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# PREDICTIVE NEURAL NETWORK CONTROLLER FOR HYDROSTATIC TRANSMISSION CONTROL

*SUMMARY*

*In this paper predictive neural network controller is applied to control rotational speed of hydraulic engine hydrostatic transmission. It describes the functional structure and design principle of predictive neural network controller. This predictive neural network control method provides control linear and nonlinear systems. In this case feed forward network with one hidden layer was used. The control objective is to minimize a control cost function. Computer simulations are provided for illustration and verification. As control plant the hydrostatic transmission was chosen. The control by using the hydraulic drive is the time variant process, consequential to inconstancy parameters of hydraulic liquid (for instance: kinematic viscosity, compressibility and thickness). The efficiency of pump control is realized by use The electrohydraulic servo – system distinguish itself by a nonlinear characteristic. Finally, a predictive neural network method to control this kind of object is successfully applied.*

**Keywords:** *neural network control, nonlinear object, predictive control*

*ZASTOSOWANIE REGULATORA NEURONOWEGO Z PREDYKCJĄ DO STEROWANIA PRZEKŁADNIĄ HYDROSTATYCZNĄ*

*W artykule zaprezentowano koncepcję regulatora predykcyjnego bazującego na sieciach neuronowych, wykorzystanego do sterowania prędkością obrotową silnika hydraulicznego przekładni hydrostatycznej. Regulator zastosowany w predykcyjnym układzie regulacji był strojony przy użyciu sztucznych sieci neuronowych. Do badań wykorzystano sieć jednokierunkową, jednowarstwową. Zasadniczym zadaniem układu jest minimalizacja określonej funkcji kryterialnej. Ostatnia część artykułu jest zestawieniem wyników badań zaproponowanego układu regulacji do sterowania obiektem nieliniowym. Jako obiekt do badań wykorzystano przekładnię hydrostatyczną. Zbudowana jest ona z pompy o zmiennej wydajności i silnika o stałej chłonności. Do sterowania wydajnością pompy wykorzystano elektrohydrauliczny układ sterujący. Układ ten składa się z siłownika hydraulicznego sprzężonego tłoczyskiem z wychylnym wirnikiem pompy oraz elektrohydraulicznego serwozaworu przepływowego. Obiekt ze względu na swoje właściwości jest nieliniowy i niestacjonarny.*

**Słowa kluczowe:** *sterowanie predykcyjne, obiekt nieliniowy, sieci neuronowe*

## 1. INTRODUCTION

Predictive control is often used in industry and a large number of implementation algorithms has been presented in literature. Most of these control algorithms use process model to predict the future behavior of a plant and because of this, the model predictive control (MPC) is often used. The most important advantage of the MPC technology comes from the process model itself which allows the controller to deal with an exact copy of the real process dynamics, implying a much better control quality. The constraints with respect to input and output signals are directly considered in the control calculation, resulting in very rare or even no constraint violation. Another important characteristic, which contributes to the success of the MPC technology, is that the MPC algorithms consider plant behavior over a future horizon in time (Fig. 1). Thus, the disturbances can be predicted and eliminated. This permits the controller to drive the output more closely to the reference trajectory. Although most processes usually contain complex nonlinearities, most of the MPC algorithms are based on a linear model of the process. The aim for most of the applications is to maintain the system at a desired steady state, rather than moving rapidly between different operating points, so a precisely identified linear model is sufficiently accurate in the neighborhood of a single operating point. Often, the output of the controller is obtained using software optimization techniques and the control algorithm cannot always be used in manufacturing applications. As linear models are reliable from this point of view, they will provide most of the benefits with MPC technology. If the process is highly nonlinear and subject to disturbances of a high frequency a nonlinear model is necessary to describe the behavior of the process. Also in servo control problems where the operating point changes frequently, a nonlinear model of the plant is indispensable.

