



NEURAL NETWORKS FOR ADAPTIVE CONTROL SYSTEM OF CATERPILLAR TURN

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Abstract: The problems of object's identification and adaptive control based on application of special neural network are considered. Two kinds of neural networks for identification of non-stationary parameters of caterpillar and its turn control system are synthesized and tested. Modeling results for adaptive control system of caterpillar confirm the high efficiency of the suggested approach and developed networks.

Key words: neural network, identification, adaptation, control system.

1. INTRODUCTION

Over the past 30 years a lot of attention was paid to adaptive control of objects with unknown parameters. Under this approach Neural Networks (NN) were used for solving control problems in the 1980-s. Currently NN are used in control problems as neural emulators and predictors (Notkyn B.S., 2005). In practice it is necessary to identify object parameters changed under the influence of internal or external disturbances. Identification problem can be considered as a multivariate function approximation when response (object dynamic parameters values) for input request (values of input and output signals) is received. It is useful to utilize NN for solving such kind of problems (Rutkovska D. et al., 2006).

2. NEURAL NETWORK FOR IDENTIFICATION

An adaptive loop for caterpillar control system (CS) was synthesized for the purpose of researching the proposed approach to identification and adaptive control of non-stationary technological objects. An example of caterpillar turn CS and its synthesis is shown in (Dorf R.C. & Bishop R.H., 2006) where it is possible to consider two non-stationary parameters: K and a (Fig. 1).

Since caterpillar is usually employed in rather complex cases, turn gear is influenced by internal and external disturbances of stochastic nature. This leads to non-stationary change of object parameters:

$$G(p) = \frac{1}{p(p + c_1(t))(p + c_2(t))} \quad (1)$$

This is initially related to changing parameters of turn gear transfer function (TF) influenced by the following factors:

- damage caused by external objects and natural phenomena (e.g. sand, dirt and dust or corrosion);
- deterioration or insufficient lubrication of rubbing parts;
- failure of some internal systems or gears;
- other types of damage.

Thus, while CS operating it is necessary to promptly adjust regulator parameters. An adaptive loop consisting of an identification unit and regulator adjustment unit was added to CS in order to solve this problem (Fig. 1).

The effective NN-structure for solving such problems is multilayer perceptron (MLP) (Rutkovska D. et al., 2006). Projecting NN must determine vector \mathbf{c} by processing several serial discrete values of signals $e(k)$ and $y(k)$ (Fig. 1.). The required vector is TF's vector of parameters (1). The moment of transient end is that moment, after which output signal value

differs from the set value not more than 2%. The stepwise signal is fed to the system input.

The influence of different number of layers and neurons on the performance of the system was tested. It turned out that the optimal NN structure is the MLP with 3 hidden layers of 13 neurons: 20-13-13-13-2 – that was trained with Levenberg–Marquardt algorithm. This NN showed that minimal relative identification error is 0.86%.

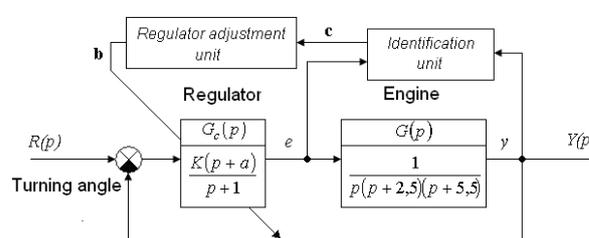


Fig. 1. Structure chart of adaptive CS for caterpillar turn (initial model)

3. REGULATOR ADJUSTMENT UNIT

The main task of adaptive control is a prompt regulator parameters adjustment for maintenance of unchangeable (constant) form of output signal in case of object's parameters changing. Projecting regulator adjustment unit must to estimate vector \mathbf{b} of regulator parameters. Regulator parameters have to be defined in such way that the target function should be minimized. As such function was defined to be a sum-square error (2) of comparison of real output signal and wishful form (Fig. 2.). One of the most common methods of new parameters values calculation is the gradient descent. The condition of small argument increase or conditions of gradient smallness are defined as a criterion for interruption of search.

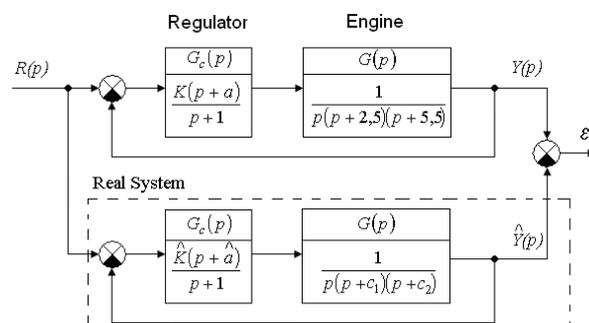


Fig. 2. Error estimation

$$\varepsilon_{\Sigma} = \sum_{k=1}^N (\varepsilon[k])^2 \quad (2)$$

Thus, a Neural Network has 2 neurons in input layer and 2 neurons in output layer. Neurons in hidden layers follow a sigmoid activation function (AF) and neurons in the output layer follow a linear AF. Training algorithm is defined to be a Levenberg–Marquardt algorithm.

