# Applications of Artificial Neural Networks in Control of DC Drive

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**Abstract.** The paper deals with the applications of artificial neural networks in the control of the DC drive. In the paper three control structures are discussed. The first control structure uses a conventional PI controller. The second structure uses a neural network predictive control. The last structure is a sensorless control of the DC drive using feedforward neural network. The DC drives were simulated in program Matlab with Simulink toolbox. The main goal was to find the simplest neural network structures with minimum number of neurons, but simultaneously good control characteristics are required. Despite used neural networks, which are very simple, it was achieved satisfactory results.

## 1 Introduction

In general, the application of artificial intelligence in drives can lead to increased performance and robustness to parameter and load variations. Artificial neural networks are used for the identification and control of non-linear dynamic systems. An artificial neural network (ANN) is a massively parallel, non-linear adaptive system containing highly interacting elements called neurons or perceptrons. The artificial neural networks are based on crude models of the human brain and contain many artificial neurons linked via adaptive interconnections (weights). In other words they are adaptive function estimators which are capable of learning the desired mapping between the inputs and the output of the system.

The artificial neural networks usually must learn the connection weights from available training patterns. Performance is improved over time by iteratively updating the weights in the network. Mostly used artificial neural network is trained off-line by set of corresponding input-output pairs of controlled system. The learning and adapting capability of neural networks makes them ideal for control purposes. An ANN can be successfully applied even if the motor which is to be controlled and the load parameters are unknown [1]-[11].

The conventional DC motor drive continues to take a large share of the variable-speed drive market. However, it is expected that this share will very slowly decline, but there are some companies that produce DC drives. Artificial intelligence belongs to modern technology. Its application can lead to improvement of parameters of electric regulated drives with DC motors. This technology allows significant innovations of DC drives.

Á. Herrero et al. (Eds.): Int. JointConf. CISIS'12-ICEUTE'12-SOCO'12, AISC 189, pp. 351–360.
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## 2 Control Structure of DC Drive

The power part of the DC drive consists of DC to DC converter (chopper or controlled rectifier) and DC motor. Block scheme of the drive is shown in Fig. 1. When a fixed DC supply is available, a DC to DC converter can be used for the purposes of the control of the DC motor, where the constant DC voltage is transformed into an adjustable voltage to control the speed of the motor. An armature current is controlled by current controller. A speed controller provides the speed control.

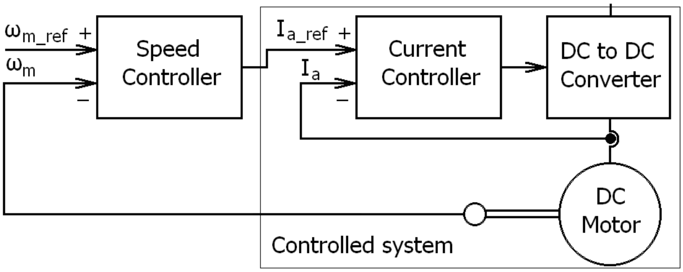


**Fig. 1.** DC drive block scheme

## 3 Conventional PI Controller

For future comparison it is important to consider the conventional control. It is conventional PI controller used as the speed controller which can be described as follows:

$$i_{a\_ref} = K_p(\omega_{m\_ref} - \omega_m) + K_i \int (\omega_{m\_ref} - \omega_m)dt + K_d \frac{d}{dt}(\omega_{m\_ref} - \omega_m) \quad (1)$$

where $i_{\mathrm{a\_ref}}$ is the reference value of the torque producing current (armature current), $\omega_{m\_ref}$ and $\omega_m$ are the reference and actual value of the rotor angular speed, $K_p$ is the proportional gain, $K_i$ is the integral gain, and $K_d$ is the derivative gain.

The quality of the control is assessed according to the response of the control loop to step changes of input variables. From a practical point of view, four factors are the most important for the assessment of the control quality: rise time, settling time, overshoot and steady state error

In control theory applications, the rise time $t_r$ is the time required to reach first the steady-state value (100%). It may also be defined as the time to reach the vicinity of the steady-state value particularly for a response with no overshoot, e.g. the time between 10% and 90%. The settling time $t_s$ is the time for departures from final value $y_f$ to sink below some specified level of final value $y_f$, i.e. $y_f \pm \Delta$. The overshoot is the maximum value $y_m$ of the controlled quantity above final value $y_f$ [12].

## 4 Neural Network Predictive Control

The model predictive control method is based on the receding horizon technique. The neural network model predicts the plant response over a specified time horizon.