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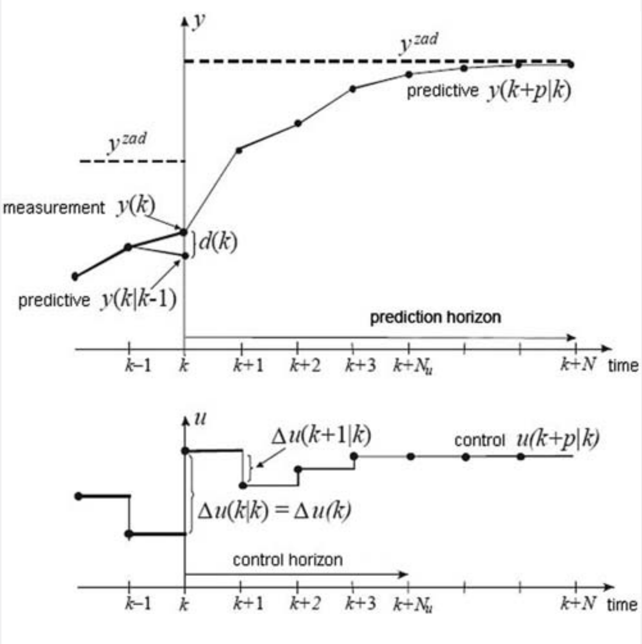


**Fig. 1.** Base of predictive control over a future horizon in time (Tatjewski 2002)

Recently, neural networks have become an attractive tool in the construction of models for complex non-linear systems, because of their inherent ability to learn and approximate non-linear functions. Most of the non-linear predictive control algorithms imply the minimization of a cost function, by using computational methods for obtaining the optimal command to be applied to the process. The implementation of the non-linear predictive control algorithms becomes very difficult for real-time control because the minimization algorithm must converge at least to a sub-optimal solution and the operations involved must be completed in a very short time (corresponding to the sampling period) (Lazar and Pastravenu 2002).

This paper analyzes a neural based non-linear predictive controller, which eliminates the most significant obstacles for non-linear MPC implementation by developing a non--linear model, designing a neural predictor and providing a rapid, reliable solution for the control algorithm (Lazar and Pastravenu 2002).

## 2. THE NEURAL NETWORK PREDICTIVE CONTROL SCHEME

The first stage of model predictive control is to train a neural network to represent the forward dynamics of the plant. The prediction error between the plant output and the neural network output is used as the neural network training signal.

The following block diagram illustrates the model predictive control process (Fig. 2). The controller consists of the neural network plant model and the optimization block. The optimization block determines the values of $u^T$ that minimize $J$, and then the optimal $u$ is input to the plant.

The objective of the predictive control strategy using neural predictors in two ways: to estimate the future output of the plant and to minimize a cost function based on the error between the predicted output of the processes and the reference trajectory. The cost function value, which may be different from case to case, is minimized in order to obtain the optimum control input that is applied to the nonlinear plant (Lazar and Pastravenu 2002).

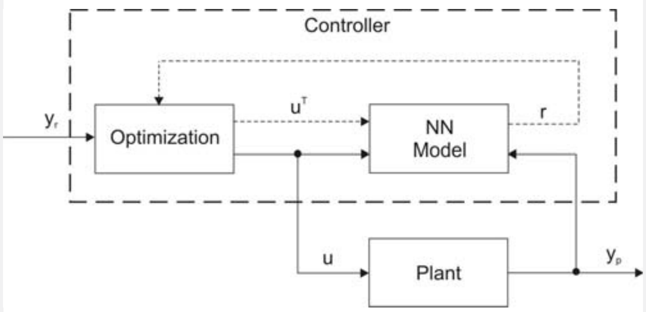


**Fig. 2.** Block diagram with control system: $y_r$ – desired response, $r$ – neural network model response, $u^T$ – tentative control signal

In most of the predictive control algorithms a squared form is used for the cost function

$$J = \sum_{i=N_1}^{N_p} [\, y_r\,(k+i|k) - r(k+i|k)]^2 + \\ + \lambda \sum_{i=0}^{N_u-1} \Delta u^2\,(k+i|k) \tag{1}$$

with requirements:

$$\Delta u\,(k+i-1|k) = 0,\ 1 \le N_u < i \le N_p \tag{2}$$

where:

$N_u$ – control horizon,
$N_1$ – minimum prediction horizon,
$N_p$ – prediction horizon,
$i$ – order of the predictor,
$r$ – reference trajectory,
$\lambda$ – weight factor,
$\Delta$ – differential operator.

The command $u$ may be subject to amplitude constraints

$$u_{\min} \le u\,(k+i|k) \le u_{\max},\ \ i = 1, ..., N_{u-1} \tag{3}$$

The cost function is often used with the weight factor $\lambda = 0$. A very important parameter in the predictive control strategy is the control horizon $N_u$, which specifies the present time, since when the output of the controller should be kept at a constant value.

