensation for nonlinearities in pneumatic systems (Richer and Hurmuzlu, 2000) has been a popular area of research in pneumatic system control. Most advanced nonlinear control strategies are based on a detailed mathematical model of the system. If a simplified mathematical model is used, then performance is sensitive to uncertainties and parameter variations. Although they show relatively good results, the requirement for model parameter identification has made these methods difficult to implement. This highlights the need for an adaptive

controller that is not based on a mathematical model.

In the last twenty years some researchers focused on the using of artificial neural networks (*NN*) for the identification and control of pneumatic systems (Abu-Mallouh, 2008; Choi, 1998; Gross and Rattan, 1997; Kothapalli and Hassan, 2008; Ning and Bone, 2005; Taghizadeh, 2010; Wang and Peng, 2003). However, the apply of modular neural networks to these systems wasn't studied too much. So, this is the main focus of the paper.

Basically, it is easier to develop local models (Jacobs et. all, 1991) or controllers (Narendra, 1997) because the dynamics are simpler locally than globally. For instance, if the system behavior changes smoothly with the operating point, then, a linear model (or controller) will always be sufficiently accurate locally (Murray-Smith and Johansen 1997).

The paper is structured as follows: Section 2 proposes a modular *NN* to be used for nonlinear system identification. In section 3, a pneumatic servo-system is used as a case study. Section 4 draws some conclusions.

2. THE IDENTIFICATION OF NONLINEAR DYNAMIC SYSTEMS USING MODULAR NEURAL STRUCTURES

In this paper, starting from the approximation of a nonlinear system using multiple linear systems, a modular neural structure for the identification of nonlinear dynamic systems is proposed. This modular structure contains *NN* that will be further called local neural models (*LNM*).

Without reducing the generality of the approach, we consider a nonlinear system with a single input and single output described by the following nonlinear discrete input-output equation:

$$(1) \quad \begin{aligned} ys(k) = f_{nel}(ys(k-1), ys(k-2), \dots, ys(k-n), us(k-1), \\ us(k-2), \dots, us(k-m)) \end{aligned}$$

where:

$ys(k)$ - is the system output at the discrete time moment k ,

$ys(k-j)$ - is the j th system output at the discrete time moment $(k-j)$ where $j = 1, n$,

$us(k-j)$ - is the j th system input at the discrete time moment $(k-j)$ where $j = 1, m$,

$$k = \overline{(\max(n, m) + 1), N} \text{ and } \{ys(i) = 0, us(i) = 0\}_{i=0, \overline{0, \max(n, m)}},$$

N - is the data set size used at identification.

Observation 1. In many engineering applications the input and output signals are bounded. This will be one of the hypotheses of the scientific approaches in this paper.

Consequently, $us(k) \in [u_{inf}, u_{sup}]$, where u_{inf} and u_{sup} represent the lower limit and upper limit of the input $us(k)$, respectively.

Usually, the models of nonlinear dynamic systems are difficult to use. For example, they are difficult to derive or to synthesize a nonlinear control law. For poorly understood systems, the derivation of a model from the first principles of physics, chemistry, biology is even impossible. To overcome this difficulty, a modular neural structure that allows the decomposition of a complex problem in several less complex subproblems will be used.

The modular structure for the nonlinear systems identification described by Eq. (1) is given in the following figure:

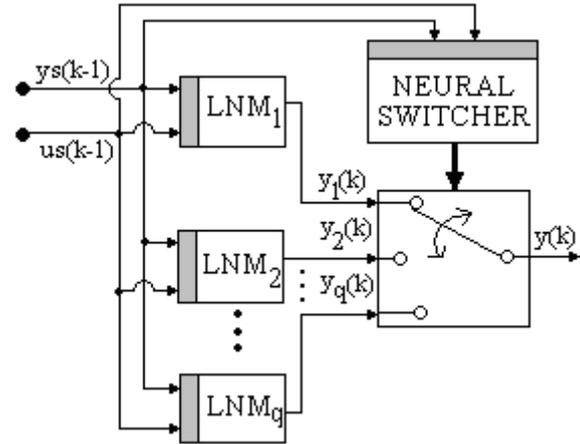


Fig. 1 MNN for system identification

where:

LNM_i - local neural models used to approximate the nonlinear dynamic system in the neighborhood of steady points;

Neural Switcher (*NS*) - enables a LNM that approximates best the nonlinear system output at a given time.

In fig.2 and fig.3 the detailed schemes of the LNM_i and of the *NS* are represented.