The predictions are used by a numerical optimization program to determine the control signal that minimizes the following performance criterion over the specified horizon [13]:

$$J = \sum_{j=N_1}^{N_2} \left[ y_r(t+j) - y_m(t+j) \right]^2 + \rho \sum_{j=1}^{N_u} \left[ u'(t+j-1) - u'(t+j-2) \right]^2 \qquad (2)$$

where $N_1$, $N_2$ and $N_u$ define the horizons over which the tracking error and the control increments are evaluated. The *u'* variable is the tentative control signal, $y_r$ is the desired response and $y_m$ is the network model response. The $\rho$ value determines the contribution that the sum of the squares of the control increments has on the performance index.

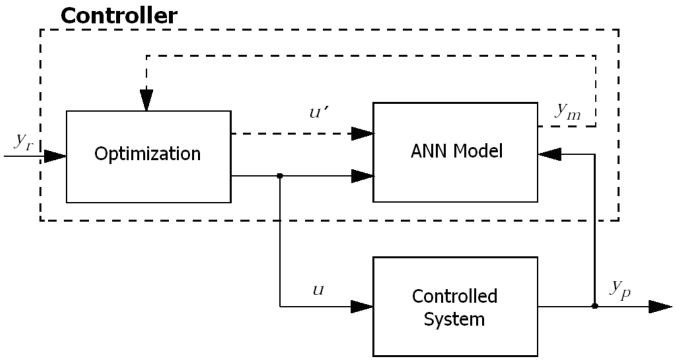


**Fig. 2.** Block scheme of NN predictive control

The figure 2 shows block diagram which illustrates the model predictive control process. The controller consists of the neural network plant model and the optimisation block. The optimisation block determines the values of *u'* that minimize *J*, and then the optimal *u* is input to the plant [13].

## 5 Structure of Artificial Neural Network

There are typically two steps involved when using neural network for predictive control: system identification and control design. In the system identification stage, development of the neural network model (5-1 ANN) of the controlled system is performed. There were used 2 delayed plant inputs, 3 delayed plant outputs and 10000 training samples. In the control design stage, the ANN model of the controlled system is used to design or train the controller. For the model predictive control, the ANN model of the controlled system is used to predict future behavior of the system (control horizon is 2), and an optimization algorithm is used to select the control signal that optimizes future performance. The controller requires a significant amount of online computation, since an optimization algorithm is performed at each sample time to compute the optimal control signal.

For realization of control system with NN predictive control, artificial neural network was used which was trained off-line by set of corresponding input-output pairs of controlled system. The weights of the ANN can be then adjusted via the so-called backpropagation algorithm using Levenberg-Marquardt method to minimize the error.

For the ANN model, a three layer neural network is used which contains five neurons in hidden layer with tanh activation function and one neuron in output layer with linear activation function. It stands to reason that structure of neural network is very simple, it consists of only six neurons. However, good results of important drive quantities are achieved. It was tested various structures of artificial neural network, but for example if it was used three neurons in hidden layer, results were not so good, especially control signal (output of the controller) contains higher ripple.

## 6 Sensorless Control Using Artificial Neural Network

The speed control requires a feedback signal which is obtained by the speed sensors such as tachogenerator or mainly digital shaft position encoder. These sensors are sources of trouble. The main reasons for the development of sensorless drives are: reduction of hardware complexity and cost, increasing mechanical robustness, reliability. Removing speed sensors from a control structure of electrical drive leads to so-called sensorless drive, which naturally requires other sensors for the monitoring of currents and voltages. The speed estimation methods can be classified into conventional, based on mathematical model of the electrical motor, or based on artificial intelligence [14]-[20].

To realize the speed estimator, it is necessary to determine the appropriate structure of the neural network with appropriate input variables, which will implement the views defined by the following equation:

$$\omega_{m(k)} = \mathbf{f}\,[i_{a(k)}, i_{a(k-1)}, u_{a(k)}, u_{a(k-1)}, \mathbf{w}\,] \tag{3}$$

where $\boldsymbol{f}$ is the activation function and $\boldsymbol{w}$ is a vector of weighting and threshold coefficients.