The use of neural networks for nonlinear process modeling and identification is justified by their capacity to approximate the dynamics of non-linear systems including those with high nonlinearities or dead time. In order to estimate the nonlinear process, the neural network must be trained until the optimal values of the weight vectors (i.e. weights and biases in a vector form) are found. In most applications, feedforward neural networks are used, because the training algorithms are less complicated (Lazar and Pastravenu 2002).

Figure 3 illustrates a one-hidden-layer feedforward neural network.

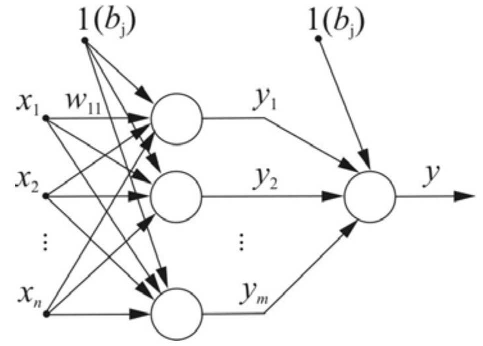


**Fig. 3.** A feedforward network with one hidden layer

The arrows at the left side in Figure 3 symbolize weights in the network. The input layer consists solely of the inputs to the network. A hidden layer, consists of an arbitrary number of neurons, or hidden units placed in parallel. Each neuron performs a weighted summation of the inputs. This signal is transferred through a nonlinear activation function (sigmoid).

Mathematically the functionality of a hidden neuron is described by

$$y_i = f\left(\sum_{j=1}^{n} w_{ij} x_j + b_j\right) \quad \text{for } 1 \le i \le m \tag{4}$$

The arrows feeding into the neuron are the symbolic representation of the weights $w_j$ and biases $b_j$.

The output of this network is given by

$$y_m = \sum_{i=1}^{nb} w_i^2 f\left(\sum_{j=1}^{n} w_{ij}^l x_j + b_{ji}^l\right) + b^2 \tag{5}$$

where:

$n$ – number of inputs,
$nb$ – number of neurons in the hidden layer.

The variables $\{w_{ij}^l, x_j, b_{ji}^l, b^2\}$ are the parameters of the network model that are represented together by the parameter vector.

The back propagation algorithm used optimization gradient method to learning weights. The cost function is defined as the sum of the square difference between the input signal $y_k$ and set value $d_k$.

The form of cost function depends on number of learning samples. The following expression is for many learning samples $j$ (were $j$ = 1, 2, ..., $p$)

$$E(w) = \frac{1}{2} \sum_{j=1}^{p} \sum_{k=1}^{M} (y_k^{(j)} - d_k^{(j)})^2 \tag{6}$$

## 3. SIMULATION TESTS

To the research model of hydrostatic transmission was used. The hydrostatic transmission consists of variable efficiency pump and a radial engine with constant working absorptivity. Pump efficiency was controlled using an electrohydraulic control system, comprising a hydraulic cylinder coupled with a pump rotor via a piston rod and a hydraulic servo-valve. For a mathematical model has been assumed that: a hydrostatic transmission is a system with lumped constants.

The static and dynamic features of the transmission do not depend upon the direction of the hydraulic engine rotation. Thus, a mathematical model was developed for only one rotation direction. It is assumed that the transmission is in a thermally balanced state, and that the module of the volume elasticity is constant.

The angular velocity of the main pump shaft is constant and pressure drop in the hydraulic cables is negligible. Leaks in the pump and in the engine can be summed, and neither the pump's efficiency, nor the absorptivity of the hydraulic engine depends upon their shaft's rotation angle. The safety valve is closed at all times. However the object is nonlinear and its control varying in time is very difficult. For that reason the neural network predictive control strategy was chosen. The software for hydrostatic transmission control system was developed in MATLAB/Simulink (Nawrocka 2006).

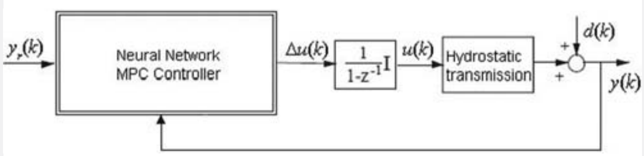


**Fig. 4.** The neural network control structure

Figure 4 shows the neural network control structure witch was used in simulation tests.

