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ASPECTS REGARDING THE NEURO-ADAPTIVE CONTROL STRUCTURE PROPRIETIES. APPLICATION TO THE NONLINEAR PNEUMATIC SERVO SYSTEM BENCHMARK

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Abstract: Generally, control techniques based on multilayer neural networks are used especially in the case of non-linear process and less in case of linear process, because classical control techniques are good enough and relatively easy to implement in linear case. In this paper it will be presented a adaptive neural control structure with application to an pneumatic servo system. This system has many advantages, such as high speed, high flexibility and low price. However, applications of this system are restricted because the physical parameters have strong nonlinearity, inaccuracy and uncertainty, so it's very difficult to find an optimal controller by means of traditional control theory.

Keyword: neural network, reference model, neuro-adaptive control.

1. INTRODUCTION

In the past years utilization of neural networks took a distinct ampleness because of following properties:

•distributed representation of information**:** Information learned by network is stored distributivelly in all network weights.

• capacity of generalization in case of uncontained situation in training data set.

•tolerance to noise: Neural networks have capacity to learn in situation that training set is affected by noise.

•resistance to partial destruction: Neural networks can operate also in the case of small region destruction or in the situation when some weights are affected by small errors, this fact because of distributed representation of information.

• rapidity in calculation: Neural networks are big time consumers in learning, but once trained, it will calculate very quickly the output for a given input.

Another major advantage of neural networks is that allows us obtaining model of investigated systems, systems that is not necessarily to be linear. In fact the truly value of neural networks it's seen in case of identification and control of nonlinear system.

The systems identification (Narendra, et al., 1990a), using neural networks presents a major interest because of the following reasons:

- it is easier to identify nonlinear systems;
- resulted models from identification process could be utilized in control structure based on neural networks, which doesn't require existence of calculation methods for.

Generally, experimental identification procedure supposes a stage of *data forming* and another stage of *data processing* in idea to adjust network parameters.

During identification, we must try to obtain as many information as possible concerning the studied process (nonlinearities, type of these, degree of system structurabillity). After obtaining this information next step is to establish the type and the structure of neural network. After that we will train the neural network. Finally we will validate the result obtained trough the analysis of residuum properties and the behavior of resulted model with other realizations of input signal.

For the success of the identification is necessary to know the aspects specifically to the process, engineer experience and intuition.

It's known that the design of a traditionally controller (Puscasu, et al., 2000), usually involves complex mathematical and supposes many difficulties regarding nonlinearities. The use of

This paper was recommended for publication by Adrian Filipescu and Emil Ceanga learning ability of neural networks facilitates the controller's design and also gives a high flexibility, especially when system's dynamic is nonlinear.

Regarding the use of the neural networks, in process control, appear two situations:

- the synthesis of a neural controller using a classical controller or a control rule of a human expert. For this reason, it transfers knowledge by an existent control system to the neural controller. This approach it's justified only by the matter that in case of the neural networks they use parallel calculations, and in some situations the human expert can be replaced through this transfer of knowledge to the neural network
- the synthesis of a neural controller using the information obtained from process. In this case, the neural controller synthesizes the control rule from the realizations obtained from the system in cause, intending the minimization of a function criterion. It's possible to say that, in this situation, they use at maximum the capacity of neural networks to extract control strategies from the process, comparatively with first case when they make only a transfer of knowledge from an existing controller to a neural network (Puscasu, et al., 1999).

Starting of these two domains, identification and control of the systems we developed and design a control structure (Tai, et al., 1992a) based on neural networks presented below.

2. PRESENTATION OF NEURO-ADAPTIVE CONTROL STRUCTURE

Adaptive control structure (Figure 1) (Chen, 1990c) uses two neural networks. First neural network identifies the process, and the second one synthesizes a PID control rule.

Neural model of process (NMP) is obtained trough off-line training of a multilayer neural network. During training, the control error e is propagated backward trough neural network NMP, for the parameters adjustment. Training procedure is considered finished when difference sum-squared between y and y_i is approximately zero. To obtain high performances during control action, the NMP must contain complete information on system dynamics for all possible data, which may appear during the working time of the control structure.

