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Synthesis and Optimization of Neural Network Parameters for Control of Non-linear Objects

***Abstract**. The possibility of using artificial neural network (ANN) for the construction of precise control of dynamic objects with variable parameters is considered. Approach to the synthesis of topology and learning algorithm based on recurrent Elman's ANN with auxiliary feedback is suggested. The results of modeling of ANN operation in the system of control guided by large-sized antennas are given.*

Streszczenie.** Opisano możliwość wykorzystania sztucznej sieci neuronowej (SSN) do precyzyjnego sterowania dynamicznych obiektów o zmiennych parametrach. Przedstawiono syntezę topologii i uczenia algorytmu opartego na SSN Elmana z dodatkowych informacji. Zaprezentowano wyniki modelowania SSN do zarządzania systemem pozycjonowania dużych anten.* ***Synteza i optymalizacja parametrów sieci neuronowych do sterowania nieliniowych obiektów

Keywords: antenna's rotating device, neural network, Hexapod, pointing error.
Słowa kluczowe: Antena obrotowa, sieci neuronowe, Hexapod

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Introduction

Precise control of complex dynamic objects often associated with technical difficulties of determining the number of real objects parameters that may change due to various factors.

In such systems it is difficult to achieve the control with optimal parameter regulator settings constructed by classical methods, e.g., PID control to achieve the desired precision value in all possible ranges.

Mathematical apparatus synthesis of control systems often is very complicated for complex mechanical systems with dynamic multidimensional interrelated nodes. The control parameters are often selected by trail-and-error approach.

There are many methods and algorithms of self adjustment for PID controllers but the results of them lead to significant complication of algebraic computation with the introduction of many new parameters of the system [1].

An alternative to the classical methods of the control could be the mathematical apparatus of artificial neural networks (ANN), dynamic and increasingly implemented in automatic control. The main advantage of ANN - is the elimination of a priory uncertainty of input, output or structural information of the system. Analysis of the sources of information on the subject of the study shows that the use of ANN can provide better control than those achieved in the framework of classical control and software [1-4].

The goal of research is a synthesis of ANN topologies with recurrent connections, the study of learning algorithms and parameters by means of mathematical modeling to control objects with dynamic multidimensional interrelated nodes of a mechanical system.

Object Peculiarities and Control System Structure

Pointing accuracy and tracking speed for low-orbit satellites of Earth's remote sensing (ERS) except angular sensors depends on special features of support-rotating device (SRD) design and antenna electrical drive control system. In the problems of low-orbit satellites tracking according to calculation trajectories it is necessary to provide dynamic error not exceeding the unit of angular minutes.

In the systems with large antenna reflector diameter with classical two-axes and especially with 3-axes full-rotating device or linear drive Hexapod mechanism [5] used for pointing and tracking of the satellites, the moments of inertia modules from reflector inclination angular and the ratio antenna module position for different axes modify, changes of mechanical gear rigidity, changes of friction resistance, backlashes, electric drive characteristics instability, stochastic influence of wind loads, etc. take place. Three different antenna communication with Earth's remote sensing (ERS) remote sensing satellite for which developed by us control systems with necessary changes of rotating device dynamic parameters are shown in Fig.1.

Fig.1. Antennas with different types of SRD as objects to be controlled

Structural-algorithmic diagram of control system for each antenna axle using ANN is shown in Fig.2. Neurocontroller produces control operation based on input tracking trajectory and feedback data from the angular position sensor. The structure of control system also includes frequency converter with local feedback of current, power with gear controlling angular velocity of rotation of antenna support-rotating platform. Antenna model as object of control and actuators of control system (frequency regulator, engine) is considered in [5].

Reasoning of ANN Neurocontroller Selection in Control Circuit

ANN synthesis requires the selection of its structure, number of layers, number of neurons in each layer and its optimal learning algorithm for given network und sufficient aunt of learning information. Depending on the problem ANN should solve, synthesis is often performed on the basis of intuitive selection of architecture and design.

Recurrent ANNs occupy a special place among different types of ANN. They are dynamic, transformed incoming data into a sequence of reactions and are the most suitable for control problems in contrast to direct propagation networks [2, 3]. They are able to produce effective control operations in case of uncertainty of complex system control if they were properly trained.

Neurocontroller of control system is built by us on the basis of Elman's ANN [3] which is an improved modification of Jordan's ANN. In contrast to Hopfield's ANN, the feedbacks in it are led from internal neurons outputs to additional inputs of intermediate layer, but not to primary inputs, making it more stable compared with other recurrent networks [3, 4].

