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SYNTHESIS OF NEURAL NETWORK CONTROLLER WITH A REFERENCE MODEL

SUMMARY

In the article there has been presented a structure of a control system with a neural network controller basing on a reference model. In the first part of the article there is a short overview of neural control models. In the following part, an identification of a non-linear object, which was a hydrostatic transmission, was conducted with the help of artificial neural networks; next, different identification structures of artificial neural networks were tested. The last stage covered a synthesis of a neural controller with a reference model and conducting simulation tests of the suggested structures in the system of the control with a non-linear object.

Keywords: *predictive control, non-linear object, reference model*

SYNTEZA REGULATORA NEURONOWEGO Z MODELEM REFERENCYJNYM

W artykule została przedstawiona struktura układu regulacji z neuronowym regulatorem bazującym na modelu referencyjnym. W pierwszej części znajduje się przegląd neuronowych modeli sterowania. W kolejnej części przedstawiono przeprowadzoną identyfikację za pomocą sztucznych sieci neuronowych nieliniowego obiektu, którym była przekładnia hydrostatyczna. Właściwości przekładni hydrostatycznej sprawiają, że jest ona obiektem wrażliwym na różnego rodzaju zakłócenia, które utrudniają sterowanie jej pracą. Ze względu na właściwości obiektu regulacji, tzn. nieliniowość i niestacjonarność, zastosowanie klasycznych regulatorów nie jest zadowalające. Z tego względu podjęto próbę wykorzystania zaawansowanych technologii do sterowania. Zbadano różne struktury identyfikacyjne sztucznych sieci neuronowych. Ostatni etap prac obejmował syntezę regulatora neuronowego z modelem referencyjnym oraz przeprowadzenie badań symulacyjnych zaproponowanych struktur w układzie regulacji z obiektem nieliniowym.

Słowa kluczowe: *sterowanie predykcyjne, obiekt nieliniowy, model referencyjny*

1. INTRODUCTION

Neural networks successfully found their use in identifying and control of dynamic objects. Approximation abilities of artificial neural networks are the main reason for using them for modeling and control of non-linear objects. During control of non-linear and dynamic objects with a help of artificial neural networks, what is crucial is the identification and creation of a neural network model, which identifies this particular model. That is why, a creation of a neural network model of an object that will be a subject to control should be the first step. In the next stage, a proper model of control should be chosen and a controller should be trained. In the below models, the first stage, so the stage of an object identification is identical; they differ regarding the choice of a controller architecture and their working concept. It should be highlighted at this point though that there do not exist any formal methods for choosing either the control model nor the controller architecture.

A diagram of the control model with the reference object is presented on Figure 1. It consists of the object, a driver, a reference object and an adaptor. The model had external and internal loops. The external one covers the object and the controller, whereas the internal loop contains the element which tunes the controller. On the controller output, there is a signal *u(t)*, which causes sustaining the signal from the object, nearest the reference model output. An error between the object output and the reference model output is used for tuning the controller.

The controller possesses many parameters, which may be tuned to the proper control of the object. Usually, the process parameters are not known, the task is limited to an object identification, that is to building its model and defining the parameters of this model in such a way, that an response of the object $y_p(t)$ and the model $y_r(t)$ to the same extortion **r**(*t*) are equal with a defined tolerance:

$$\lim_{t \to \infty} \| y_r(t) - y_p(t) \| \le \varepsilon$$
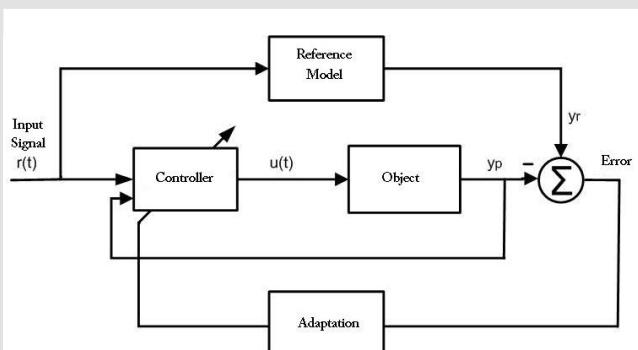
Fig. 1. A diagram of a control system with a reference model (Douratsos and Gomm 2007)