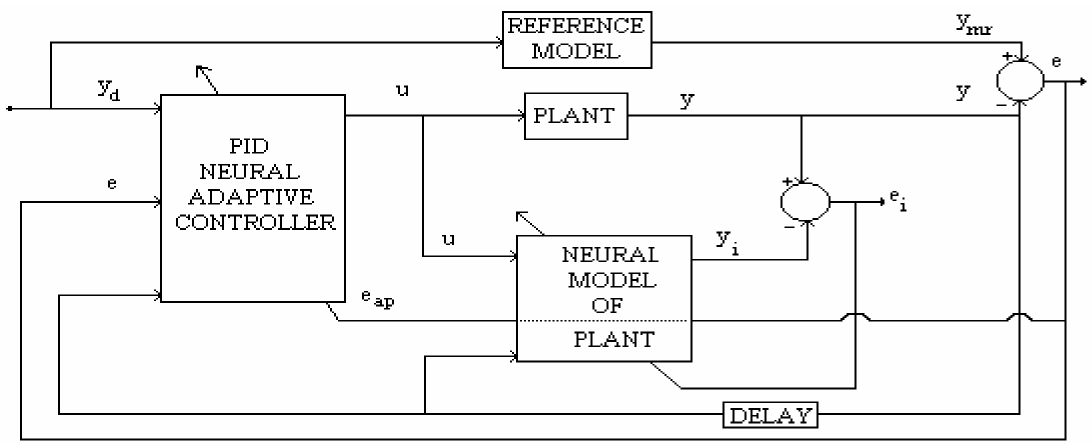

Figure 1 Control structure

y_d - the reference value for the output;
u - the command generated by the neural adaptive controller, implemented with a multi-layer neural network;
y - the plant output
y_{mr} - the reference model output; y_i - the neuroidentifier output

The neuro-adaptive controller (Psaltis, et al., 1988) is trained on-line (Tanomaru, et al., 1992b) and uses parameters adjustment error e_{ap}, which is obtained using the backpropagation of the control error trough the NMP, but by introducing as input vectors in the neural network that simulates the controller the sum of errors until step k, e(k)+e(k+1)+…+e(0) (this sum is corresponding to the integrating component), the difference e(k)-e(k+1) (corresponding to the derivative component), and also again the control error e(k) but this time introduced as an input vector in the neural network (corresponding to the proportional component). The weights of neuro-adaptive controller will stabilize, in some cases, at well known values after the control process covered enough time, which it's necessary to extract „knowledge" concerning the control method.

The stabilization of weights at fixed values depends of the fact that the process parameters must remain unchanged during the working time of the control structure.

The reference model has the purpose to impose a certain profile to the prescribed value and to limit the effort of the command involved in a short period of time by the execution elements. Generally, if the prescribed value of the output has big changes then the control error has also big variations and to reduce it quickly to zero involves in many cases a big command effort Also, using a reference model into a control loop, we can give to the process the dynamic of the reference model

It's noticeable the fact that we didn't imposed any restriction concerning the nature of the process or restrictions concerning the type of nonlinearities which may be contained by the plant. The method is generally and if the two neural networks have the capacity to model the given process and synthesis the control method then control success is guaranteed in most cases. In the following chapter the transfer function of the model will be considered.

3. CASE STUDY AND SIMULATION RESULTS

The proposed approach has been applied successfully to real application example: a pneumatic servo system (Khalid, et al., 1995) used in vehicle testing equipment. In the test of fatigue, the adaptive controller must be insensitive to change of the test, and also, insensitive to change in time of the real parameters during the testing process.