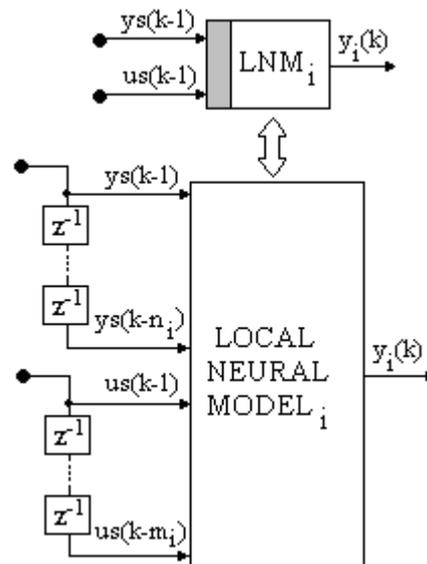


Fig. 2 The detailed scheme of the LNM_i

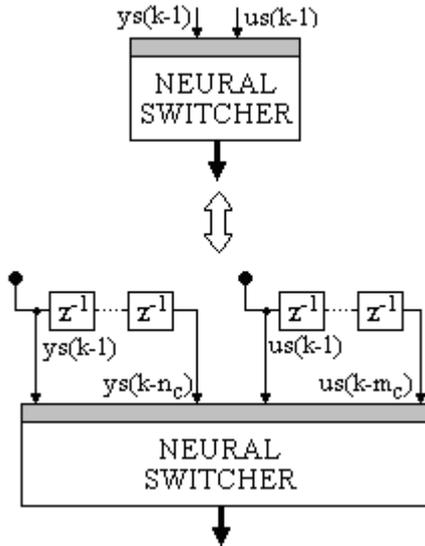


Fig. 3 The detailed scheme of the NS

The significance of the variables from the figures above is:

- $y_i(k)_{i=1,q}$ – is the output of the LNM_i ;
- $y(k)$ – is the output of the modular structure which approximates the nonlinear system output - $ys(k)$ at a given time;
- $ys(k - j)$ - is the j th system output at the discrete time moment $(k - j)$ where $j = 1, n_i$,
- $us(k - j)$ - is the j th system input at the discrete time moment $(k - j)$ where $j = 1, m_i$,
- and z^{-1} is the delay operator.

In the popular approach *gain scheduling control*²⁵, the nonlinear system is approximated by a certain number of linear systems. In this case the performances are guaranteed only for small variations in the neighborhood of the operating points. The approach of this paper is that the nonlinear system is approximated by q NN which are also nonlinear systems. The LNM_i used requires a smaller number of parameters and their training is easier than the training of a single network that should approximate the nonlinear system described by eq. (1).

The NS from Fig.3 is a NN that should determine the static point where the system operates at a given time and decide which LNM_i provides the output closest to the nonlinear system output given by eq.(1). The NS must be trained so that its decision is dependent on the input and output data on a time range. In some applications the decision is based only on the input data or on the error data. This approach will not guarantee a good performance in dynamic regime.

The LNM from fig.3 implements a nonlinear function described by the following nonlinear discrete equation:

$$(2) \quad y_r(k) = f_{NN}^r(ys(k-1), ys(k-2), \dots, ys(k-n_r), us(k-1), us(k-2), \dots, us(k-m_r))$$

where:

- f_{NN}^r - is the nonlinear function implemented by each LNM_r ;
- $y_r(k)$ - is the NN output at the discrete time moment k ,
- $ys(k - j)$ - is the j th system output at the discrete time moment $(k - j)$ where $j = 1, n_r$,
- $us(k - j)$ - is the j th system input at the discrete time moment $(k - j)$ where $j = 1, m_r$,
- $us(k) \in [u_{inf}^r, u_{sup}^r]$, $r = \overline{1, q}$ is the system input at the discrete time moment k
- u_{inf}^r, u_{sup}^r represent the lower value and the upper value, respectively, of the input interval associated to LNM_i .
- $k = (\max(n_i, m_i) + 1), N$,
- $\{ys(j) = 0, us(j) = 0\}_{j=1, \max(n_i, m_i)}$,
- N - represents the size of data set used at the nonlinear system identification.

For a good approximation of the nonlinear system described by eq. (1) by the nonlinear functions (2) implemented by LNM, we need a data set to cover all operating areas of the system.

An advantage of the system identification by LNM_i is: the values of the parameters n_r and m_r depend on the operating point. The number of LNM_i parameters is correlated with the system nonlinearity in the neighborhood of the operating point.