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After limiting to one output and one input, and with an assumption that vectors **r** and $\mathbf{y}_p$ are vectors composed of delayed components, a general description of a non-linear dynamic model may be presented in the following way:

$$\mathbf{y}_r\left(k+1\right) = f\left(\mathbf{y}_p\left(k\right), \mathbf{r}\left(k\right)\right)$$

where:

$\mathbf{r}\left(k\right) = \left[r\left(k\right), r\left(k-1\right), \dots, r\left(k-p\right)\right]^T$ – a vector of delayed components set value;

$\mathbf{y}_p\left(k\right) = \left[y_p\left(k\right), y_p\left(k-1\right), \dots, y_p\left(k-q\right)\right]^T$ – a vector of delayed components the object output;

$\mathbf{y}_r\left(k\right)$ – the response of the neural model of an object.

The error signal $e\left(k+1\right) = y_p\left(k+1\right) - y_r\left(k+1\right)$ is used in the control of the adaptation process of the model parameters.

A neural network used in the object identification process was included in the control system on the serial-parallel basis. The advantage of such neural network placement is confidence that input signals of the model, which are delayed samples of the object responses are limited, thus, it can be taken as granted that the object is stable. Moreover, it influences the simplification of the gradient generating formula and also provides a one-way flow of signals in the network.

This control algorithm is often complicated, and a solution does not always exist. Designing such a controller is difficult and time-consuming. A simpler, but not always satisfying solution may be received by a linearization, in which linear controllers are used for non-linear objects. The usage of neural networks may give positive results. They are used in the controller, in which the weighs are properly chosen, so that the results were satisfactory.

In the literature, the most often described are two control methods with a reference model, depending on the object characteristics. For a linear object, a direct control is used; whereas for a non-linear object- an indirect one (Kumpati and Narenda 1990). More attention will be paid to the latter method of control. In this structure, a crucial element is an object identification, which has been described below.

The next stage is creating of a neural network, which is a controller. This controller takes into account the behavior of the reference model (Fig. 2).
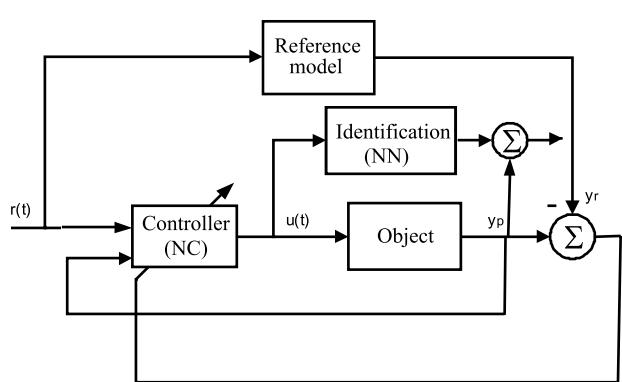

Fig. 2. A diagram of an indirect control with a reference model with the usage of neural networks

2. IDENTIFICATION OF THE CONTROL OBJECT

The first stage of the research was a choice of a proper structure that would allow for an object identification.

Below there is presented an identification process with a help of artificial neural networks of a non-linear object, which is a hydrostatic transmission.

The features of a hydrostatic transmission as a hydraulic system cause that it is a device sensitive to different kinds of disturbances, which hamper its operation. Besides, the hydraulic drive is characterized by non-stationarity, resulting from the instability of parameters of hydraulic liquid (kinematic viscosity, compressibility, thickness). On the other hand, control of pomp efficiency is often realized with a use of electro-hydraulic servo-system, which characteristics are strongly non- linear. The above features of the object cause big difficulties with the selection of a sustainable structure of the control system, and especially with designing a controller working correctly in all the range of the rotational speed variability of a hydraulic motor.

In order to compare the influence of specific parameters, i.e. the sampling time, the number of delayed inputs and outputs of a model and the number of neurons in a hidden layer, there have been proposed three identification structures, which are presented in the Table 1.