To illustrate the behavior of control structure from figure 1 it's considered the following pneumatic nonlinear dynamic system:

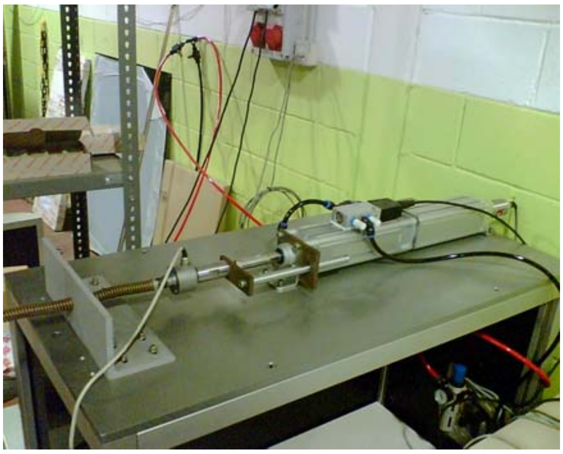

Figure 2 Pneumatic cylinder and proportional valve

The system nonlinearities are due to proportional pneumatic valve (the actuator) and double effect pneumatic cylinder (the system).

The steady state (cylinder position vs. input in the proportional valve) is depicted in figure 3.

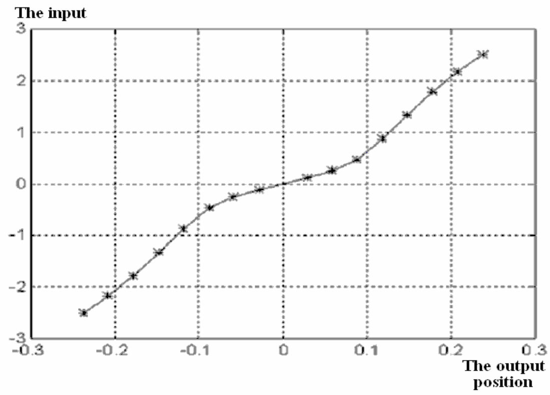

Figure 3 Steady state

The neural model of process is obtained covering the following steps:

- forming of training set,
- defining of network structure,
- Training of the multilayer neural network.

It must be used a training data set which described the whole dynamics of the process because otherwise the process will not be identified correctly and the control procedure will be a failure.

The training data set applied to the network input (P) and the target (T) are defined as follows:

$$P = \begin{bmatrix} y(1)\ y(2)\cdots y(N-1) \\ u(1)\ u(2)\cdots u(N-1) \end{bmatrix}$$

$$T = \left[y(2)\ y(3)\cdots\cdots\ y(N) \right]$$

The training of the neural network, stage, which follows the forming of training set, it's performed with an improved back-propagation algorithm (Puscasu, et al., 1996).

During the learning period it's expected that the sum-squared error between the network output and the target to be minimum:

$$Er = \sum_{m=1}^{S_2} (A^2(m) - T(m))^2$$

where: S_2 –number of neurons belong to the output layer.

The network weights after training, if training is a success, are those for which we have minimum error.

For each vector which belongs to the training set, the weights w and the biases b adjustment is done using the gradient method with decreasing step:

$$w^{kp} = w^{kp-1} - \eta(kp)\cdot\frac{\partial Er}{\partial w},$$

$$B^{kp} = B^{kp-1} - \eta(kp)\cdot\frac{\partial Er}{\partial B},$$

where η(kp) represent the learning rate.

The set up of learning rate imply a stage of seeking. During that it's observed the variation of sum-squared error for different initials conditions. These conditions are referring especially to the number of layers and neurons. They retain those conditions that promise a fast convergence of the training algorithm.

The obtained model is validated comparing the system output with the neural network output for input signals applied both system and neural network, signals different from those applied to the network training. It's expected that the neural network obtained after training to minimize the following criterion:

$$J = \frac{\sum_{t=1}^{n} (y(t) - y_i(t))^2}{\sum_{t=1}^{n} y^2(t)}.$$

After the end of the off-line network training which models the process follows the on-line training of the neural network which simulates the controller (Hoptroff, et al., 1990b).

The training data set applied to the network input (P) and the target (T) are defined as follows:

$$P = \begin{bmatrix} e(4) & e(5) & \dots & e(N-3) \\ e(4)-e(3) & e(5)-e(4) & \dots & e(N-3)-e(N-4) \\ e(4) & e(5)+P(3,1) & \dots & e(N-3)+P(3,N-1) \end{bmatrix}$$

$$T = [y_d(4)\; y_d(5) \cdots\cdots\; y_d(N-3)]$$

The performances of control structure are presented in figure 4.

