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Optimal configuration of the artificial neural network to estimate the speed of the BLDC motor

***Abstract**. The article presents the optimal configuration of the artificial neural network to estimate the rotational speed of the BLDC motor. The results of computer simulations of an electromechanical system containing a voltage converter, a BLDC motor and an artificial neural network block are presented. The simulation model used was designed in MATLAB/Simulink. The results of computer simulations for three different configurations of the artificial neural network are presented.*

***Streszczenie.** Artykuł przedstawia dobór optymalnej konfiguracji sieci neuronowej do odtwarzania prędkości obrotowej silnika BLDC. Przedstawiono wyniki symulacji komputerowych układu elektromechanicznego zawierającego przekształtnik napięcia, silnik BLDC oraz blok sieci neuronowej. Model symulacyjny został zaprojektowany w programie MATLAB/Simulink. Zaprezentowano wyniki symulacji komputerowej dla trzech różnych konfiguracji sztucznej sieci neuronowej. (**Dobór optymalnej konfiguracji sieci neuronowej przy odtwarzaniu prędkości silnika BLDC**)*

Keywords: artificial neural networks, BLDC motor, rotational speed estimation
Słowa kluczowe: sieci neuronowe, silnik BLDC, estymacja prędkości obrotowej

Introduction

The estimation of the angular velocity of electric motors is most often carried out with the use of observers, which in the computational process use the measured currents and voltages, and their mathematical relationships. In the scientific literature, the equations that describe the motor speed observer take into account the measured or estimated motor supply voltages and the measured phase currents in the αβ0 coordinate system (Clarke transformation) or in the dq0 coordinate system (Park transformation) as input data [5]. When detailed data regarding motor parameters are not available, a simpler implementation is an observer that operates in the αβ0 coordinates. It is worth emphasizing that the correct operation of the observer heavily depends on properly defined motor parameters. Modelling and simulation of dynamic operating states of drive systems is a common approach due to the possibility of studying phenomena and parameters that are difficult to measure in a real drive system [7], [8], [9], [10].

In the case of a BLDC motor, the electromotive force induced in the unpowered motor winding is often used to control the voltage converter appropriately. The problem arises at speeds below a dozen radians per second, when the value of the electromotive force is low. In this situation, relying solely on the aforementioned property can lead to disturbances in the motor's operation, manifested as speed fluctuations and electromagnetic torque ripples.

Artificial neural networks (ANN) are gaining increasing popularity in speed estimation algorithms of sensorless drive systems [6]. In electromechanical systems where the use of conventional measurement systems is challenging or impossible due to harsh operating conditions, such as high temperature or other external factors, the speed is most commonly estimated. The development of microprocessor systems, increased computational capacity, implementation of hardware units performing floating-point arithmetic, etc., enable the use of advanced methods for estimating the parameters of an electric motor.

The aim of the study is to select ANN parameters to achieve a satisfactory motor response in terms of the angular velocity. It is assumed that the number of hidden layers, the number of neurons for each layer, and the type of ANN will change (it is planned to use a feedforward ANN). The process of ANN training takes place within the MATLAB/Simulink environment using tools designed for artificial neural network development. For the purposes of the study, a script has been prepared that, upon activation, automatically sets parameters for the model of the motor along with the voltage converter, initiates the simulation model, and collects measurement data. Based on the gathered data, the ANN training process commences automatically at the end of the simulation. The generated neural network block, containing layers along with neurons and calculated weights, is implemented into the model of the electromechanical system.

