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Speed Control of BLDC Motor With Ripple Effect Reduction Using Recurrent Wavelet Neural Networks

Romanela Lajić, Petar Matić

Faculty of electrical engineering, University of Banja Luka

E-mail address: romanela.lajic@etf.unibl.org, petar.matic@etf.unibl.org

Abstract— ***The interest in research and use of the Brushless DC (BLDC) motor has increased significantly over the last few years, due to development of electric vehicles (EV) as well as to its use in other growing areas. With further predicted growth of the EV industry, it is expected that the BLDC motor will become even more significant. BLDC motor is a highly nonlinear, dynamic system, which in terms of its control makes tuning of controllers difficult, especially when high precision is required. Because of its operating principle BLDC motor also has issues with torque ripple which affects the speed response in a speed controlled system. In this paper an intelligent controller that combines a proportional-integral-derivative (PID) controller with a recurrent wavelet neural network is proposed. By using an intelligent controller, as an adition to a standard PID, the approximation ability of neural networks is used not only to deal with the nonlinearity of the system, but also to reduce the torque ripple influence on the speed response. By computer simulations it is verified that the proposed controller is able to completely neutralize the ripple effect and achieve good transient speed response. It is also shown that improved robustness against load disturbance compared to the system containing only a PID controller is achieved.***

Keywords- BLDC motor, modelling and simulation, motor control, recurrent WNN

I. INTRODUCTION

Brushless direct current (BLDC) motor has been heavily researched for the past few decades and has only increased in popularity during this time. Among other things, the use of BLDC in electric vehicles has further increased interest in its development. With the predicted surge of demand for electric vehicles in the upcoming years, BLDC motors are expected to play a vital role in the industry's development [1]. The BLDC has certain advantages when compared to conventional DC and induction motors such as: high dynamic response, high efficiency, high torque-to-weight ratio, long operating life and low operating noise. These qualities make the BLDC motor particularly suitable for uses where weight and noise are critical factors, such as aerospace, computers, automotive industry, and previously mentioned electric vehicles [2-4].

Proportional-Integral-Derivative (PID) controller, due of its simplicity and low cost, is still the most widely used type of controller in motor control systems for all types of motors. BLDC motor, combined with other components necessary for its running, such as the inverter and Hall sensors, makes a dynamic and highly nonlinear system [4]. These characteristics make the tuning of the PID controller parameters difficult, particularly for uses where high performance is required. Also, due to the construction and working principle of the BLDC motor, the torque, which should theoretically have constant value at steady state, in practice has a ripple effect which creates a ripple in the speed response. This effect cannot be neutralized with the use of a simple, conventional PID controller, resulting that the use of more complex controllers should be considered. The intrinsic approximation ability of neural networks makes them suitable for application as intelligent controllers in nonlinear dynamic systems [5]. In motor control drives neural networks are applied for various uses, such as position tracking [6], speed control [7-8], and online tuning of the PID controller [9].

In this paper we propose an improved speed control system for a BLDC motor containing an intelligent controller as an upgrade to conventional speed control scheme. The controller is a combination of a PID controller and a recurrent wavelet neural network. The proposed controller regulates the speed of the motor by directly changing the stator voltages, without inner current loop. The parameters of the controller are tuned using the Particle Swarm Optimization (PSO) algorithm. The parameters of the PID and the neural network parameters are trained simultaneously, which allows unison operation of both parts of the controller. The model of the motor, other elements of the system and the controller are created using MATLAB-Simulink to verify the results.

The paper is organized as follows: in Section II the basic functioning principle of the BLDC motor and its mathematical model are explained; In Section III basics of recurrent wavelet neural networks and the architecture of the network used in this paper are overviewed; In Section IV the structure of the new controller which combines the PID and the neural network is proposed, with the Simulink model of the system, and the training parameters; Experimental results obtained by using the model are presented in Section V. Section VI is the conclusion, with remarks on the main results.

II. BLDC Motor Speed Control System Model

BLDC motor is categorized as a synchronous motor with permanent magnets, due to its construction. The BLDC consists of a permanent magnet rotor, and a three phase stator winding. As opposed to other types of synchronous motors, which have sinusoidal current waveforms and sinusoidally distributed stator windings [10], the BLDC is ideally fed with rectangular currents, and the windings and the rotor magnets are distributed, so that the waveforms of back-EMFs are trapezoidal [11]. Ideal waveforms of back-EMFs and corresponding currents for the three phases of the BLDC motor are shown in Figure 1. [12]