Still, for a correct classification, parameters n_c and m_c from fig. 3, must verify the following relations $n_c = \max(\{n_r\}_{r=1,q})$; $m_c = \max(\{m_r\}_{r=1,q})$. Otherwise, the classifier will give erroneous results, if there are LNM for which $n_r > n_c$ and/or $m_r > m_c$.

A useful nonparametric representation of a dynamic system is the static characteristic that provides a clearer understanding of the system. The points from the static characteristic are obtained when the input, the output and the system states remain the same.

3. STUDY CASE. THE IDENTIFICATION OF A PNEUMATIC SYSTEM USING MODULAR NEURAL NETWORKS.

To check the ability of the modular neural structure in identification we have chosen a complex nonlinear system, a pneumatic system. The pneumatic system components are:

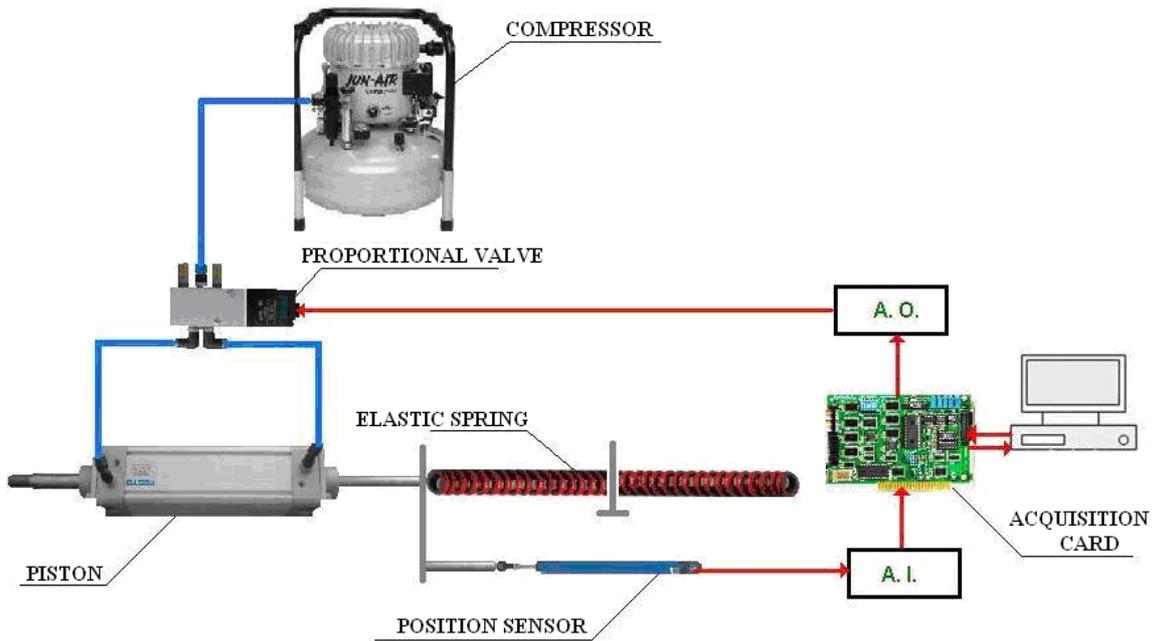


Fig. 4. The general scheme of the pneumatic system

- a double piston effect(Festo);
- a compressor (Festo Jun-Air type);
- a proportional valve (Festo DAS-SDE-4-GD);
- a linear position sensor (SLS 095);
- an acquisition card (Advantech PCI 1711);
- two elastic springs to simulate the load to be driven by the piston.

The described pneumatic system is a system with several types of nonlinearities introduced by the proportional valve and the pneumatic cylinder etc.

On a closer look the dynamic system nonlinearities can be identified due to frictional forces from the system or static nonlinearities due to hysteresis phenomena, the saturation or delay times (for example around the 5V voltage the valve does not respond).

All these types of nonlinearities can be observed on the static characteristic of the pneumatic system represented in fig. 5.