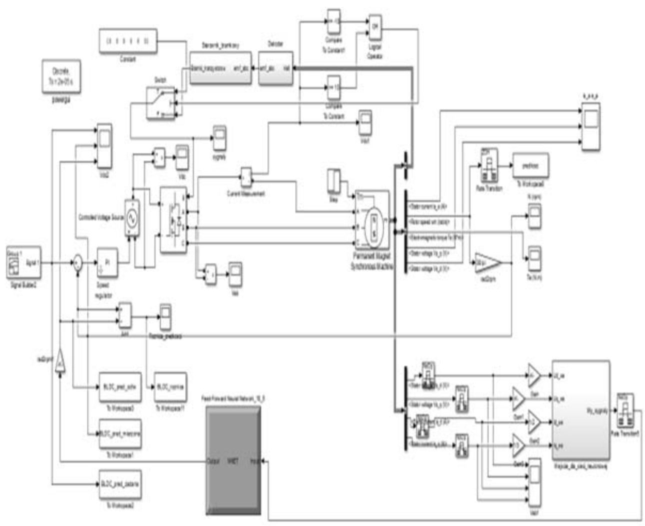

Fig. 1. Simulation model of a system containing a BLDC motor and ANN

Construction of the Simulation Model

The simulation model was developed using the MATLAB/Simulink package. The simulation model was prepared with the following assumptions:

- the motor block and the power supply section are based on blocks from the MATLAB/Simulink library,
- input signals to the ANN block are filtered by a low-pass filter,
- all simulations are conducted using the same parameters of the motor model and peripheral blocks,

- all simulations are carried out using the same reference velocity profile and a load torque of 3 Nm,
- the computer-based simulation is initiated using the same configuration parameters.

The BLDC motor model in the MATLAB/Simulink has been formulated based on the following equations, which describe the electrical and mechanical aspects of the motor:

$$u_d = Ri_d + L_d \frac{di_d}{dt} - N\omega i_q L_q, \tag{1}$$

$$u_q = Ri_q + L_q \frac{di_q}{dt} - N\omega i_d L_d, \tag{2}$$

$$u_0 = Ri_0 + L_0 \frac{di_0}{dt}, \tag{3}$$

$$T = \frac{3}{2} N\left(i_q i_d L_d - i_q i_d L_q\right) + [i_a \; i_b \; i_c] \begin{bmatrix} \frac{\partial \Psi_a}{\partial \theta_r} \\ \frac{\partial \Psi_b}{\partial \theta_r} \\ \frac{\partial \Psi_c}{\partial \theta_r} \end{bmatrix}, \tag{4}$$

$$\frac{d\omega_m}{dt} = \frac{1}{J}\left(M_e - M_{obc} - B\omega\right). \tag{5}$$

where: i_d, i_q, i_0 are motor currents in dq0 system; u_d, u_q, u_0 are motor voltages in dq0 system; L_d, L_q, L_0 are motor inductances in dq0 system; R is phase resistance; N is motor pole pairs; ω_m is angular velocity of motor; M_e is motor torque, M_{obc} is load torque, B is coefficient of friction in the motor bearings.

For the simulation, the BLDC motor model from the MATLAB/Simulink library, described by the above equations, was used. In this study, the main focus was on integrating the simulation model with the ANN block. Facilitating the entire process of the artificial neural network learning and creation was the use of scripts that automatically introduce variables, assign values to them, and initiate the simulation along with the start of the learning process.

To the control block governing the voltage converter operation, signals from Hall-effect sensors are additionally fed (Figure 2). These signals are directed to a decoding block for processing the Hall-effect sensor signals. Subsequently, they are input to a gate driver connected to the power converter block, which directly controls the operation of the BLDC motor.

Artificial Neural Network Model

The angular velocity is the most important parameter in the control process of a BLDC motor, affecting the efficiency, precision and energy saving of the entire system. In order to optimally select the artificial neural network to estimate the angular velocity of the BLDC motor, several crucial aspects were taken into account. Initially, an adequate amount of training data was collected, prepared during system simulations under normal operation. The collected relevant data was then archived and prepared for loading by the ANN learning algorithm. It's important to note that data must be appropriately filtered, as otherwise, the network might act as a low-pass filter without effectively estimating the output signal.

First-order low-pass filters were applied in this work to adequately prepare the signal used in the learning process. Since the ANN structure is intended to be used in a real SoC (System on Chip) setup, where simplicity is desired, a feedforward ANN architecture was chosen. The use of a cascade network was disregarded as the straightforward feedforward architecture yielded satisfactory results. After data preparation and ANN architecture selection, the model training process was initiated [2], [4].