Training data forming was processed the following way. For every couple of object parameters from training data formed for NN-identifier proper regulator parameters were calculated with gradient descent method. Object parameters vectors were formed in input signals matrix, and regulator parameters vectors were formed in target values matrix. Since orders of parameters K and a differs considerably (e.g. initial values are $K=70, a=0.6$), it is expedient to normalize target matrix.

Quality assurance of adaptive CS was processed the following way. For every couple of object parameters from training data identification procedure processed. Resulting parameters values are fed to the Regulator adjustment unit that calculates normalized regulator parameters vector. This vector is denormalized, so required parameters values vector is received.

After regulator adjustment the stepwise signal is fed to the system input and the transient form is received. It is compared with wishful signal (Fig. 2.). Quality functional is defined to be the average relative comparison error:

$$\bar{\varepsilon} = \frac{1}{N} \sum_{n=1}^N \frac{|y_n - y_n^i|}{y_n} \cdot 100\% \quad (3)$$

where N is a number of transient samples;

y_n – n -th object transient sample;

y_n^i – n -th identificational model sample.

Research showed that optimal NN structure is the MLP with 2 hidden layers of 17 neurons: 2-17-17-2 – that was trained with Levenberg–Marquardt algorithm. This NN showed that minimal relative identification error is 3.6%.

4. MODELING RESULTS

Let test received adaptive CS with the following example.

Step 1. Initial caterpillar TF is:

$$G(p) = \frac{1}{p(p+2.5)(p+5.5)} \quad (4)$$

Accordingly, initial regulator TF is:

$$G_c(p) = \frac{70(p+0.6)}{p+1} \quad (5)$$

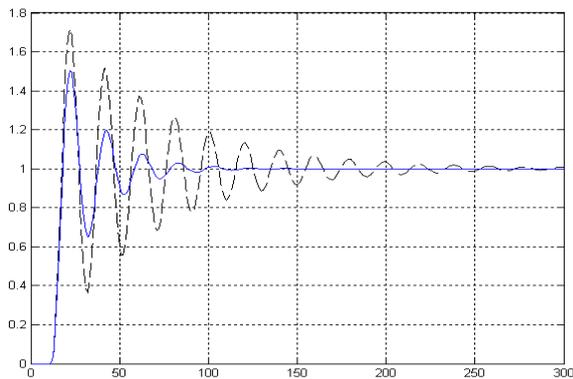


Fig. 3. Initial and changed objects transients' comparison

Solid line at the fig.3 is the transient of initial caterpillar turn CS. And dotted line is the transient of CS with changed object parameters. Wishful transient is derermined by TFs (4) and (5).

Step 2. Let object TF parameters changed under some disturbances (Fig. 3.), so new TF is:

$$G^i(p) = \frac{1}{p(p+2)(p+5)} \quad (6)$$

Step 3. Parameters identification is processing by first syntesized NN. Identificational model of TF $G^i(p)$ is built by new parameters values (vector \mathbf{c})

$$G^i(p) = \frac{1}{p(p+2.1432)(p+4.986)} \quad (7)$$

As we can see, identified parameters are sufficiently close to real.

Step 4. Received vector of object's parameters is fed to regulator adjustment unit where second syntesized NN allow finding new regulator parameters (vector \mathbf{b}) for TF $G_c^a(p)$:

$$G_c^a(p) = \frac{63.378(p+0.3342)}{p+1} \quad (8)$$

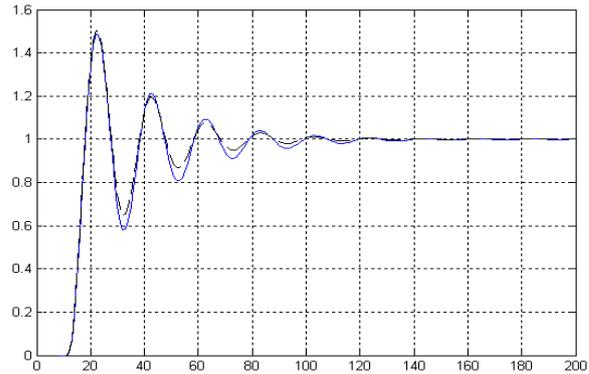


Fig. 4. Initial and adaptive CS transient's comparison

Solid line at the fig.4 is the transient of initial caterpillar turn CS and dotted line is the transient of adaptive CS.

As we can see, transfer functions are almost identical, at that identifier doesn't receive prior knowledge about initial parameters values, and the regulator adjustment unit doesn't have initial regulator parameters values. It implies that adaptive loop work is satisfactory.

5. CONCLUSION

Neural networks for adaptation of caterpillar turn CS were developed and trained. Results can be utilized as software for different CS like: adaptive neural identification of objects with unknown parameters system (ship energetic systems, manipulation robots, vibration isolation system etc.); systems of adaptive control of non-stationary objects that were synthesized with modern intelligent technologies. Created neural networks are able to restore non-stationary object parameters and calculate new values of regulator parameters adequately using object input and output signals without taking prior knowledge about its parameters into account. Using neural approach is useful and makes a possibility to solve adaptation problems in minimal time with minimal error.

6. REFERENCES

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