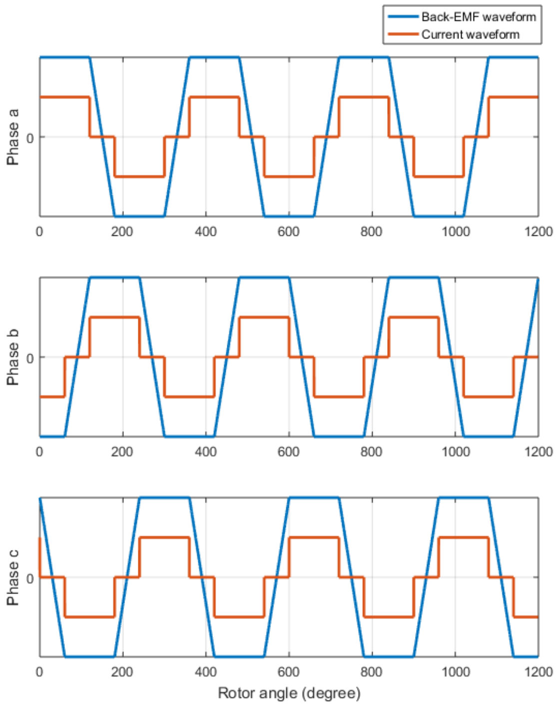

Figure 1. Ideal back-EMF and current waveforms of the BLDC motor

To achieve such characteristics, the stator windings of the BLDC motor are connected to a three phase inverter. Based on the rotor position (mechanical angle of the rotor measured to the stator), the inverter generates the appropriate stator voltages, and by doing that, it adjusts the directions of the currents in the stator phases. The information on the rotor angle is obtained through three Hall sensors, mounted on the stator. Based on the combination of states of the sensors, the trigger signals for the switches in the inverter bridge are generated. This operating principle is similar to that of an inverse DC motor. Whereas the currents in the conventional DC motor are commutated mechanically, in the BLDC commutation is performed electronically. As a result, the mathematical model of the BLDC motor is also similar to that of a DC motor.

Due to these similarities, and the absence of mechanical commutator and brushes, the BLDC has good dynamic response and relatively simple control algorithm of the DC motor, but with other advantages such as a long operating life, less required maintenance and low noise [13]. The lack of a commutator which is a limiting factor in the DC motor also makes the BLDC suitable for high-speed applications [14].

A. *Mathematical model*

In this subsection a short overview of the mathematical model of BLDC motor will be given. Based on this model we will create a Simulink model of the motor which subsequently becomes the basis for development of the control system. With the purpose of simplifying the model we have adopted the following assumptions: the magnetic circuit saturation, mutual inductance of stator phases and hysteresis and eddy current losses are neglected.

The circuit equations of the three stator phase windings are:

$$V_a = Ri_a + L\frac{di_a}{dt} + e_a\,, \tag{1}$$

$$V_b = Ri_b + L\frac{di_b}{dt} + e_b\,, \tag{2}$$

$$V_c = Ri_c + L\frac{di_c}{dt} + e_c\,, \tag{3}$$

where: V_a, V_b and V_c are the stator phase voltages; R is the stator winding resistance; L is the self-inductance of each phase; i_a, i_b and i_c are the phase currents, and e_a, e_b and e_c are induced back electromotive forces.

The equations for trapezoidal induced back electromotive forces, with waveforms as shown in Figure 1. are:

$$e_a = K_\omega f(\Theta_e)\omega_m\,, \tag{4}$$

$$e_b = K_\omega f(\Theta_e - 2\pi/3)\omega_m\,, \tag{5}$$

$$e_c = K_\omega f(\Theta_e + 2\pi/3)\omega_m\,, \tag{6}$$

where K_ω represents the electromotive force constant and ω_m the angular speed of the rotor. $f(\Theta_e)$ is a trapezoid-shaped function of rotor position which represents back-EMF reference, and is described as:

$$f(\Theta_e) = \begin{cases} 1, & 0 \le \Theta_e < \frac{2\pi}{3} \\ 1 - \frac{6}{\pi}(\Theta_e - \frac{2\pi}{3}), & \frac{2\pi}{3} \le \Theta_e < \pi \\ -1, & \pi \le \Theta_e < \frac{5\pi}{3} \\ -1 + \frac{6}{\pi}(\Theta_e - \frac{5\pi}{3}), & \frac{5\pi}{3} \le \Theta_e < 2\pi \end{cases}. \tag{7}$$

Mechanical and electrical angle of the rotor position, Θ_m and Θ_e are defined as:

$$\Theta_m = \int_0^t \omega_m dt\,, \tag{8}$$

$$\Theta_e = \frac{p}{2}\Theta_m\,. \tag{9}$$

The final two equations, which describe the BLDC motor, are the electromagnetic torque and the mechanical movement equations:

$$M_e = \frac{e_a i_a + e_b i_b + e_c i_c}{\omega_m}, \tag{10}$$

$$M_e - M_{opt} = J\frac{d\omega_m}{dt} + B\omega_m, \tag{11}$$

with M_e being the electromagnetic torque, J the rotor inertia and B the friction coefficient.