In this study, three artificial neural network models were presented, differing in the number of layers and neurons. The first two models with two hidden layers demonstrated that ANN accurately estimates the angular velocity while maintaining a simplified model. The third model illustrated that increased complexity in the artificial neural network's architecture did not necessarily lead to an enhancement in the quality of the estimated signal.

Table 1. Artificial Neural Network configurations

Configurations	Network 1	Network 2	Network 3
Hidden layers	2	2	3
Number of neurons on 1 layer	10	20	50
Number of neurons on 2 layer	5	5	20
Number of neurons on 3 layer	0	0	5
Activation function	tansig		
Learning function	trainbr		

The neural controller was prepared based on the following assumptions:
- a feedforward network is used,
- the number of hidden layers and the number of neurons in each layer can change,
- all simulations are conducted using the same activation function,
- all simulations are carried out using the same artificial neural network training function,
- training of the artificial neural network takes place using the same configuration parameters.

Computer Simulations

Computer simulations were conducted using the MATLAB/Simulink. In the first stage, the model of the motor along with the voltage source inverter was activated using the written scripts. The simulation time was set to 30 seconds. This stage aimed to collect a sufficient amount of measurement data, which is essential for the artificial neural network learning process. The currents and voltages in the dq0 coordinate system and the motor speed were archived. Additionally, the script was designed to archive the load torque, enabling the network to be prepared for dynamic changes in the electromechanical system's load.

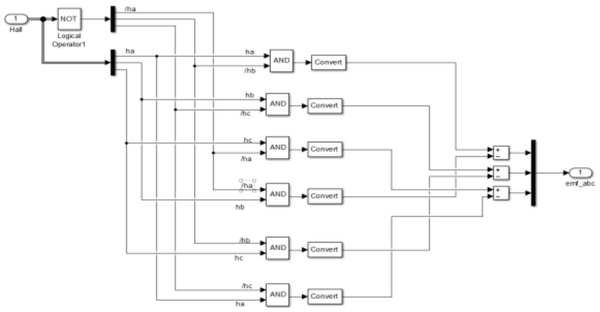

Fig. 2. Hall sensors decoder

The input signals to the filtering block are appropriately scaled, as an artificial neural network performs optimally when the input signals have a similar amplitudes. Additionally, several test signals have been extracted to verify the simulation model. The BLDC motor has five test signals extracted: stator current, rotor angular velocity, motor torque, stator voltage U_d, and U_q. The above-mentioned signals are essential to diagnose the operation of the BLDC motor in the simulation model.