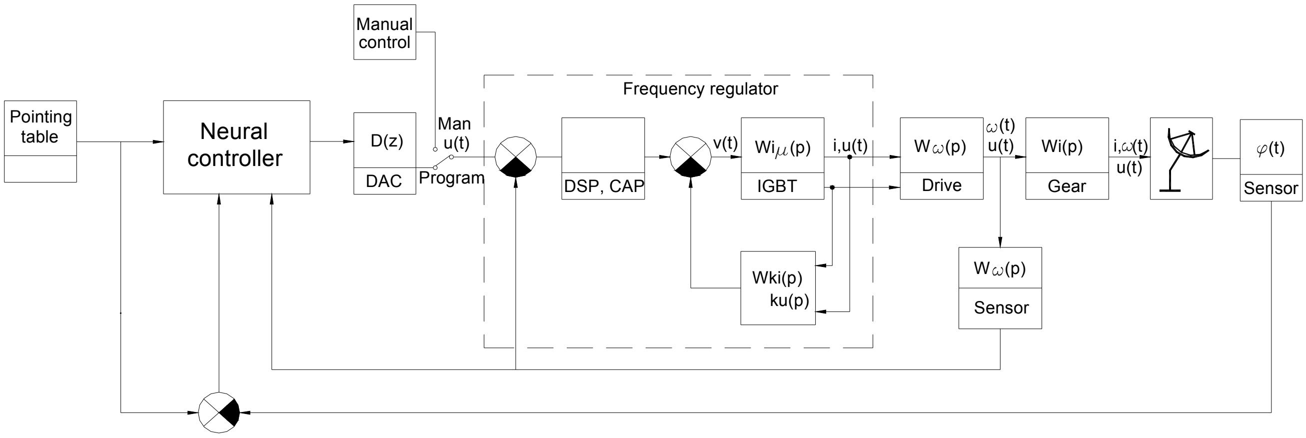


Fig. 2. Structural-algorithmic diagram of control system for each axle of antenna system

To determine the optimal network structure and investigation of its operation effectiveness in MatLab/Simulink software complex, Elman's ANN model containing one output layer and various neurons in the intermediate layer with possible proper number of delays in the context layer is built (Fig. 3).

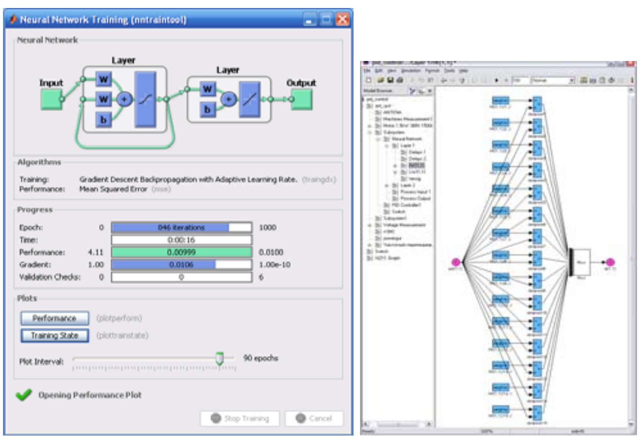


Fig.3. Model Elmana ANN with 15 neurons in the intermediate layer

We also added feedback coupling through dynamic delay line z^{-1} from the outcoming of control object to the structure of Elmana's ANN (Fig. 4). The using of external feedback couplings allow to reduce the memory requirements for ANN, taking into account the behavior of the object and store information to develop more effective control actions.

The state of neuronal recurrent network layer is described by the equations:

(1) $$\begin{cases} \mathbf{n}^1(k) = \mathbf{LW}^{11}\mathbf{a}^1(k-1) + \mathbf{IW}^{11}\mathbf{p} + \mathbf{b}^1, \ \mathbf{a}^1(0) = \mathbf{a}_0^1; \\ \mathbf{a}^1(k) = tansig(\mathbf{n}^1(k)), \end{cases}$$

where: ***n*** – output combiners neurons of corresponding layer*;* ***a*** – neurons output after activation function in the *k-th* iteration; ***p*** – input vector; ***b*** – vector of displacements added to the weighted input neurons; **IW, LW** – synaptic weights matrix set during ANN learning for input vector ***p*** and recurrent connections accordingly; *k* – time counts steps of ANN adjustment; ANN output layer is defined by:

(2) $$\begin{cases} \mathbf{n}^2(k) = \mathbf{LW}^{21}\mathbf{a}^1(k) + \mathbf{b}^2; \\ \mathbf{a}^2(k) = purelin(\mathbf{n}^2(k)). \end{cases}$$

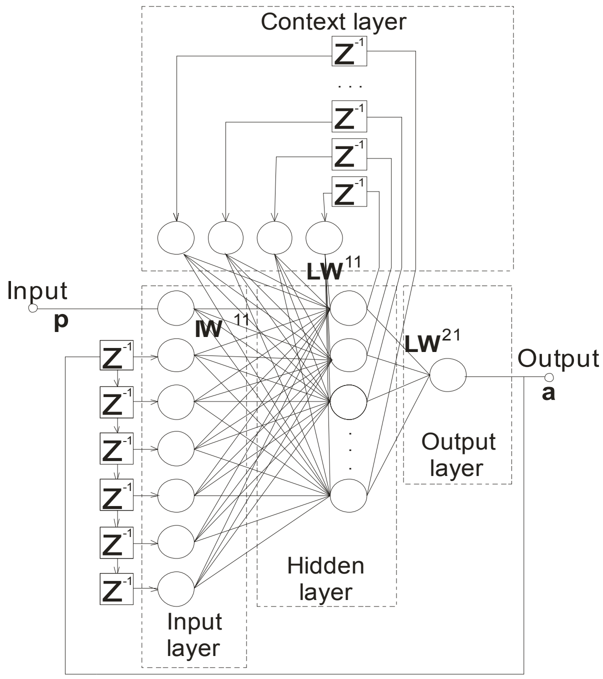


Fig. 4. Structural model of Elman's ANN with external feedback

The sequence of values of the output error signal reaches the line of feedback delay, containing N-1 blocks delay z^{-1}. The outputs of the delay line consist of input values at time points k, k-1,…,kN-1 and are described by the expression:

(3) $$a(k) = \sum_{i=1}^{k} w_{1i}a(k-i+1) + b$$

The model of antenna control system with neurocontroller on the basis of Elman's ANN and with PID-regulator was created to compare efficiency of ANN operation in Maltab/Simulink system (Fig. 5). The model of antenna (AS) with angular sensor is observed in [5].

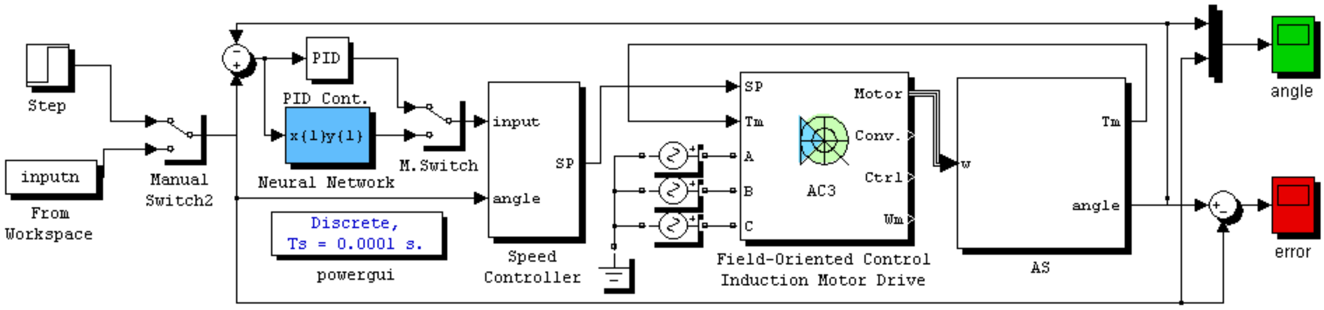


Fig. 5. The model of antenna control system with PID and neurocontroller in Simulink

ANN Learning Algorithm for Recurrent ANN

Learning of recurrent ANN is more complicated compared with the direct propagation networks as input signals depend not only on the current and previous input state, but also on the past values of the output signal of its intermediate layer. That is why the selection of ANN learning algorithm is of great importance.

The well known methods for back error propagation find out the minimum point of function in general, only at infinite number of iterations [6]. The advantage of learning methods based on gradients conjugation is their optimal formation of steps changes of parameters growth in learning by solving a quadratic optimization problem with a finite number of steps.

To find the minimum of error functional in ANN learning Fletcher-Reeves algorithms is used. It is characterized by perfect convergence of calculation process: for sufficiently determined quadratic function of ***n*** variables is reached at least no more than ***n*** steps [6].