Table 1

Identification structures

	Identification structure I		Identification structure II		Identification structure III	
	Ident. I	Ideat. II	Ideat. I	Ideat. II	Ident. I	Ideat. II
Sampling time	0.001	0.01	0.001	0.001	0.001	0.001
Number of delayed inputs and outputs	2,2	2,2	2,3	3,3	3,3	3,3
Number of neurons in a hidden layer	10	10	10	10	5	25

In the initial studies, there was conducted an efficiency comparison of teaching algorithms. Different teaching algorithms are compared with each other in regards to the number of teaching cycles, the number of calculations of goal functions, the number of floating- point multiplications, calculation time, sensitivity to local minima and so on (Osowski 2006). For the comparison, the following algorithms were used: GD – an algorithm of the biggest fall, GDM – GD algorithm with a moment, BFGS – an algorithm of changeable metrics, and LM- Lavenberg–Marquardt algorithm. On the picture, there are presented teaching curves with the usage of the above algorithms. The conducted efficiency analysis of teaching algorithms shows that the most efficient algorithm is the algorithm of Lavenberg–Marquardt (Fig. 3).

Due to this reason, this algorithm was chosen. The suggested network has one hidden layer. Activation functions are a sigmoidal function in a hidden layer and a linear one in an output layer. In Table 2, teaching results for networks with identification structures I and II were put together. Calculation time and the number of epochs were also included.
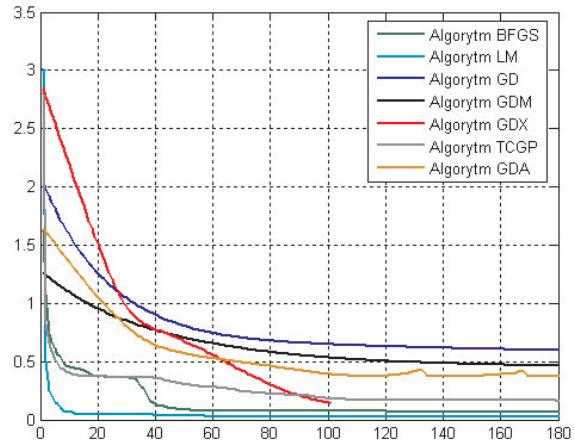

Fig. 3. Presentation of teaching curves with chosen algorithms for networks with 5 hidden neurons

The above research shows that the most effective architecture of an artificial neural network is an architecture with six inputs (three delayed inputs, three delayed outputs) and with 10 neurons in a hidden layer. Teaching time of the network in comparison with other structures was long.

Table 2

A comparison of teaching results for networks with identification structures I and II

	Structure I, Ident I	Structure II, Ident I
Teaching curve	194 epochs	57 epochs
Calculation time	57 s	17 s
Network output		
Error		

Similar results are achieved also with 25 neurons in a hidden layer, with the same amount of inputs. Teaching time of this network was shorter. Due to this, this architecture may be successfully used to identify an object and it may be used to create a controller.

2.1. An analysis of neural controller architecture with a reference model

For the research was chosen a structure (Fig. 4) in which a controller with a reference model was used. The system was later used for control a rotational speed of a hydrostatic transmission hydraulic motor.

A reference model with a following step response (Fig. 6) was chosen. Below (Tab. 3 and 4) there is presented a response to a value step of rotational speed equaling to 300 rpm.

An algorithm of teaching in a neural controller with a reference object is LM algorithm. It is one of the gradient algorithms of teaching. In this method, the exact value of hessian was replaced by its approximate value $\mathbf{G}(\mathbf{w})$, defined on the basis of information included in the gradient with the regard of the regulating factor. The applied objective function has the following form:

$$E(\mathbf{w}) = \frac{1}{2}\sum_{i=1}^{M}\left[e_i(\mathbf{w})\right]^2$$

where: M – a number of the network inputs and $e_i = \left[y_i(\mathbf{w}) - d_i\right]$.