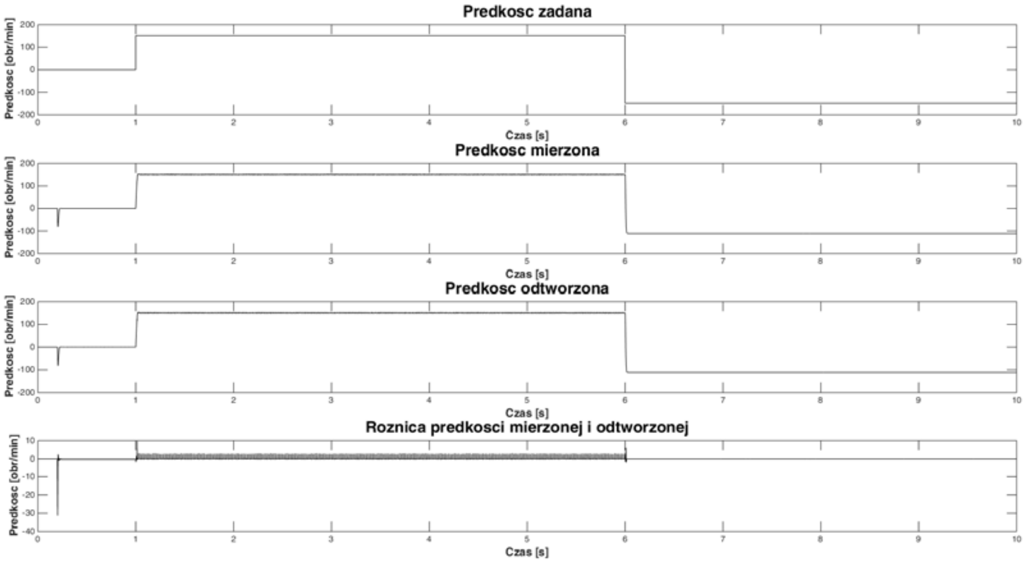

Fig. 3. Comparison of the rotational speed measured and estimated by the network with two hidden layers (number of neurons in the first layer: 10, in the second layer: 5)

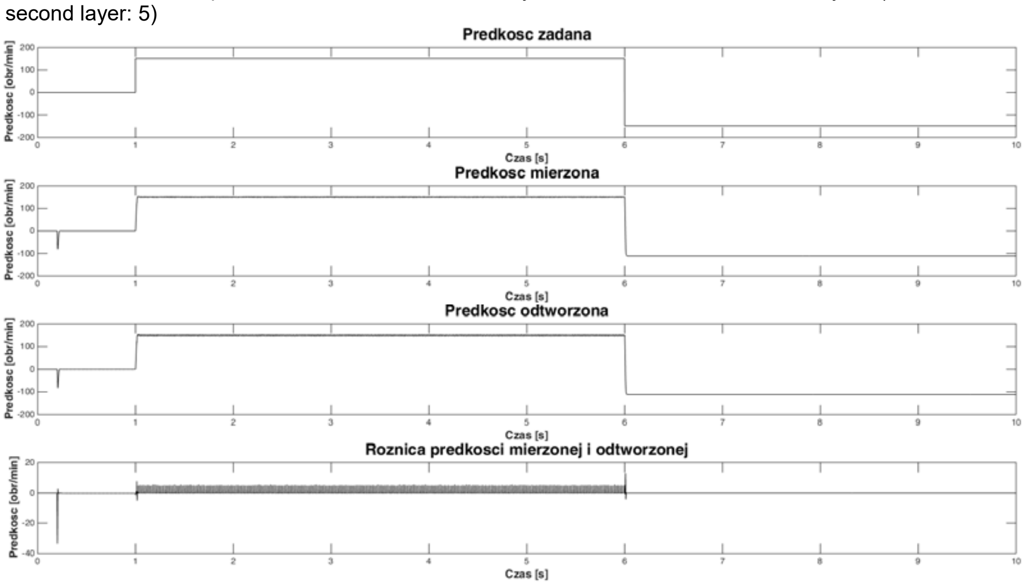

Fig. 4. Comparison of the rotational speed measured and estimated by the network with two hidden layers (number of neurons in the first layer: 20, in the second layer: 5).

