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A Comparison of PI and RBF Brushless DC Motor Speed Control Methods

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***Abstract*—Brushless Direct Current (BLDC) widely used in electromobility and industrial robots. BLDC motors are essential in many production applications. However, they encounter significant challenges when it comes to executing control of speed. Due to their simplicity, speed controllers are often designed using Proportional Integral (PI) regulation. The saturation of standard PI control makes the system unreliable, hence an online radial basis function (RBF) neural network is proposed. The paper compares and evaluates the speed response of two regulators under a reference speed of 3000 RPM. The purpose is to examine and contrast the performance of these regulators in regulating the speed of the system. In comparison to the traditional PI controller, the presented controller demonstrates superior characteristics such as lower overshoot, improved response speed and greater anti-disturbance capability. The studies are conducted in MATLAB/Simulink.**

Keywords*—*Brushless DC Motor, PI Controller, RBF, Speed Response

I. Introduction

DC motors were the most commonly used for manufacturing purposes, partly because of their ease of control. But because of the substantial risk of sparks developed by the brushes of a DC motor, it is not suitable in applications which demand a long lifespan. To compensate for this, the BLDC has grown into one of the most prevalent machines in power systems owing to its improved torque, vital speed, and exceptional preciseness [1]. As a consequence of its improved dynamic performance and lack of frequent servicing, it is regarded as one of the top selections for applications such as electric vehicles [2], [3].

There are many other switching techniques that are now being used for BLDC motor controllers, such as trapezoidal and sinusoidal commutation [4]. When using a trapezoidal commutation, it is possible for two of the three windings to continue to receive electricity at the same time. The phase shift that is used in the sinusoidal control strategy is compliant with the law of sines [5]. It enables a more seamless transitioning of current between the phases than would otherwise be possible. Trapezoidal commutation is easier; however, it may disturb the motor at low speeds. Sinusoidal current waveforms run smoothly, although high-speed commutation is challenging [6], [7]. The trapezoidal control approach is one that is utilised frequently.

Controllers affect BLDC motor operation. It regulates the current and voltage needed for one complete rotation. The Proportional-Integral-Derivative (PID) approach is extremely popular due to the fact that it is both practical and efficient. Three gain parameters—K_p, K_i, and K_d—identify a PID controller. These three parameters are usually fixed. PID controllers struggle with system unpredictability, parameters change, and environmental interference. Maintaining BLDC motor speed under fluctuating loads can be challenging [8], [9].

The utilisation of neural networks is deemed appropriate for the regulation of nonlinear systems. The utilisation of the radial basis function neural network (RBFNN) results in the acquisition of a distinctive network structure. It possesses notable benefits in comparison to alternative forms of neural networks. The benefits encompass enhanced approximation capability, streamlined network architecture, and expedited learning velocity [10]–[12]. The utilisation of RBF neural network controllers exhibits promising potential in the domain of controlling nonlinear and uncertain targets.

To accomplish the desired outcomes of stability, speed, precision, and resilience in BLDC motor drivers, an online RBF controller is developed and compared to a traditional PI controller. The primary purpose of this study is to investigate a controller strategy, via the use of a more straightforward approach, regulates the fluctuating speed of a motor. The simulation work is conducted via MATLAB/Simulink, and the results of each scenario are provided with a comprehensive analysis and explanation.

II. BLDC Motor

A. Architecture

BLDC motors are constructed similarly to three-phase synchronous motors. The stator contains three separate windings, while the rotor is equipped with permanent magnets. The motor operates using a semiconductor-based electronic commutation circuit [13]. By turning electronic components on and off, this circuit delivers electric power to the motor. The circuit diagram for a BLDC motor driving system is presented in Figure 1.

Hall effect detectors analyse the rotor's location to establish the order of switches. The rotor will revolve due to the torque created as current flows through the windings. The controller analyses the rotor's current orientation to decide where the power switches should be moved (Decoder). Figure 2 depicts the rotation of the rotor as a result of the six-step synchronisation.

