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NONLINEAR MODELING OF LABORATORY MODEL AMIRA DR300 BY RECURRENT NEURAL NETWORK

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Abstract: *Purpose of this paper is to design a nonlinear recurrent neural network model of a laboratory device AMIRA DR300 made by a company AMIRA in Germany. This apparatus consists of two direct-current engines, whose shafts are connected together by a fixed shaft coupling. A shaft coupling rotation speed is an output value of this laboratory model and it is possible to measure it either by a tachometer generator or an incremental position sensor. Recurrent neural network was trained to achieve similar properties to the first engine which is called as motor. The second engine can be used as a generator of a faulty measured value.*

Key words: *nonlinear model, recurrent neural network, AMIRA DR300, modeling*

1. INTRODUCTION

Predictive control is very popular nowadays because of its inclusion possibility of input, output or other constraints in a control algorithm itself (Mikleš & Fikar, 2007).

The basic principle of the model predictive control (MPC) is shown in Fig. 1 (Mikleš & Fikar, 2007).

The principle follows.

- The identified model of the controlled process is an explicit part of the controller and it predict future output values $\hat{y}(t)$ over some horizon N. Predictions are calculated based on the information available to the time k and a trajectory of control values, which has to be compute it, because it is unknown.
- The control trajectory is obtained as a solution of the optimization problem, which consists of some possible constraints and an appropriate cost function, which includes the future output and control signal and the future reference signal.
- The first element of the whole control trajectory is used for actuation itself. These points are repeated in an every sampling period and it is called as a *Receding Horizon* concept.

Any type of discrete model can be used for prediction of future output values. Linear version of MPC called LMPC is the most often used version in industry. It uses linear mathematic models of controlled industrial devices (Muske & Rawlings, 1993). However there are a lot of high nonlinear systems, which are frequently occurring in practice. This fact leads to use control algorithms and methods based on nonlinear mathematical models NMPC (Potočník & Grabec, 2002). These methods can be used for nonlinear systems, when an empiric model can be obtained from input-output data. There is a possibility of using neural networks, because of their ability of approximation of any nonlinear mathematic function. The main problem of MPC methods is the identification and the modeling of process, because the quality of the predictive control is closely associated with a model quality of an identified process.

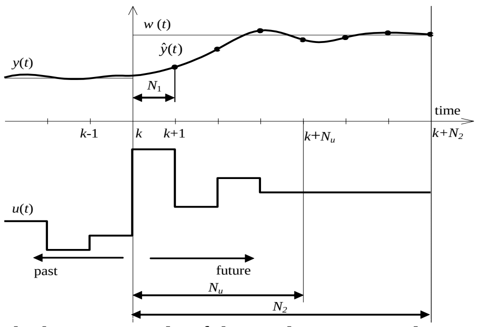

Fig. 1. The basic principle of the predictive control

Using of neural networks can improve the quality of predictors. First efforts of the neural networks utilization was appeared in (Zhan & Ishida, 1997), where the neural network with one hidden layer was used for the prediction.

The neural network disadvantage is a huge growth of a neural network complexity with a horizon lengthening.

The goal of this paper is the project of the recurrent neural network which can be used in the future research as the discrete model of the laboratory device AMIRA DR300 in the predictive control as the predictor of the future behavior of this process. This neural network was trained on a random signal in the whole extensity of a measured static characteristic of the AMIRA DR300. This trained model was tested on a signal in a shape of step responses in the whole extensity of training data. Experimental results prove that the neural network is acceptable as the nonlinear model of this laboratory model.

2. LABORATORY MODEL AMIRA DR300

The laboratory model AMIRA DR300 represents a nonlinear one-dimensional process, which can be used for a checkout of a designed identification and control algorithms in the laboratory environment in the real time.

This system consists of two main parts. The first part is the transmission housing and the second part is the mechanism itself, which can be seen in Fig. 2.

The mechanism is comprised of two engines whose shafts are linked together by the shaft coupling. The first one is a direct-current motor, which input signal is a controllable voltage u, and the output signal is a shaft speed ω, which is measured either by a tachometer generator or by an incremental position sensor. The second one serves as a generator and it is possible to use it as a source of the faulty measured value (Hubáček & Bobál, 2010).