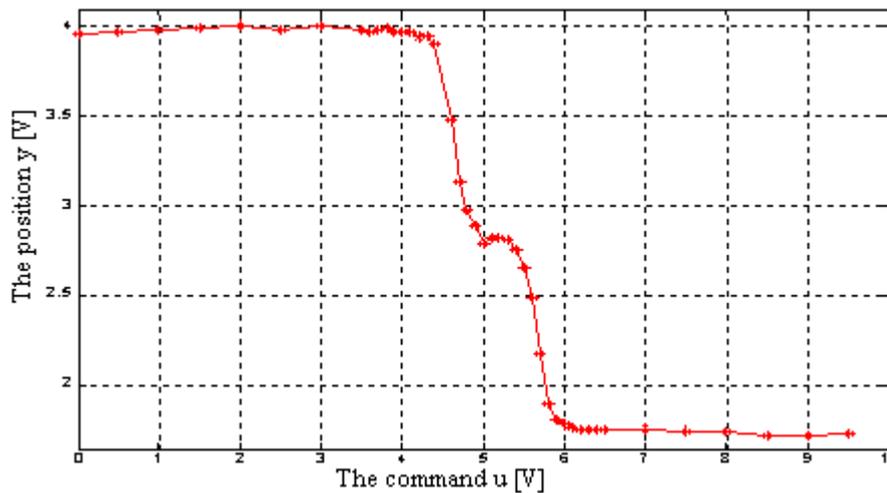


Fig. 5. The static characteristic of the pneumatic system

Since NN can approximate nonlinear functions it's not necessary to partition the input interval in a large number of subintervals.

The search algorithm of the subintervals which correspond to LNM must achieve a compromise between the nonlinearity degree of the static characteristic on a subinterval and the number of the neural modules used.

A partition algorithm was used to determine the adequate number of neural modules to be used. This one involves minimizing a quadratic criterion. Also a threshold value which quantifies the nonlinearity degree of the static characteristic must be established.

If this value is lower, then the intervals' number is large, otherwise if the value is higher, then the intervals' number is smaller.

In our case three modules are used: one NN for the left part of the static characteristic, one NN for the middle part and one NN for the right part. The structure of each LNM is 5-7-1 neurons on the three layers with tansig-tansig-purelin activation functions. The training was conducted until a sum squared error of at least 0.01 was obtained.

In the fig. 6 are depicted the data sets used at the training of the neural modules used at the identification of the pneumatic system.