Table I depicts the hall sensors and switches that modify position values while the rotor is turned [14]. The rotor's interaction with the push and attract depends on its current location. The rotor's rotation is maintained using quick switching operations.

B. Mathmatical modelling of BLDC

The BLDC motor is characterised by a symmetrical and balanced three-phase configuration. The permanent magnet's high resistance value results in the rotor current being ignored [15].The BLDC motor is trained as a consequence of the interaction that occurs between the permanent magnet and its coils [6], [16]. Figure 1 displays the corresponding circuit model of a BLDC motor. The matrix representation of the phase voltage mathematical equations is presented in Eq. (1).

$$\begin{bmatrix}E_a\\E_b\\E_c\end{bmatrix}=\begin{bmatrix}R&0&0\\0&R&0\\0&0&R\end{bmatrix}\begin{bmatrix}i_A\\i_B\\i_C\end{bmatrix}+\frac{d}{dt}\begin{bmatrix}L-M&0&0\\0&L-M&0\\0&0&L-M\end{bmatrix}\begin{bmatrix}i_a\\i_b\\i_c\end{bmatrix}+\begin{bmatrix}E_a\\E_b\\E_c\end{bmatrix} \quad (1)$$

Where
E_a, E_b, E_c: Voltage of each phase (V)
i_A, i_B, i_C: Current of each phase (A)
R: Resistance of each windings (Ω)
L -M: Mutual and self-inductances (H)

An expression for the electromagnetic torque produced by a BLDC motor is given in Eq. (2).

$$T_e = \frac{E_a\, i_a + E_b\, i_b + E_c\, i_c}{\Omega} \quad (2)$$

Where
T_e: Electromagnetic torque (Nm)
Ω: Angular velocity (rad/sec)

Mathematical model of the electromechanical system that is associated with the action of the motor is presented in Eq. (3).

$$T_e - T_L = J\frac{dw}{dt} + \beta_v \quad (3)$$

Where
T_L: Load torque (Nm)
J: Moment of inertia of the motor and the load it drives
β_v: Damping constant (Ns/m)

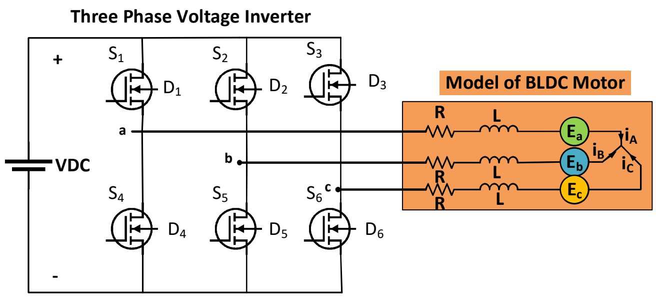

Fig. 1. Three-phase voltage inverter for BLDC motor control

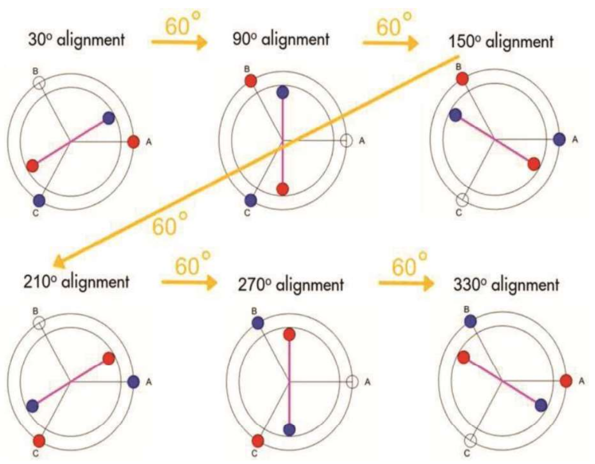

Fig. 2. BLDC motor with six-step commutation [17]

Table I. Truth table for the gate pulse and decoder [14]