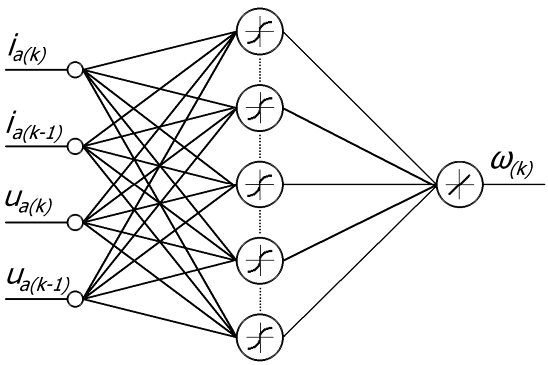


**Fig. 3.** Speed estimator with artificial neural network

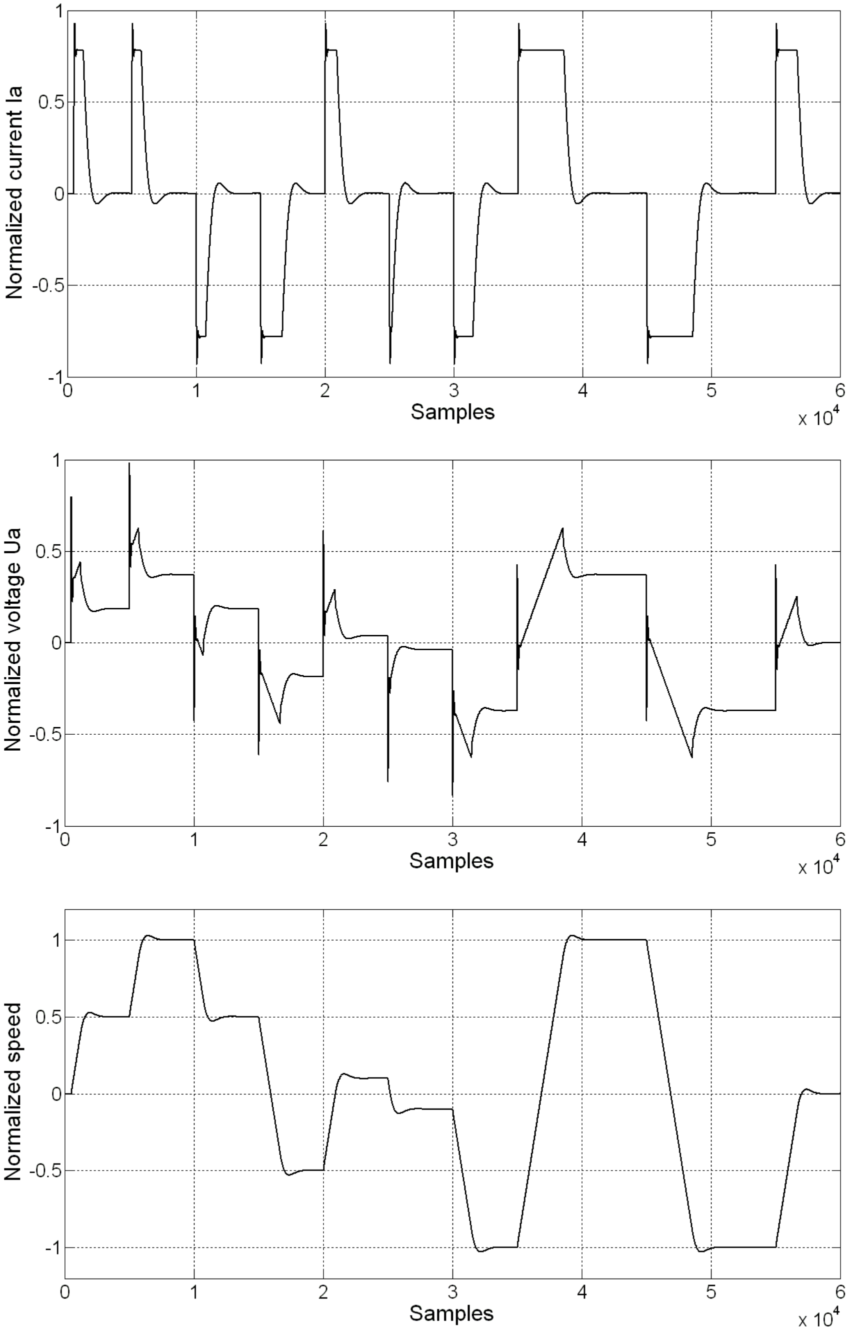


**Fig. 4.** Example of the training data set for ANN speed estimator

First it is necessary to design right structure of the artificial neural network and it is also important to determine such inputs to ANN, which are available in structure of the speed control and from which is able to estimate a rotor speed of the DC motor. A recommended method for determination of ANN structure does not exist, so the final ANN was designed by means of trial and error. The main goal was to find the simplest neural network with good accuracy of speed estimation. This is the key for industry use of ANN´s.