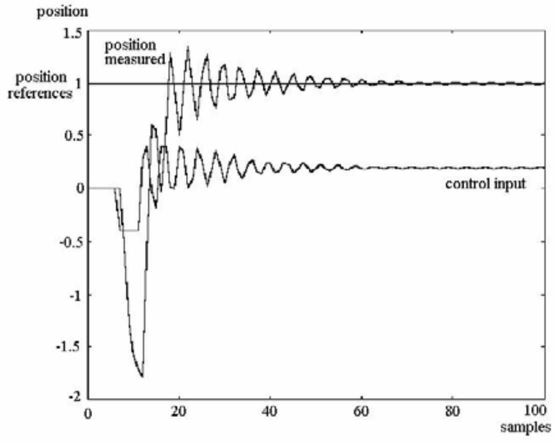

Figure 4 Control performance for the pneumatic system

We notice that the structure follows very well the reference (after 60 samples) having only a small error.

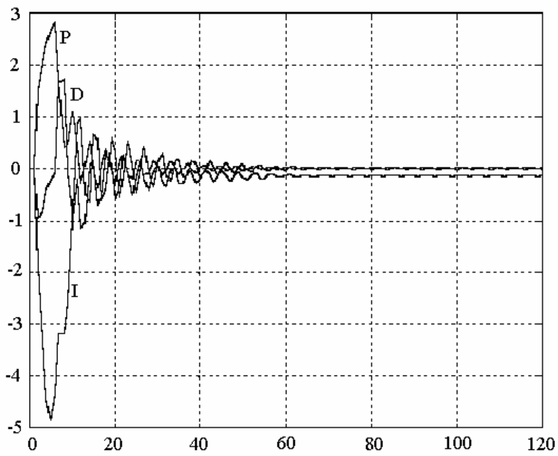

Figure 5 Neuro-controller parameters

From this figure it's noticeable how the controller's parameters modify theirs values so that the error be the smallest (the process output may follow the reference).

In the first 40 samples the system output has oscillations around the reference. These oscillations appear because the neuro-controller parameters were initialed with random values. In this case the neural network used for control has not any information about the system dynamics and it is necessary some samples in order to capture knowledge from the system. After 50 samples the neuro-controller will be able to follow quite well the reference.

After 100 samples the experiment is stopped and the neuro-controller parameters are saved. We will provide another experiment for different references using the previous neuro-controller parameters as initial parameters in this second example. If the neuro-controller contains information about the system behavior, it can be notice from figure 6 that the process output follows very well the reference for two points from steady state. In this case the initial oscillations in system output are avoided and the process output follows very well the reference.

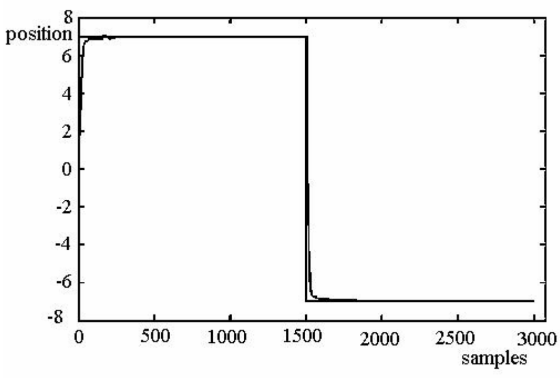

Figure 6 Control performances

4. CONCLUSIONS

In this paper we presented and analyzed some of the controllers properties based on neural network such:

- the neuro-controller adaptability, no matter what is the nature of the process and the nonlinearities;
- the possibility to train on-line of a neuro-controller designed for a real time process:
- the similarities with classical controllers, concerning their parameters: in the case of the linear process the parameters stabilized at fixed values, like in the classical case.

The case study is the control of a pneumatic servo system. The results were very promising and could be an alternative to the classical control.

Using artificial neural networks, because of the non-linear nature of the units, they are able to capture very well the non-linear structure of the most real-world processes. Thus, the problem of modeling non-linear systems is a problem of matching the network nonlinearity with the process nonlinearity. According to (Narendra, et al., 1990a), the success of neural networks in control problems is based on the capabilities of the neural networks to cope with three main difficulties encountered in control: complexity, nonlinearity, and uncertainty.

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