The states of the Hall sensors determine the current position of the rotor, providing the information for electronical commutation. An example of outputs of Hall sensors during the running of the motor are shown in Figure 2. The outputs of the inverter must, at any given moment, correspond to the rotor position in order to run the motor continuously. There are six possible states determined by three Hall sensors, and each of those states corresponds to exactly one switching state of the inverter, as shown in TABLE I. The states of three phase inverter switches are marked as Q_1-Q_6 and the outputs of Hall sensors as X,Y and Z.

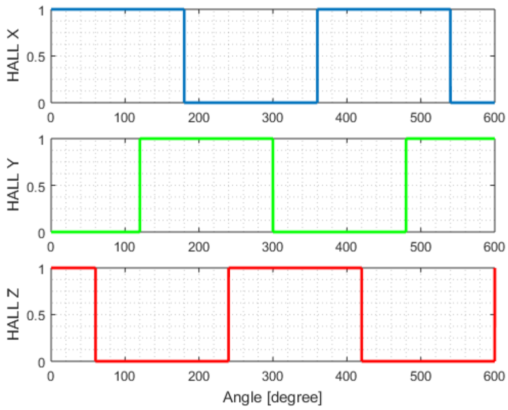

Figure 2. Example of Hall sensor outputs

TABLE I. MOTOR COMMUTATION TABLE

State of the inverter switches						State of the Hall sensors		
Q_1	Q_2	Q_3	Q_4	Q_5	Q_6	X	Y	Z
0	1	0	0	1	0	0	0	1
0	1	1	0	0	0	1	0	1
0	0	1	0	0	1	1	0	0
1	0	0	0	0	1	1	1	0
1	0	0	1	0	0	0	1	0
0	0	0	1	1	0	0	1	1

B. Speed control system

The model of the speed control system for the BLDC motor is shown in Figure 3. The Hall sensors provide information on the current position of the rotor, which is used to define the states of the switches in the inverter bridge for proper commutation. The rotor speed information, together with the speed reference is the input to the speed controller. The output of the controller is fed into a DC/DC bridge, which provides voltage reference proportional to the required speed. The inverter bridge commutates the phase voltages according to the commutation table. This base system contains only a speed loop, without inner current control, and the speed is controlled by directly changing the voltage level. The most frequently used type of controller in such system is the PID controller, widely used due to its simplicity, simple tuning and low cost.

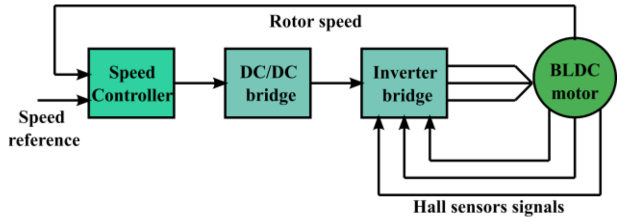

Figure 3. Block diagram of a BLDC motor control system

With the waveforms of currents and back-EMFs from Figure 1. the BLDC motor should theoretically produce constant torque. However, in reality, during the commutation in a certain phase, the average voltages in non-commutated phases are abruptly changed, which causes torque ripple [15]. The torque ripple produces unwanted speed ripple, which should be eliminated. However, use of a simple PID controller cannot reduce this effect, and several different methods are developed for this purpose [15-19]. Most of these methods require measuring of the phase currents using current sensors, which adds to the overall cost of the motor drive.

Both the problem of system nonlinearity and the torque ripple effect can be solved simultaneously by adding an intelligent type of controller, such as a neural network, to the PID controller. Since the controller is realized digitally, this modification adds no hardware costs to the system, and does not significantly complicate the control algorithm.

The proposed intelligent controller is added parallel to the PID controller as shown in Figure 4. Operating principle is equivalent to the one previously described for the system which contains only the PID controller, but in this case the control signal is the summation of the signals generated by the intelligent controller and the PID.