It has been designed three layer feedforward 4-22-1 ANN (see Fig.3) with following inputs $i_{a(k)}$, $i_{a(k-1)}$, $u_{a(k)}$, $u_{a(k-1)}$, (armature current and voltage of the DC motor) and output $\omega_{m(k)}$ (mechanical speed). The activation functions in hidden layer are tansigmoids and output neuron has linear activation function. The network has been implemented in the speed structure of the DC motor and entire electrical drive was simulated in program Matlab - Simulink. Training stage is performed in Matlab using Levenberg-Marquardt algorithm.

For implementation of neural speed estimator onto control structure of the DC drive, it is necessary to obtain such training data, which determine the desired behavior of artificial neural network. The training data set was obtained from simulated DC drive in Matlab-Simulink (see Fig.4). For this purpose 60 000 samples were recorded for each of the input and output signals. It was achieved an error $1.10^{-4}$ during training stage.

## 7 Simulation Results

As it was mentioned above, all kinds of control systems were simulated in program Matlab - Simulink. The parameters of the DC motor are: $P_n = 15$ kW, $U_{an} = 440$ V, $I_{an} = 37.5$ A, $n_n = 2800$ rpm, $J = 0.24$ kgm$^2$, $R_a = 0.7\ \Omega$, $L_a = 8$ mH, $c\Phi_n = 1.42$ Vs.

First reference speed is changed from 100 [rpm] to -80 [rpm]. During this operation the drive works without load. Reference and actual speed responses of DC drive are shown in Fig. 5, 6. These characteristics show that speed response achieves better parameters (speed overshoot, settling time) when it is used NN predictive control than it is used conventional speed controller.

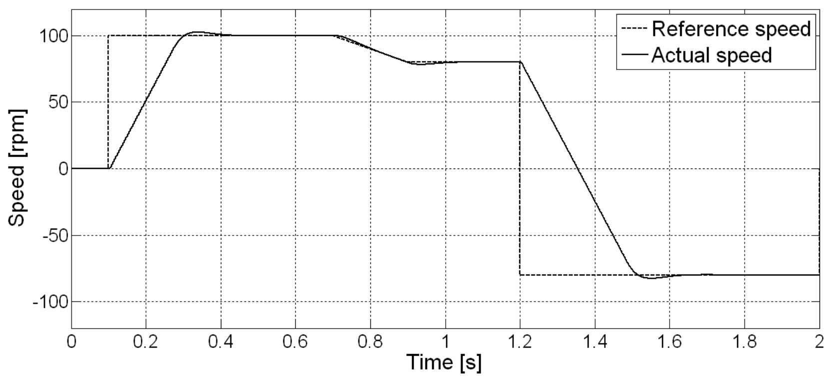


**Fig. 5.** Reference and actual angular speed responses of DC drive - conventional PI controller

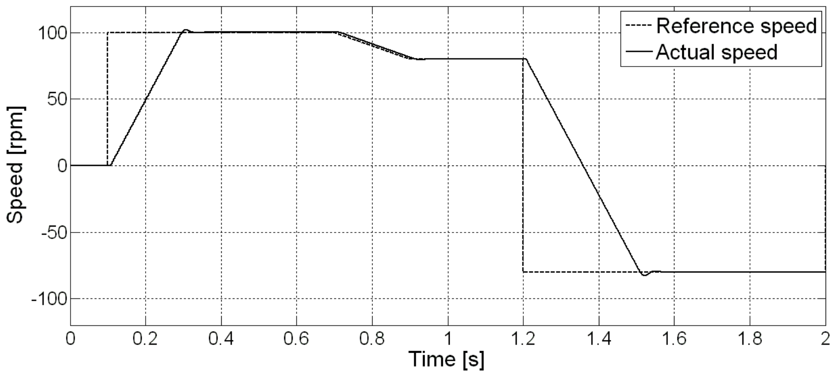


**Fig. 6.** Reference and actual speed responses of DC drive - Neural network predictive control

In the second stage after run-up, the electrical drive was loaded with rated torque. We can find out a conclusion that the NN predictive control achieves a shorter control time while the drive is subjected to load than conventional PI controller. So it is sure that NN predictive control increases robustness of the drive. Of course, it was tested another values of reference speed and load too.

For the control quality evaluation of the sensorless DC drive, it is important to assess the speed time course in different situations. Thus, the time course of reference speed was defined. The simulation was performed for the reference speeds which represent two speed areas: area of very low speed ($\omega_{m\_ref}$ = 10 rpm), area of low speed ($\omega_{m\_ref}$ = 100 rpm). The estimated speed is used as the feedback signal for the speed control.

For presentation, the simulation results in the area of the low speed ($\omega_{m\_ref}$ = 100 rpm) were selected (see Fig.7, 8). The figures 7 and 8 show the time response reference, actual and estimated speed for the sensorless control with feedforward artificial neural network. The difference between actual and estimated speed is shown in the Fig. 9.