In the first step the signal for training neural network was generated. In the next step the training data for neural network predictive control were generated (Fig. 5). After that the validation data for neural network predictive control were prepared (Fig. 6).

The last part of the research consisted of the test performed to the trained neural network. A step response for the system with neural network controller is presented in Figure 7. There are three values of rotational speed, set value are 300, 500 and 700 rpm.

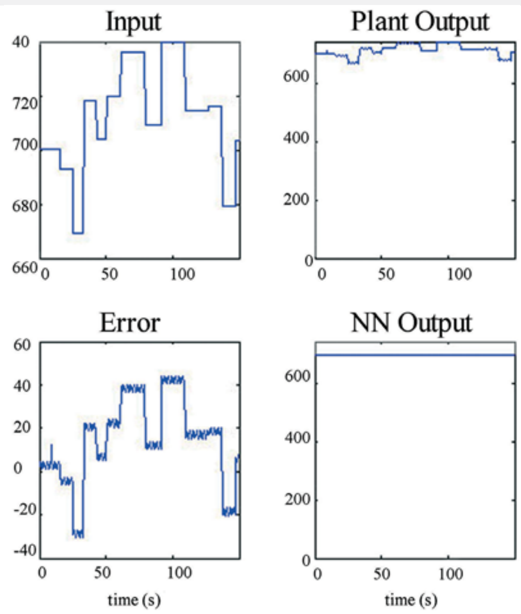


**Fig. 5.** Training data for NN predictive control

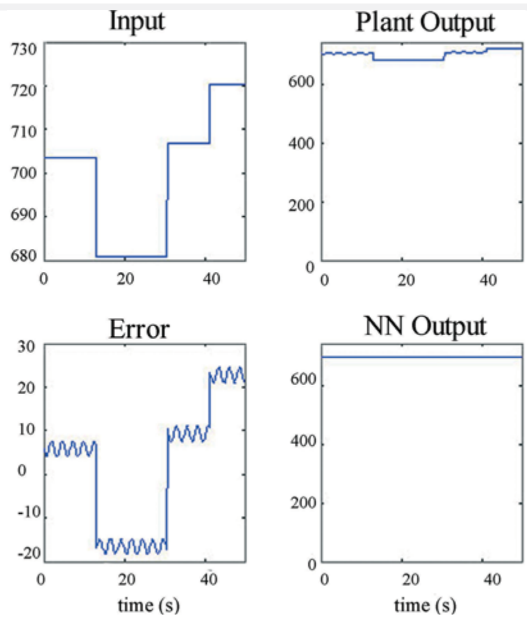


**Fig. 6.** Validation data for NN predictive control

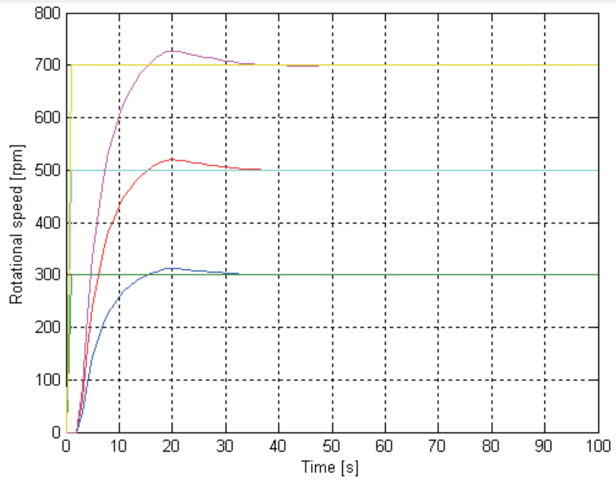


**Fig. 7.** Results of simulation tests

## 4. CONCLUSION

In this paper the predictive neural network control has been studied. The neural network controller is designed by minimizing an MPC cost function. This kind of controller has advantages over standard nonlinear model predictive control. The neural network controller has substantially reduced on-line computational requirements. Because the neural training depends mainly on the network complexity, not on the length of the control horizon.

As a control object the hydrostatic transmission was analyzed. This kind of object is very difficult to control because of its properties. Especially nonlinearities and non-stationary behavior cause a problem during control design process. Simulation tests with MPC algorithm provide a satisfied result.

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