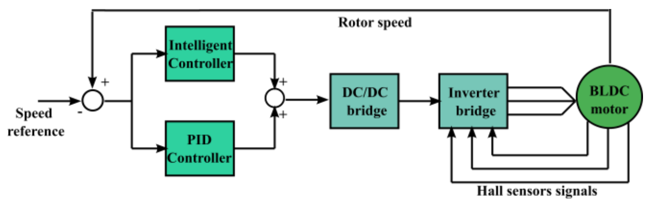

Figure 4. Block diagram of a BLDC motor control system with the addition of an intelligent controller

III. Recurrent wavelet neural network

Because of their adaptation abilities, neural networks have become a powerful tool frequently used for identification and control of dynamic systems. Besides adaptive learning, neural networks have characteristics such as generalization abilities and nonlinear mapping between inputs and outputs, which also makes them suitable to deal with complex nonlinear dynamic systems [20]. Theoretically, the weights of a neural network in any control system can be tuned to produce an ideal control signal [21]. Classic feed-forward networks were historically the first architecture utilized for this purpose. These types of networks have certain drawbacks when it comes to their use in control area. They typically have slow convergence, require a lot of computing power and have a tendency to settle in local minima [22].

In [23] a model of a wavelet neural network (WNN) is proposed as an alternative to feed-forward networks for approximating nonlinear functions. Wavelets are generally used in wavelet transform for frequency analysis of non-stationary signals. By combining the capability of wavelet decomposition and the adaptive abilities of neural networks, a high level of accuracy can be achieved in control of complex systems [24].

The activation function is what separates the WNNs from other types of neural networks. Instead of a sigmoid function, the neurons in the WNN's hidden layer, which are in that case called wavelons, use wavelets derived from the mother wavelet function Ψ as follows:

$$\Psi_{a_i,b_i} = \Psi\left(\frac{x-b_i}{a_i}\right), \tag{12}$$

where x represents the input of the wavelon, and a_i and b_i are the dilation and translation factors of the i^{th} wavelon. In this paper the Mexican hat wavelet function is used as a mother wavelet, and is described as follows:

$$\Psi(x) = (1-x^2)e^{\frac{x^2}{2}}. \tag{13}$$

Further improvements in the use of WNNs in system control came with the introduction of recurrent wavelet neural networks (RWNN). Recurrent networks add the advantage of their dynamic response and information storing ability to produce superior results to those when using feed-forward networks [25]. The input of the neurons in a recurrent network depends not only on the current input of the network, but also on the previous output of that neuron, which means that it can capture past information of the network and adapt rapidly to sudden change. These advantages also allow the use of a simpler model with fewer neurons compared to WNNs, and consequentially less computing power [26].

Architecture of an RWNN with M inputs and N wavelons in the hidden layer is shown in Figure 5. The three-layer network architecture, consisting of an input, an output and one hidden layer is common for all types of WNNs. In this paper we will focus on the architecture which has recursive connection only in the nodes of the hidden layer. The input of each node depends on the input of the network and the previous output of that node, but not the previous outputs of the other nodes in the network. By choosing this architecture we made balance between control simplicity and system performance.

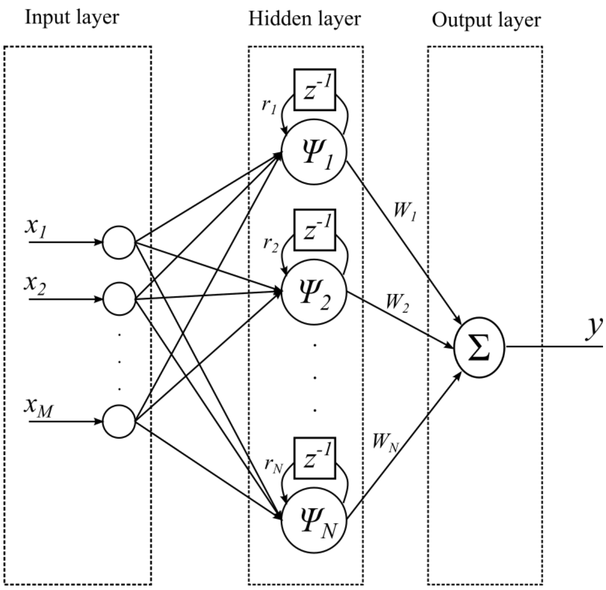

Figure 5. Architecture of a recurrent wavelet neural network

IV. Design of Modified Intelligent Speed Controller

In order to combine the advantages of both the PID and the RWNN, we parallel connect them to create a modified speed controller. We tune the parameters of the controller using the Particle Swarm Optimization algorithm by tuning the parameters of the PID and the RWNN simultaneously. The parameters of the RWNN which are tuned are the translation and dilation coefficients of each wavelon, as well as the weights of the network. The goal of the controller is to improve the transient speed response, robustness, and to reduce the ripple in the steady state response. Based on this, we choose the fitness function, which is minimized by the PSO algorithm as:

$$fitness = \int_0^T e^2(t)dt + e^2{}_{\max}. \tag{14}$$

The errors $e(t)$ and $e_{\max}$ are defined as follows:

$$e(t) = n(t) - n_{ref} \tag{15}$$

$$e_{\max} = n_{\max} - n_{ref} \tag{16}$$

where: n_{ref} is the speed reference (user input); $n(t)$ is the the rotor speed; n_{max} is the maximum value in the speed response, and T is the runtime duration.