A training process finishes when the following conditions are fulfilled:

– a maximum number of epochs (repetitions) is achieved,
– too long time of calculations,
– the minimum is found,
– the gradient falls below a defined value.
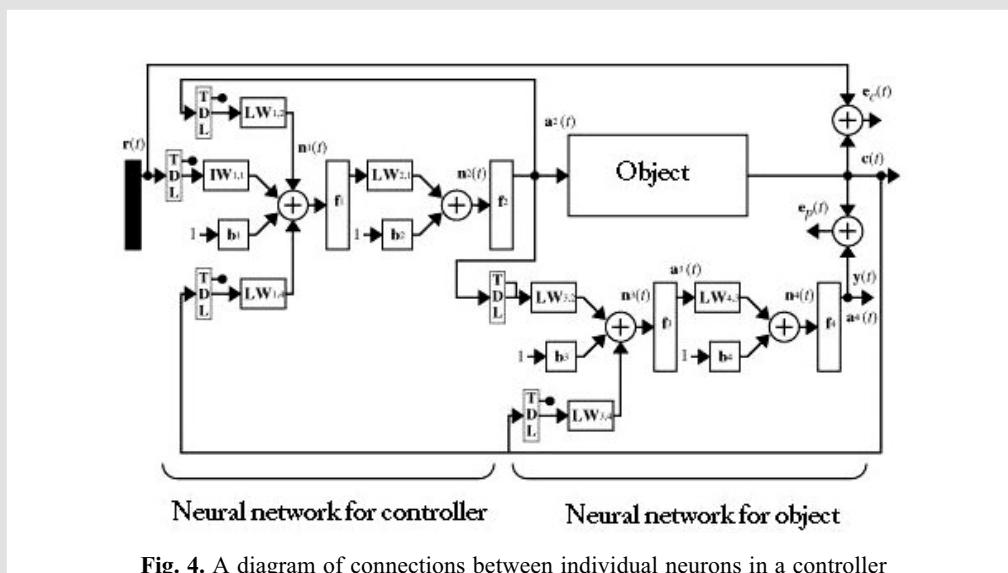
**Fig. 4.** A diagram of connections between individual neurons in a controller
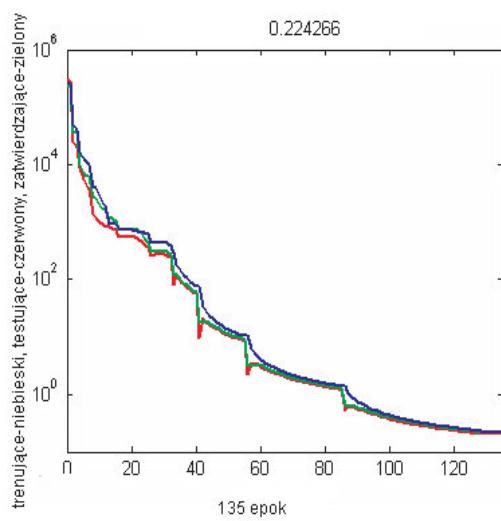
Fig. 5. A teaching curve at identifying of an object
(a hydrostatic transmission)
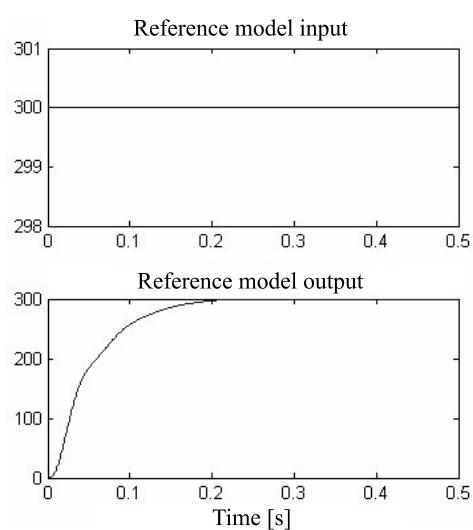
Fig. 6. Response to a value step of rotational speed
of the reference model

Table 3

Simulation results for different time delay spaces with 25 neurons in a hidden layer