The strategy of the method is to construct a sequence of points $\{x_k\}$, *k*=0, 1, 2, ... such that

(4) $$f(x_{k+1}) < f(x_k),\ \text{k=0, 1, 2, ...,}$$

Sequence of points is calculated according to the rule:

(5) $$\mathbf{x}_{k+1} = \mathbf{x}_k + a_k \mathbf{p}_k,$$

where: $\mathbf{x}_{k+1}$ – new vector value of settings parameters;

$\mathbf{x}_k$ – parameters vector for the k-*th* iteration;

a_k – learning rate parameter.

(6) $$\mathbf{p}_k = -\mathbf{g}_k + \beta_k \mathbf{p}_{k-1},$$

where: $\mathbf{g}_k = -\nabla f(\mathbf{x}^k)$,

β_k – constant, which is determined as follows:

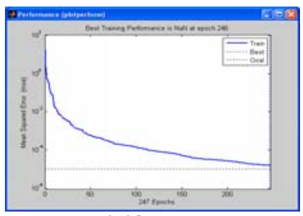
(7) $$\beta_k = \frac{\mathbf{g}_k^T \cdot \mathbf{g}_k}{\mathbf{g}_{k-1}^T \cdot \mathbf{g}_{k-1}}.$$

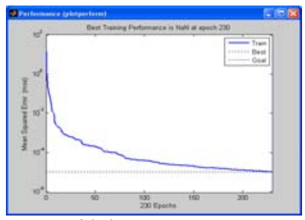
Performing the criterion of reaching the sufficient mismatch error $\|\mathrm{x}_k\| < \varepsilon$, the learning is stopped.

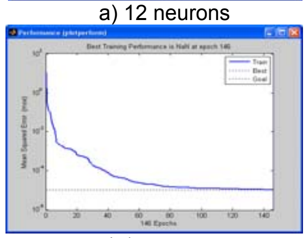
Optimization of Parameters of ANN neurocontroller

For efficient ANN operation in this task the structure is important as well as the selection of learning sequences. ANN learning was performed on harmonic signals which amplitudes varied from 1 to 10 degrees angular with discrete 1 degree. The time signal parameters were set according to the calculation of trajectories of support Earth's remote sensing (ERS) using a Keplerian data of satellite orbit parameters [5]. The range of possible changes of incoming values and goals of the learning set for ANN were selected for variations in the control parameters of control object model and based on apriori information about the parameters of antenna station. Fig. 6 shows graphs of ANN learning for setting various number of neurons in the recurrent layer (from 12 to 19). The learning error is depicted on axis of ordinates, the length of learning in the epoch before reaching the specified error (goal = 10^{-5}) is depicted on abscissa axis of ordinates.

The modeling results (Fig. 6) shows that a small number of neurons in the recurrent layer requires more learning epochs, or can not be learned (Fig. 6a). Too large number of neurons leads to the increase in the number of learning epochs because of the growth of number of connections between neurons. For 19 neurons in the recurrent layer (Fig. 6d) the learning time is equal to 259 epochs. The optimal number of neurons for given ANN in the control system is 17 (Fig. 6c) and the learning time is 146 epochs. ANN with 15 neurons (Fig. 6b), the learning time of which is 230 epochs can be considered as acceptable version.


a) 12 neurons


b) 15 neurons


c) 17 neurons

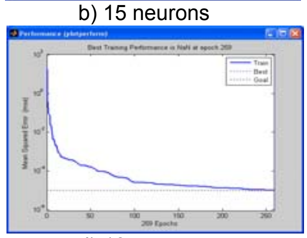

d) 19 neurons

Fig. 6. Speed Training Elman ANN with different number of neurons in the recurrent layer

Testing results of the operation of neurocontroller on ANN basis in comparison with PID-regulator

The tests were carried out on stepped signal and test pointing table as trajectory in rotation for PID and neurocontroller on AS model (Fig. 5). Testing trajectory was previously loaded in Matlab\WorkSpace operation space. Control efficiency was investigated for stability to changes of dynamic parameter of control object (twice Ts time constant).

Obtained the following graphs in transient testing stepped signal (Fig. 7,a), where 1 – given incoming trajectory, 2,3 – results of testing neurocontroller, 4,5 – results of testing PID controller. Fig.7b shows the graphs of control errors, where 1 – error for neurocontroller operation, root-mean square deviation σ = 0.1764, 2 – error for neurocontroller, the parameters of the mechanical part AS are changed, σ = 0.1765, 3 – error for PID-regulator, σ = 0.1964, 4 – error for PID-regulator, the parameters of mechanical part AS are changed, σ = 0.1996.