By defining the fitness function this way, we train the controller to minimize the steady state error and the overshoot. Minimizing the steady state error reduces the ripple and keeps the steady state response at a required constant value.

A. Simulink model

In order to validate the performance of the proposed intelligent controller, a Simulink model of the overall system shown in Figure 4. is created. The overall model is shown in Figure 6. with subsystems shown in Figure 7. (model of the BLDC) and Figure 8. (model of the proposed intelligent controller). Main characteristics of those systems will be described briefly.

BLDC motor is fed from a three-phase inverter supplied from a controlled DC source, Figure 6. Inverter states are determined from the commutation table, and speed is regulated using a controller in speed feedback.

Figure 7. shows the model of the BLDC created based on the mathematical model (1-11). Trapezoidal base function of the back-EMF is implemented as a lookup table, where the output of each phase depends on the angle of the rotor. Hall sensors are also modeled as a lookup table with rotor position as an input and the logical levels of the states as outputs.

The intelligent controller, Figure 8. consists of the PID controller connected parallel to the RWNN. The RWNN portion of the controller has three layers, with four wavelons in the hidden layer. The speed reference and the mechanical speed of the rotor act as the input signals of the controller. The fitness function, which is minimized during the training procedure, is computed directly in this subsystem of the model.

B. Training parameters

The parameters of the controller are tuned using the Particle Swarm Optimization algorithm. The algorithm is implemented as a MATLAB function which starts the simulation of the system for each particle, in order to compute the value of the fitness function. The number of particles we have chosen is 50.

The dimensionality of the problem depends on the number of parameters of the controller being tuned. In our case we have 18 parameters: 16 network parameters and 2 PID parameters. Network parameters include the dilation and the translation factor of the wavelet activation function in each of the nodes in the hidden layer, and the weights of the direct and recursive connections. PID parameters are the proportional and integral gains, with the derivative gain set to zero.

The training is done in 200 iterations. In the first iteration the parameters of each particle are initialized with random values. After that, the parameters are updated by the PSO algorithm, until the selected number of iterations is reached.

The convergence of the model and subsequently the final performance of the system are affected by how well the particles are initialized in the first step. We selected a range of values from which to set the parameter values, and in this case those values are drawn from uniform distribution in the range [-10, 10].