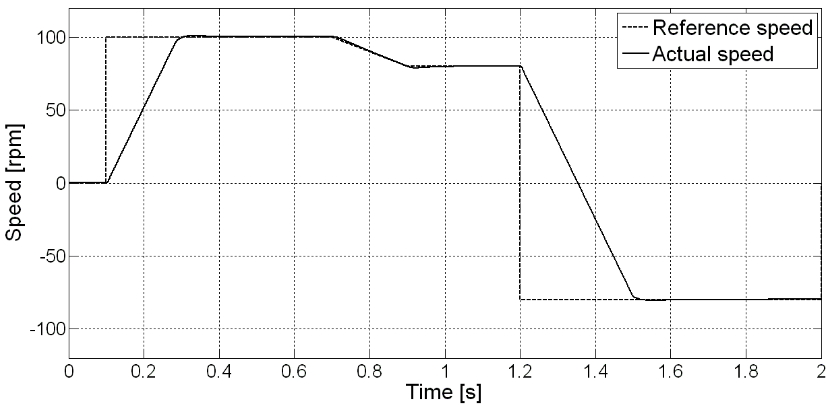


**Fig. 7.** Reference and actual speed responses of DC drive - sensorless control

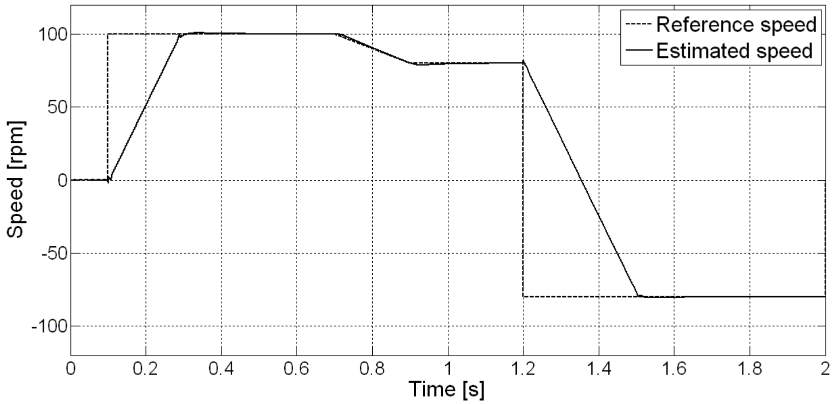


**Fig. 8.** Reference and estimated speed responses of DC drive - sensorless control

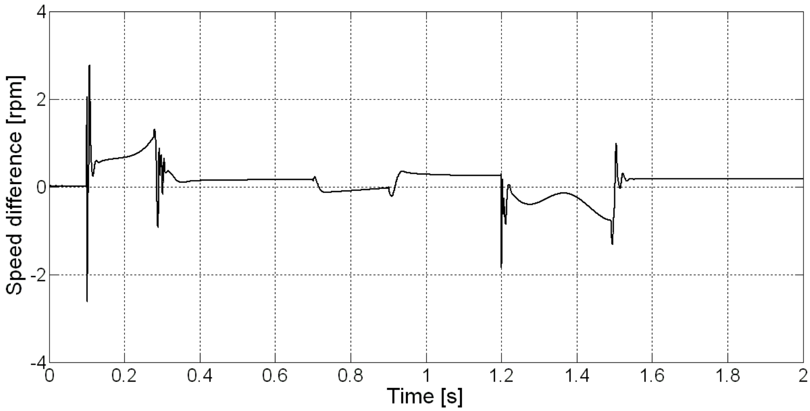


**Fig. 9.** Difference between actual and estimated speed response of DC drive - sensorless control

## 7 Conclusion

In the paper three kinds of control structures of the DC drive are presented. Two of them use artificial neural networks. The good results are achieved by the NN predictive control, especially while the drive is subjected to nominal load. This control method achieves a small overshoot and short settling time and increases robustness of the electrical drive.

The estimation method for sensorless DC drive with the speed control was presented further in the paper. The speed estimator is based on application of feedforward neural network. The sensorless DC drive with the presented speed estimator gives good dynamic responses and the estimation of the mechanical speed is satisfactory in steady state and also in transient state.

**Acknowledgments.** The article has been elaborated in the framework of the IT4Innovations Centre of Excellence project, reg. no. CZ.1.05/1.1.00/02.0070 supported by Operational Programme 'Research and Development for Innovations' funded by Structural Funds of the European Union and state budget of the Czech Republic and in the framework of the project SP2012/85 which was supported by Student Grant Competition of VSB-Technical University of Ostrava.

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