Time delay space	Teaching curve	A reference model response and a neural controller object response
1-2-1		
3-2-2		
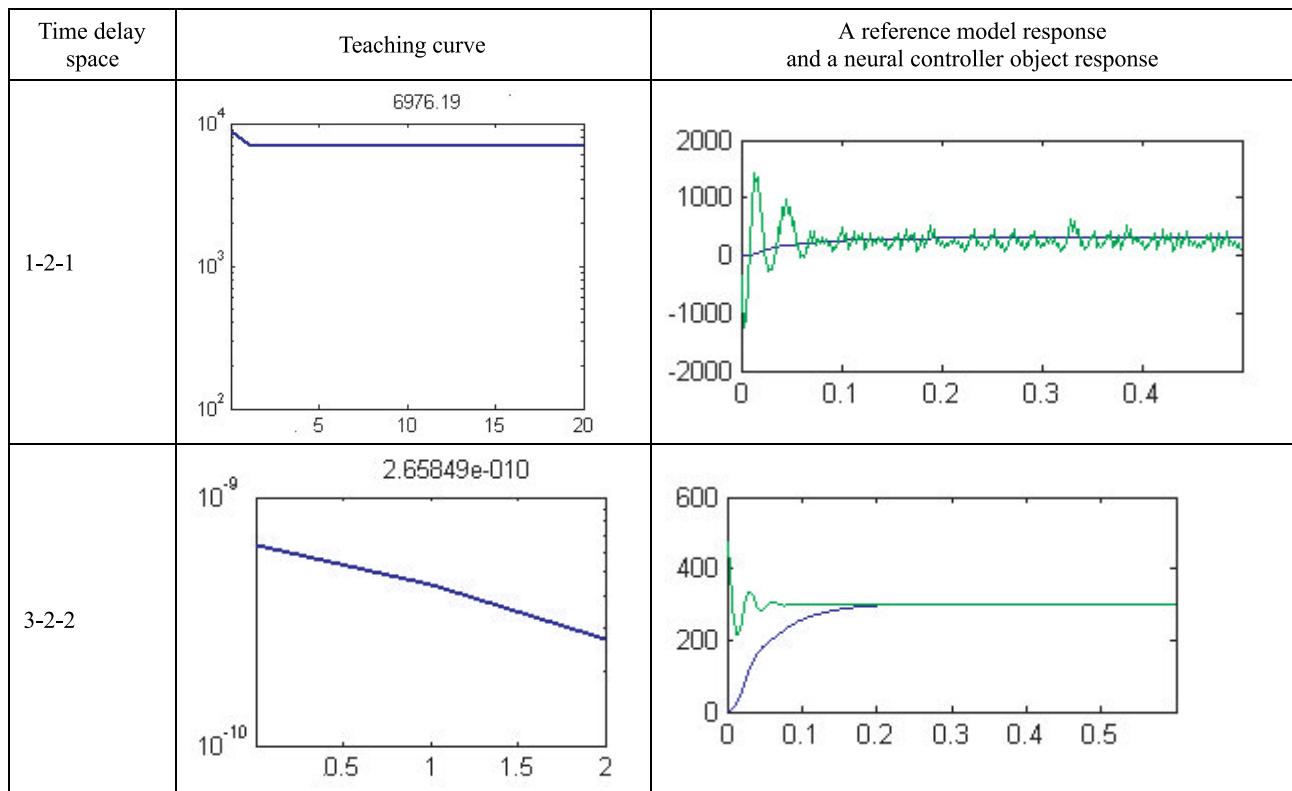
Table 4

Simulation results for different time delay spaces with 18 neurons in a hidden layer