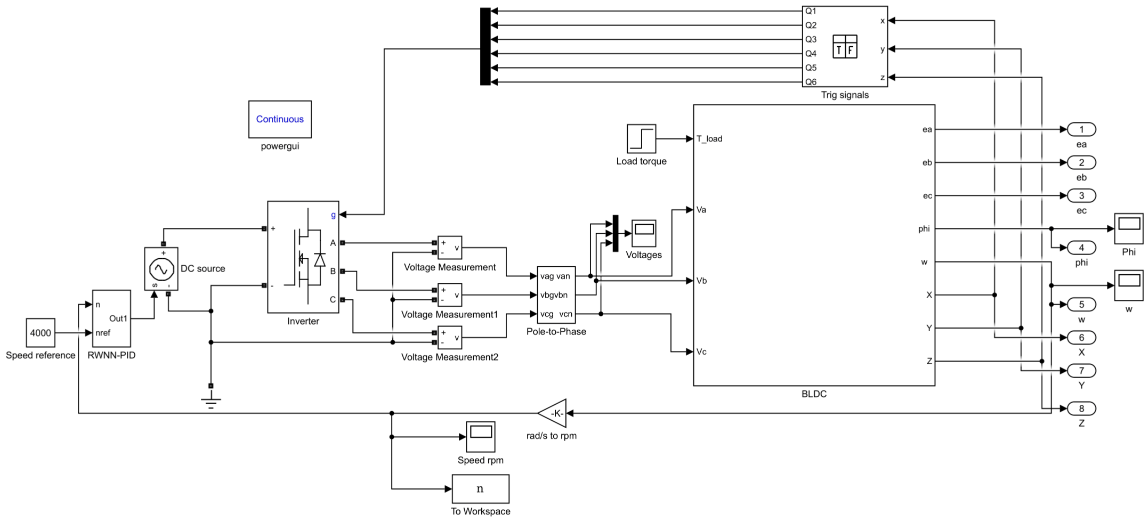

Figure 6. Model of the overall system

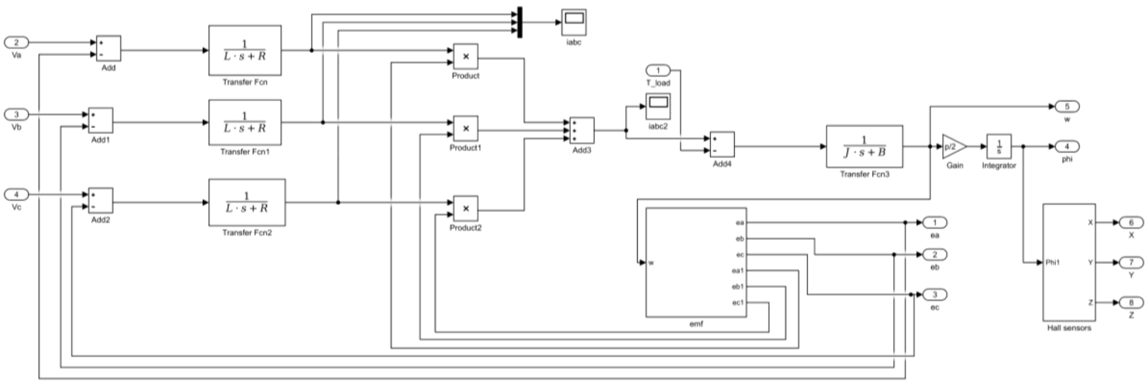

Figure 7. Model of the BLDC motor

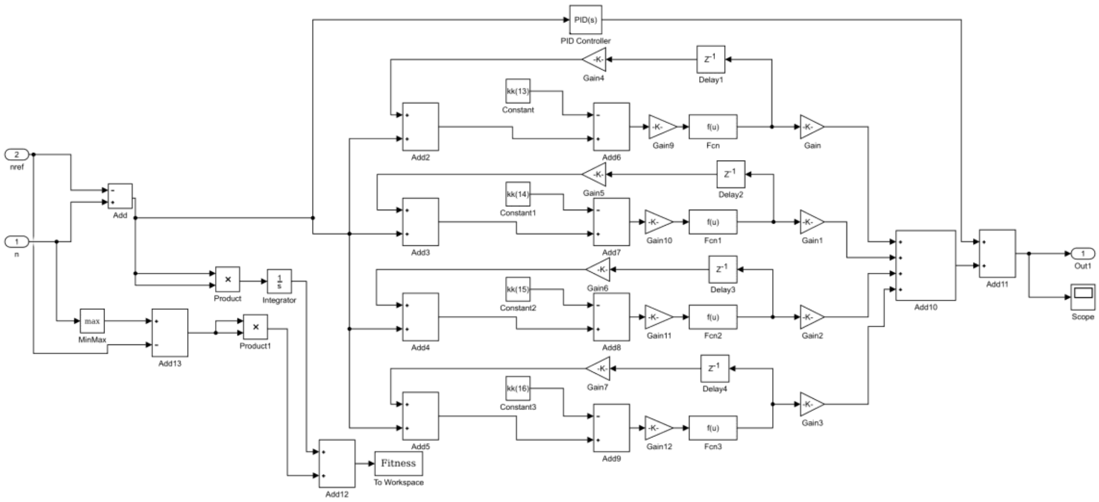

Figure 8. Model of the proposed intelligent controller

V. SIMULATION RESULTS

The performance of the BLDC motor speed control system with the modified, intelligent controller is validated by the results of computer simulations in three different modes and compared with classical PID structure. In the first mode we set a constant speed reference with no load torque to both systems, Figure 9. and Figure 10. In the second mode we set a constant speed reference and apply the load torque to both systems also, Figure 11. Figure 12. and Figure 13. In the third mode we set a step speed reference to the intelligent controller only, Figure 14.

In the first mode we set a constant speed reference of 5000 rpm with no load torque to both systems. The results are shown in Figure 9. By comparing the two responses, we can see that the modified controller completely neutralized the ripple in the speed response, compared to the classical PID. The modified controller also achieves good transient response, which can be seen in Figure 10. in which the enlarged traces of output speed are shown. The proposed controller has shorter rise time than classical PID but with larger overshoot.