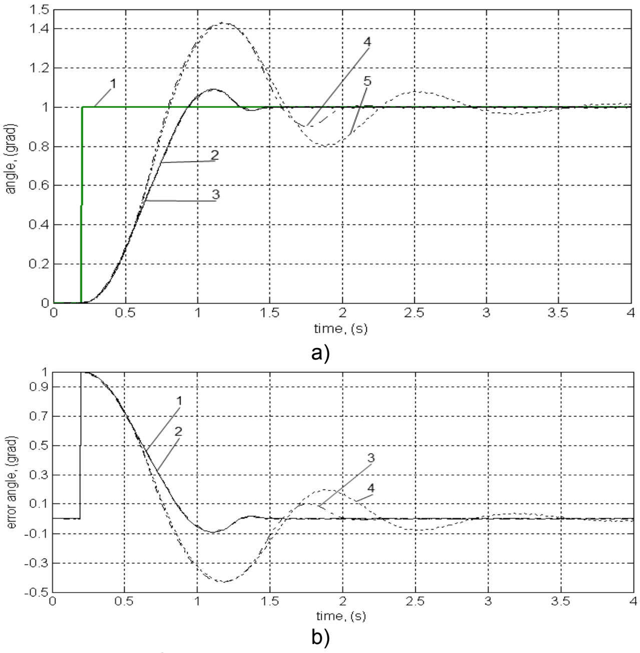


Fig. 7. Results of the stepped signal

There are obtained the following results of testing to the test trajectory simulation (fig.8a), where 1 – given incoming trajectory, 2,3 – results of neurocontroller testing, 4,5 – the results of PID controller testing.

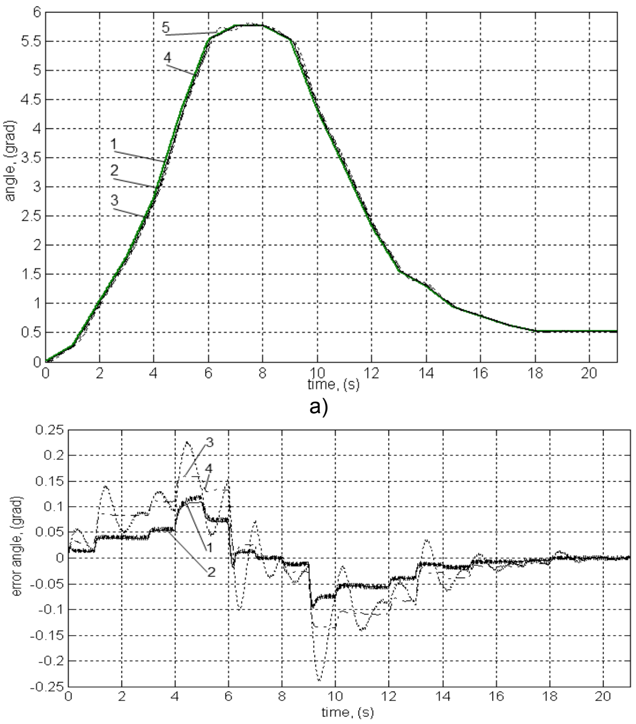


Fig. 8. Testing results on testing trajectory

Graphs of regulation errors shown in fig.8b, where 1 – control errors using neurocontroller, root-mean-square deviation σ = 0.0433, 2 – the same as when changing the mechanical part of the AS, σ = 0.0417, 3 – control errors using PID-regulator, σ = 0.0757, 4 – errors with PID controller when changing of the mechanical part AS parameter σ = 0.0806.

Conclusion

The results of performance of ANN operation modelling and synthesis-based on Elman's reccurent ANN modification introducing additional feedbacks for the problems of antenna system control adjustment under possible of dynamic parameters in mechanical design are given. The selection of neuron number in recurrent layer of network and its learning algorithm according to the method of conjugate gradients is reasoned.

Control system operation with neurocontroller compared with PID-regulator in the mode of testing input trajectory processing is investigated by means of AS model.

Modelling results demonstrated that offered AAN topology and its learning on sequences covering possible versions of system behavior were able to provide increase of control accuracy with modifications of testing object dynamic parameters compared with classical PID-regulator. The use of neural network in loop control gives a significant advantage over traditional control systems, due to the fact that their implementation does not require accurate mathematical model of control object.

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