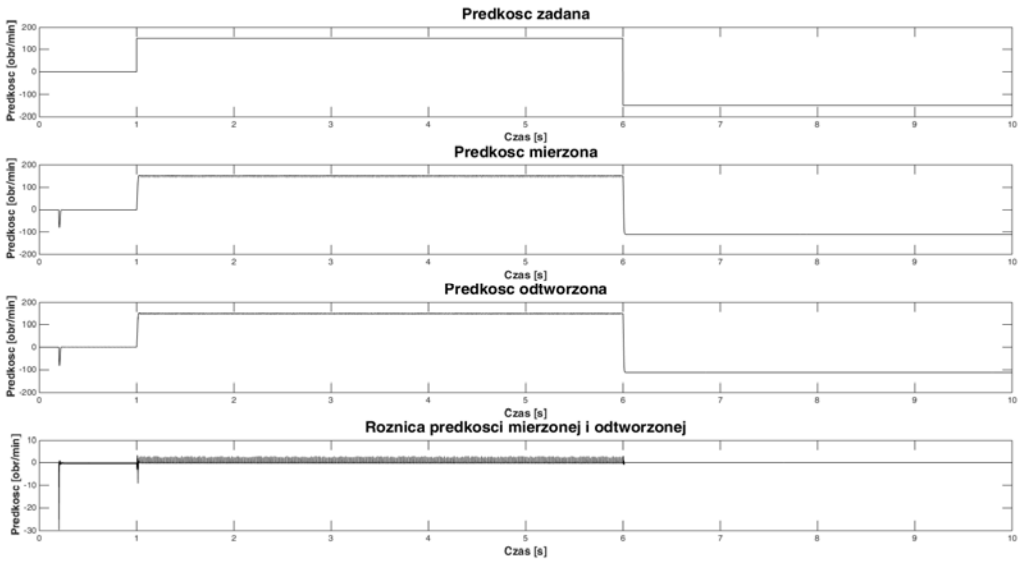

Fig. 5. Comparison of the rotational speed measured and estimated by the network with three hidden layers (number of neurons in the first layer: 50, in the second layer: 20, in the third layer: 5).

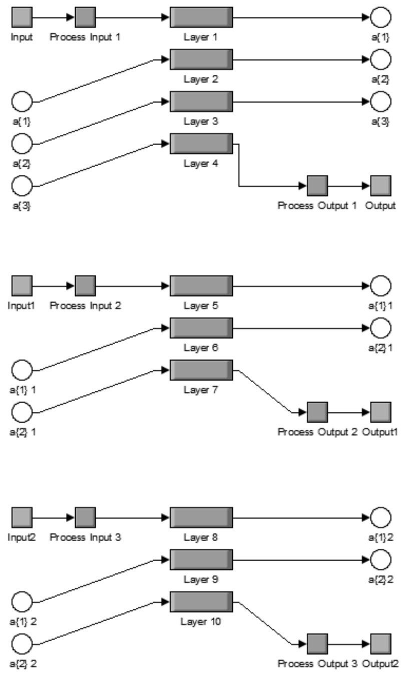

Fig. 6. Internal structure of three artificial neural networks used in the simulation model

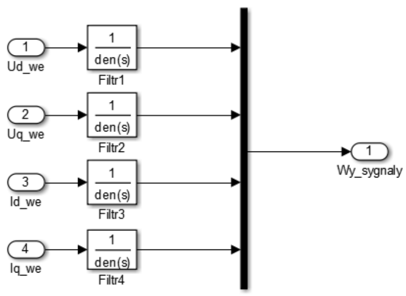

Fig. 7. Internal construction of a signal filtering block for an artificial neural network

Conclusions

The simulation model of the electromechanical system (illustrated in Figure 1) with a BLDC motor has been successfully formulated and executed. The construction of the model involved using simulation blocks from the MATLAB/Simulink package. The simulation model comprises the motor model, the power electronic converter model, and peripheral systems for archiving measurement data and controlling the operation of the electromechanical system. The modelled motor was energized by a three-phase voltage source inverter. The model of the electromechanical system has been equipped with a control system using signals from Hall-effect sensors. The model was used in the data archiving process, and the collected data was used in the learning process of the artificial neural network. The neural network training took place in MATLAB/Simulink. The "useParallel" command was used during ANN training to leverage parallel numerical computation, significantly reducing the network training time.

The artificial neural network was prepared in three different configurations, differing in the number of hidden layers and the number of neurons in each layer. The primary objective was to maintain a simple internal network structure, as it is intended for implementation in a real Zynq series SoC setup. Consequently, a cascade network was not employed due to its considerably higher complexity compared to the straightforward feedforward network. The simple feedforward artificial neural network accurately estimates the angular velocity, and it is worth noting that increasing the number of layers and neurons did not enhance the quality of the estimated angular velocity of the BLDC motor.

The conducted simulation studies demonstrate that the artificial neural network remarkably estimates the BLDC motor's rotational speed. Figures 3 to 5 show the reference speed, measured speed, estimated speed, and the difference between the measured speed and estimated speed for the three different artificial neural network configurations. The simulations were conducted according to the assumptions adopted for the formulation of the simulation model.

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