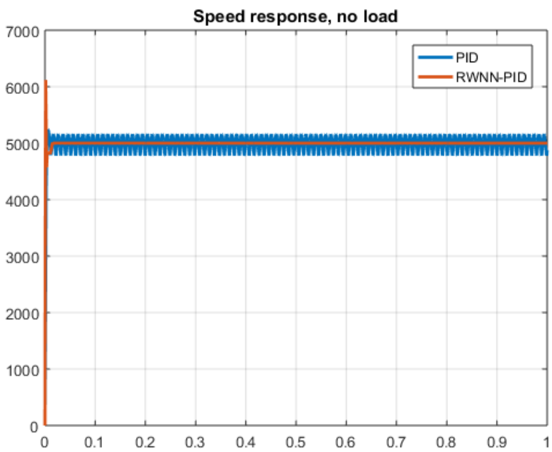

Figure 9. Speed response of the two systems with no load torque

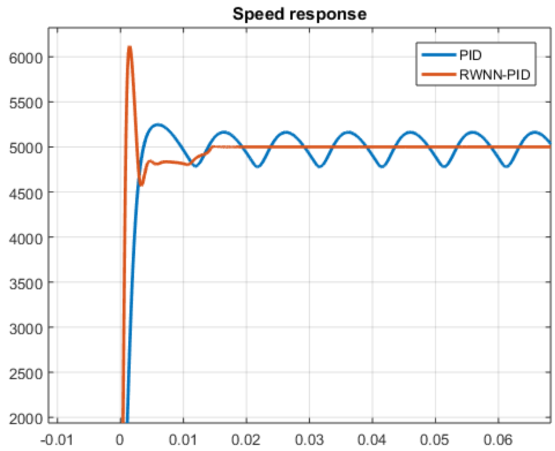

Figure 10. Transient speed response of the two systems with no load torque

In the second mode we set the same speed reference to both systems, but with load step at t=0.5 s. The results are shown in Figure 11. and Figure 12. (enlarged view).

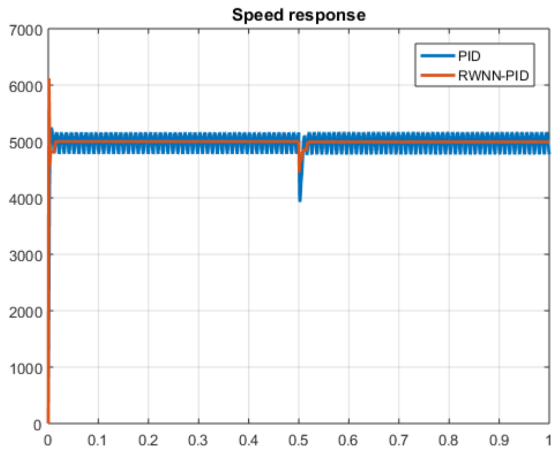

Figure 11. Speed response of the two systems when load is applied

By observing the results it is noticeable that the controller provides good steady state response with and without load torque. It can be concluded that the modified controller shows better robustness than the PID controller, because the speed drop is lower.

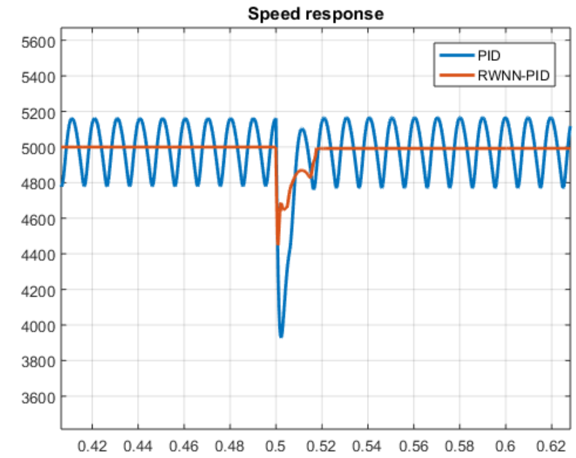

Figure 12. Speed response of the two systems in the moment the load is applied

Torque response is shown in Figure 13. from which it can be seen that the proposed controller provides fast torque response with the ripple eliminated.

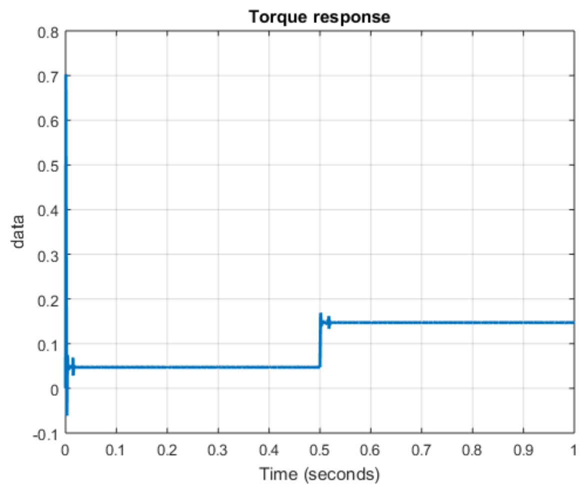

Figure 13. Torque response of the system containing the modified controller when load is applied

In the third operating mode, we set a step reference with a train of step increase of 1000 rpm every *t*=0.2 s. The results are shown in Figure 14. As it can be seen, the system response is satisfying for different reference values and in speed changing conditions. Also, it can be seen that speed ripple is eliminated by the proposed intelligent controller.