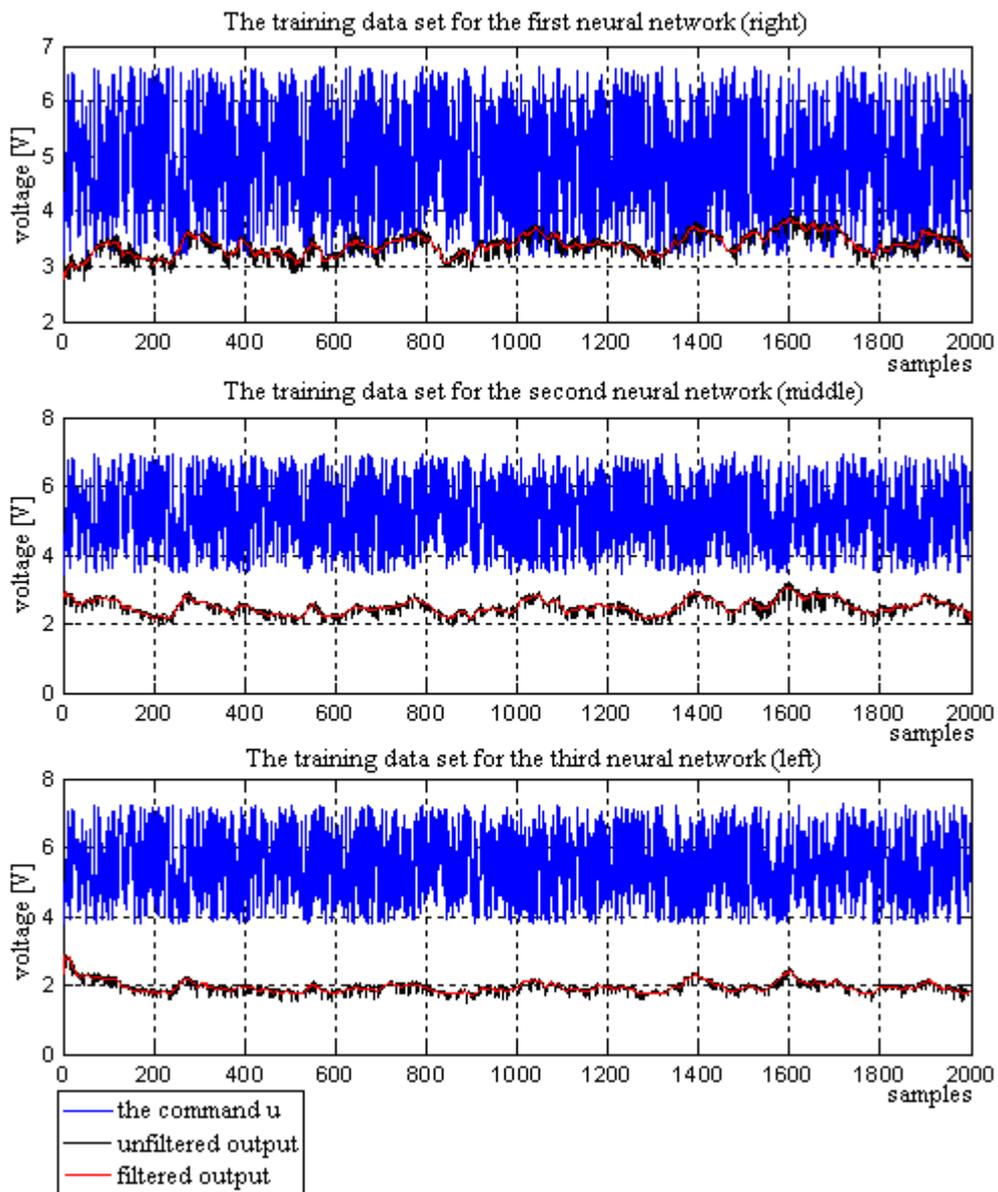


Fig. 6. The training data sets for the three neural modules

After the training stage a validation stage is necessary. This is made with other data sets then the ones used the *LNNs* training. The results are

presented in the figure bellow. One can observe that each *LNN* output manage to follow the response of the pneumatic system.