Time delay space	Teaching curve	A reference model response and a neural controller object response
1-2-1		
3-3-3		
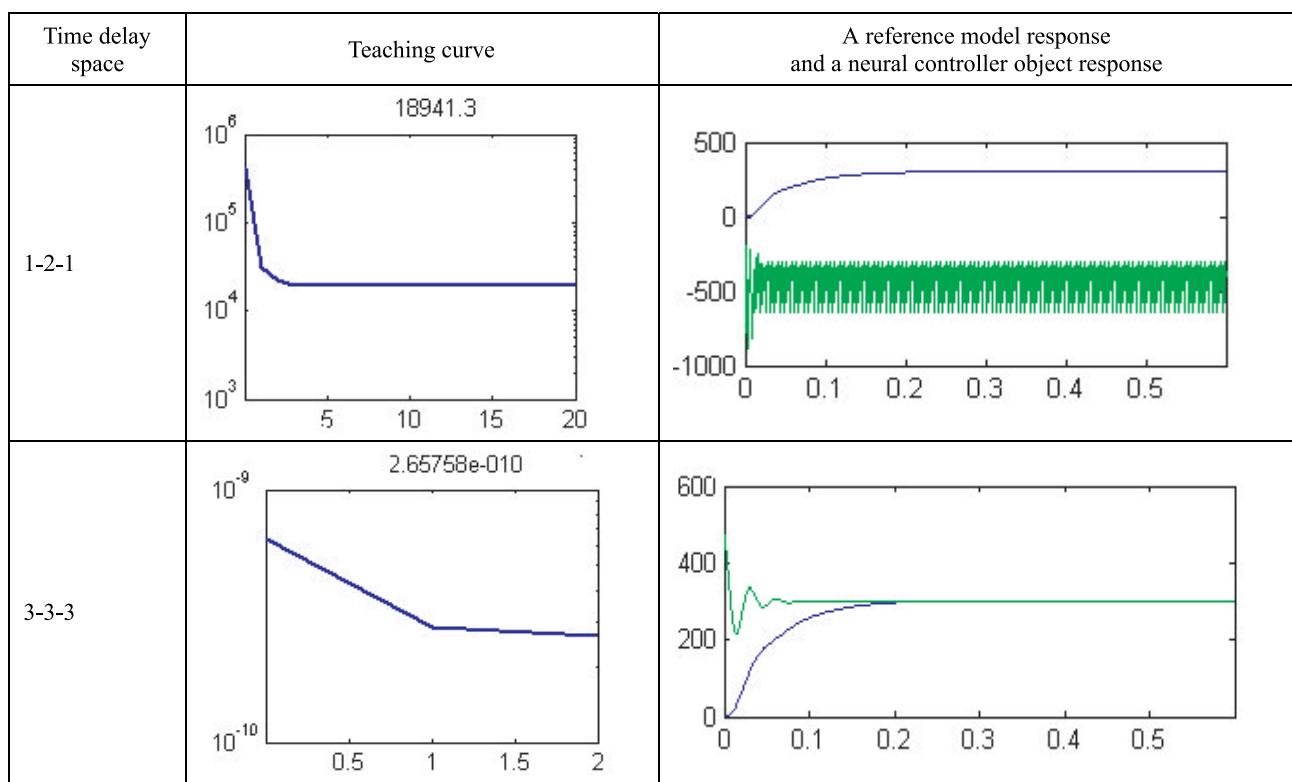
3. SUMMARY

On the basis of the conducted experiments, one can state that neural networks may be successfully used for an identification of dynamic and non-linear objects. A necessary condition for this aim is a suitable choice of a neural non-linear model, as well as a proper assortment of the network architecture, that is: a choice of proper time delay space, proper number of neurons in a hidden layer and also a proper algorithm of teaching the network.

In the present work, the influence of individual parameters on the controller teaching result was checked. In every of 60 training cycles (Controller Training Segments), there are 20 iterations (Controller Training Epochs). It was decided that such a configuration will be used due to the fact that with a larger number of training cycles and a smaller number of epochs in every cycle, the result is achieved faster and it is more precise. The suggested structure has been used for control a non-linear object, which, in this case, was a hydrostatic transmission. What was steered was a rotational speed of a hydraulic engine.

In the thesis, basing on the simulation, was shown that the architecture of a neural controller with a reference model is not suitable for an object which was a hydrostatic transmission, being a non-linear and non- stationary object. Simulation results clearly show that. Further research is being conducted in order to design a proper structure of a controller basing on neural networks, which will be successfully working in a control system with an object of a hydrostatic transmission.

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