Finally the waveforms of the reference phase voltages for PID controller , Figure 15. and modified intelligent controller, Figure 16. are shown. In both cases the load torque is set to zero. By observing the figures it is clear that intelligent controller adjusts the voltages to neutralize the speed ripple.

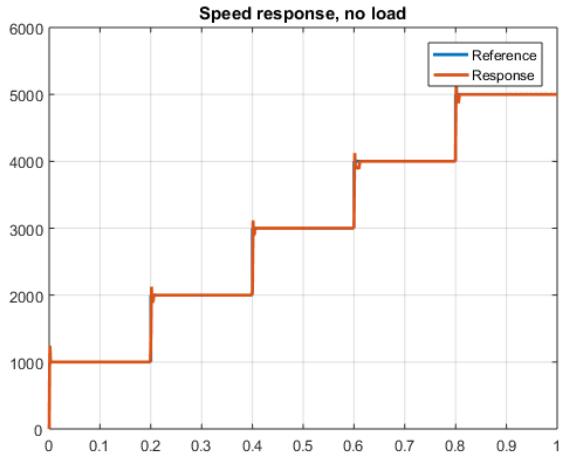

Figure 14. Speed response of the system to a step reference

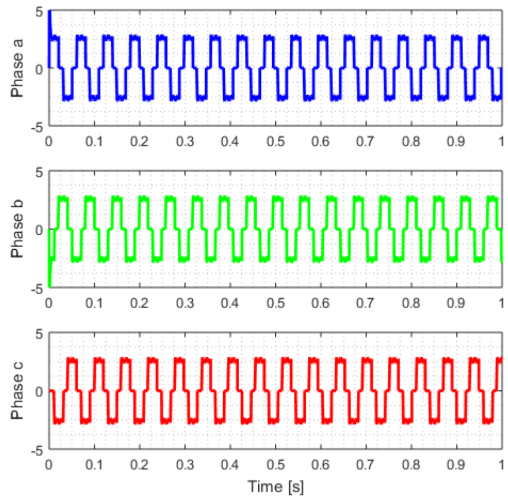

Figure 15. Motor phase voltages in no load condition, PID controller system

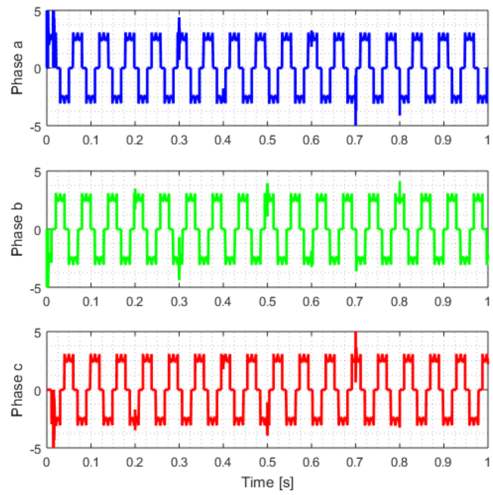

Figure 16. Motor phase voltages in no load condition, modified intelligent controller system

VI. CONCLUSION

In this paper we propose a control system for a BLDC motor which contains modified, intelligent type of controller. The controller consists of a PID controller and a recurrent wavelet neural network, operating in parallel. The intelligent portion of the speed controller is able to deal with the nonlinearity and dynamic characteristics of the BLDC motor, and to minimize the ripple effect in the torque and speed response.

The proposed controller is modeled in the MATLAB/Simulink environment, the parameters of the controller are tuned and the performance of the overall system is tested in different modes. We compared the results to a system containing only a classical PID controller in order to justify the performance. We have shown that the proposed controller, when properly tuned, does not only achieve good transient and steady state response, but is also able to completely neutralize the ripple effect in the torque and speed. We have achieved this only by modifying the control algorithm, without the use of current control or adding current sensors to the system. The modified controller also shows good behavior in load and speed changing conditions, and improves robustness of the drive compared to the PID controller.

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Romanela Lajić received the B.Sc. degree in Electrical Engineering from the University of Banja Luka, Republic of Srpska, Bosnia and Herzegovina in 2020, where she is employed as a teaching and research assistant. She is currently working toward the M.Sc. degree at the University of Banja Luka. Her current research interests include electrical machines and drives and machine learning.

Petar R. Matić received the B.Sc. and M.S. degree in Electrical Engineering from the University of Novi Sad, in 1999 and 2002, and Ph.D. degree from the Electrical Engineering Faculty, University of Belgrade, in 2011. He is an associate professor (2017-present) and Head of Department of Electrical Power Engineering, Faculty of Electrical Engineering, University of Banja Luka,. His research area includes power engineering, electrical machines and electrical drives.