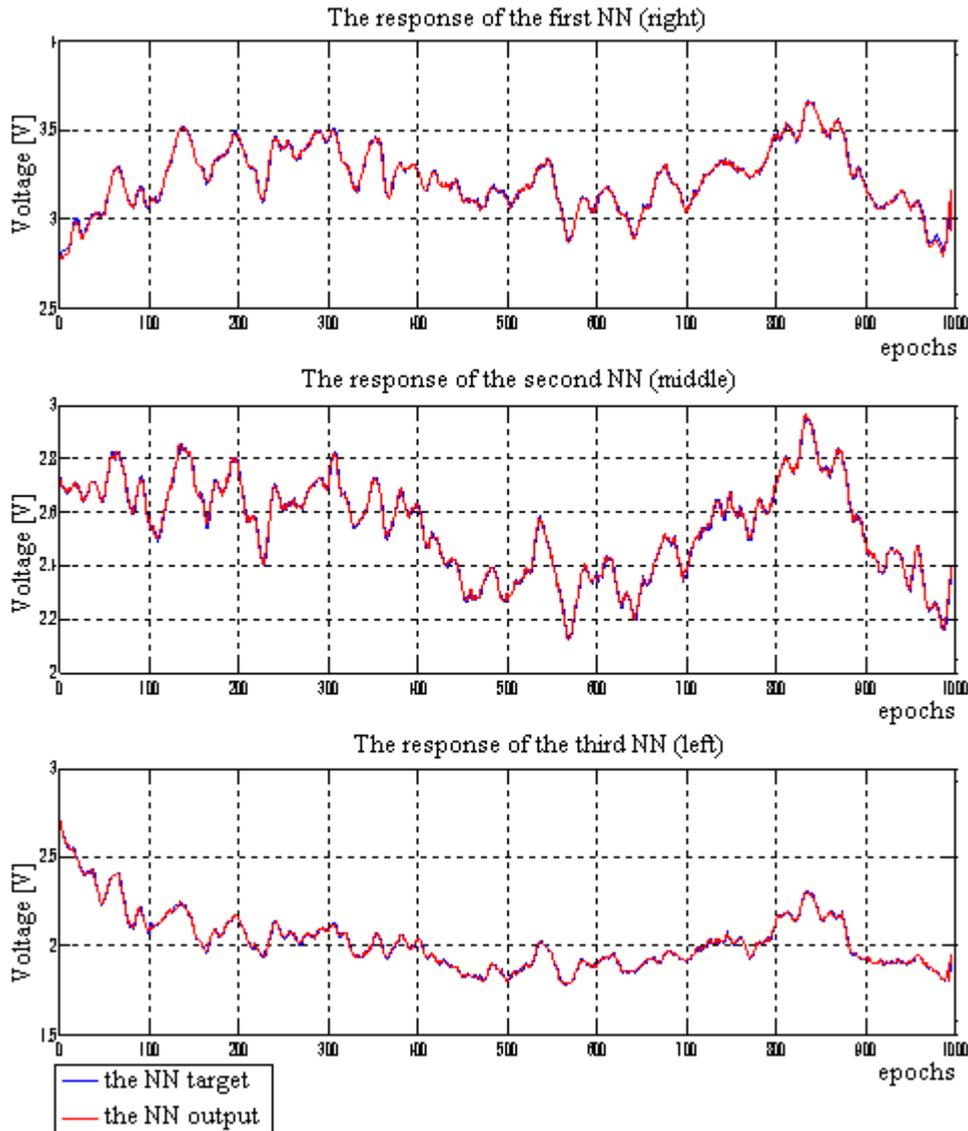


Fig. 7. The validation of each *LNN*

In fig. 8 the response of the modular NN together with pneumatic system response are shown. Also the way how *NS* choose the module that best approximates the system output is shown in the figure below.

One can observe that in some area (the zoomed area in the fig. 8) the *NS* output balances between two modules. However, the modular NN output does not suffer despite these oscillations because both modules approximate very well the pneumatic system in that area.

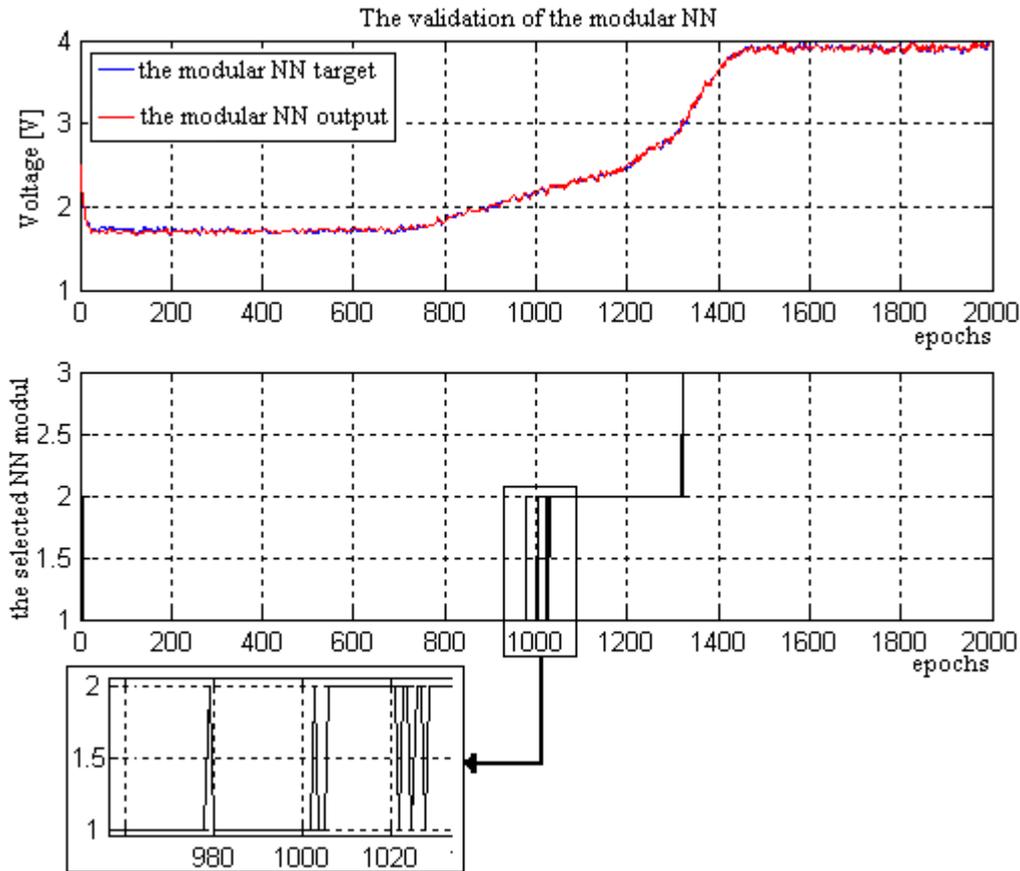


Fig. 8. The identification performances using modular NN

4. CONCLUSIONS

In this paper, a modular neural structure for nonlinear pneumatic servo system identification has been presented. The principles of modularity were used at system identification with multiple nonlinearities.

Based on the obtained results this approach could be a good alternative to the classical methods of system identification.

Future direction consists in implementing a controller based on modular neural networks for the pneumatic servo system.

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