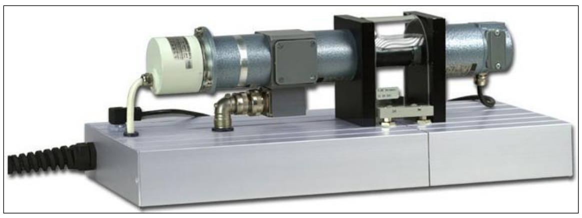
Fig. 2. The laboratory model AMIRA DR300

3. NEURAL NETWORKS

The recurrent neural network respectively NARX (Nonlinear AutoRegressive model with eXogenous input) recurrent neural network structure was used as a model of the first motor of the laboratory device.

The quality of the neural model is given by the following criterion.

$$E(s)=\sum_{i=1}^{M}\left[\hat{y}_i(s,k)-y_i(k)\right]^2 \qquad (1)$$

Where

- s is the count of bringing the training set into the input of the neural network.
- M is the count of examples in the training set.
- k is the sequence number of training set example.
- $y(k)$ is the vector of reference output signal.
- $\hat{y}_i(s,k)$ is a vector of real outputs from neural network.

The minimization of the criterion (1) is the main object of learning algorithms.

The Matlab neural network toolbox was used for the neural network learning. This toolbox uses a modified version of the Backpropagation algorithm called Levenberg-Marquardt algorithm (Hagan & Menhaj, 1994). This algorithm is an approximation to the Newton's method. Parameters increments for this method are obtained from the following equation

$$\Delta\gamma_j(s)=\left[J^T(s)J(s)+\mu I\right]^{-1}J^T(s)e(s) \qquad (2)$$

where

- $J(s)$ is the Jacobian matrix,
- μ is the parameter. If it is large this method becomes the steepest descent and if it is small this method becomes the Gauss-Newton.

The Levenberg-Marquardt algorithm can be considered a trust-region modification of the Gauss-Newon. It can be seen that the key step of this algorithm is the computation of the Jacobian matrix (Hagan & Menhaj, 1994).

The Levenberg-Marquardt algorithm is generally faster and less demanding on hardware than the Backpropagation algorithm.

4. RESULTS

The NARX recurrent neural network with one neuron in the input layer, ten neurons in the hidden layer and one neuron in the output layer was used for the modeling of the laboratory model AMIRA DR300. Number of neurons in the hidden layer was chosen experimentally. One step of a delay for the input vector and two steps of the delay for the output sequence were set for this network.

A response of the real device on the input random signal was used as a reference output signal for the neural network learning. A graphical comparison of responses of the laboratory model and the recurrent neural network on the input random signal is shown in Fig. 3. Responses of the AMIRA DR300 and the neural model on the test signal in a shape of steps are graphical compared in Fig. 4. It can be seen, that the output of the trained network traces the output of the real device with some perturbation. These responses were compared by the following criterion

$$S_y=\frac{1}{N}\sum_{i=1}^{N}\left(y_r(i)-y(i)\right)^2 \qquad (3)$$

where

- y_r is the real device response,
- y_i is the identified model response,
- N is the number of measured data.

The value of criterion (3) is $Sy=3.4\cdot10^{-3}$.

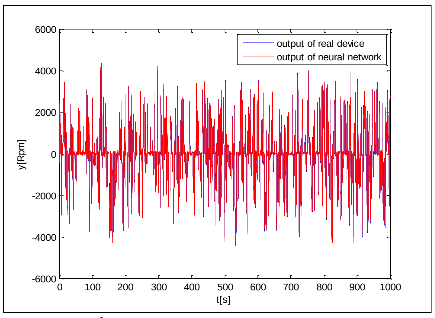

Fig. 3. Responses of real device and its model on random signal

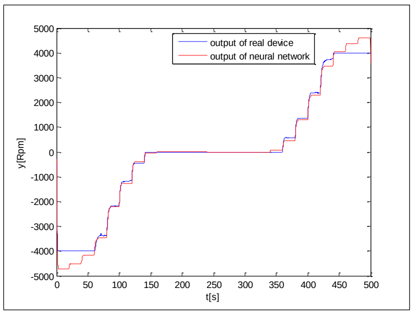

Fig. 4. Responses of AMIRA DR300 and its model on reference steps

5. CONCLUSION

This paper deals with proposal of the NARX recurrent neural network as the nonlinear input-output model of the nonlinear time varying system – the laboratory model AMIRA DR300. This model will be used in the future research like the predictor for the predictive control of the AMIRA DR300 to improve a basic CARIMA (*Controller Auto-Regressive Integrated Moving-Average*) linear model. The comparison between the real device response and the neural network model response on the random signal and reference steps proved that this model can be used as a nonlinear predictor for the predictive control of this device. But this network is suitable only for offline learning, because of its long and demanding learning calculations. So this model is unsufficient for dynamic models, where an online learning is needed.

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