Back Emf			Hall sensors			Location of switches					
E_a	E_b	E_c	H_1	H_2	H_3	Q_1	Q_2	Q_3	Q_4	Q_5	Q_6
0	0	0	0	0	0	0	0	0	0	0	0
0	-1	+1	0	0	1	0	0	0	1	1	0
-1	+1	0	0	1	0	0	1	1	0	0	0
-1	0	+1	0	1	1	0	1	0	0	1	0
+1	0	-1	1	0	0	1	0	0	0	0	1
+1	-1	0	1	0	1	1	0	0	1	0	0
0	+1	-1	1	1	0	0	0	1	0	0	1
0	0	0	1	1	1	0	0	0	0	0	0

III. Controller Design

A. PI Controller

The primary reason for the widespread adoption of PI controllers is the ease of which they may be adjusted and regulated. The BLDC motor is a system, and like other systems, it contains a number of different parameters and, as a result, the danger of saturation. Control methods that are based on PI regulators are utilised in the majority of instances for the purpose of regulating speed [6].

Figure 3 illustrates the block diagram of a PI controller. PI controllers are primarily utilised for the purpose of regulating the duty cycle, as reported by previous research in ref [18]. It can be inferred that the velocity of a BLDC motor is directly proportional to the magnitude of the applied voltage (input voltage). The speed of the motor is cross-referenced with the intended speed. Any deviation in the speed caused by environmental factors will be detected as an error signal and transmitted to the PI controller, which will subsequently modify the duty cycle in response to the generated error. The possibility of response delay is a potential outcome attributed to the controller's inherent characteristics [4].

The PI controller Eq is presented in Eq. (4).

$$r(t) = K_p\, e(t) + \frac{K_p}{T_i}\int_0^1 e(t)dt \quad (4)$$

Where
$r\,(t)$: Output signal's function
$e\,(t)$: Input signal's function
T_i: Integral time constant

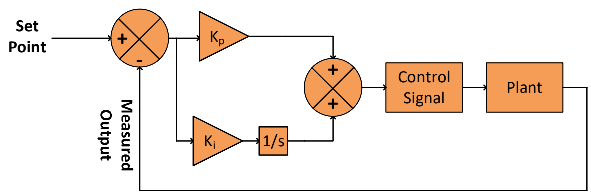

Fig. 3. Block diagram of PI controller

One issue with PI controllers is that their outputs can overshoot if the controller's parameters are set too high. A

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BLDC motor's speed can be controlled with the help of an RBF controller, which offers improved dynamics as well as greater response [19].

B. RBF Controller

Several distinct varieties of ANNs (Artificial Neural Network) have been developed. The RBFNN is highly effective, due to its characteristics of responding to the system changes and requires less computation time. For example, if the system is subject to a great deal of instability, such as from outside influence and communication lag, this approach can be used to great success to boost the controller's reliability. The RBF neural network is a feedforward network with an input, hidden layer, and output layer, depicted in Figure 4.

RBFN is structured into three distinct layers, namely the input layer, the hidden layer, and the output layer. The information is transmitted from the input layer to the hidden layer via a signal. The data being processed is transmitted from the hidden layer to the output layer, where it is linearly summed and outputs the result [20]. RBFN can undergo training through either offline or online methods which can also know as batch learning and pattern learning, which exhibit distinct differences in their respective methodologies and utilise data for training [21]. During pattern learning mode, the model is continuously updated with new data as it becomes accessible, as opposed to a batch learning mode where all data is already provided. Online RBF enables the network to dynamically adjust and learn from new observations in real-time, making it well-suited for environments that are constantly changing and evolving [21].

The RBF input trajectory is denoted by $X = [x_1, x_2, \dots x_n]$, the hidden layer's radial basis trajectory is denoted by $H = [h_1, h_2 \dots h_m]$ and the network's output is denoted by y_m [22]–[24]. Different schemes of different activation function can be seen in Figure 5 that are available such as sigmoid, and gaussian etc. In this paper, gaussian function has been opted as an activation function because of its straightforward structure, balanced arrangement and excellent stability. Eq. (5) is a mathematical expression to obtain gaussian activation function [22]–[24].

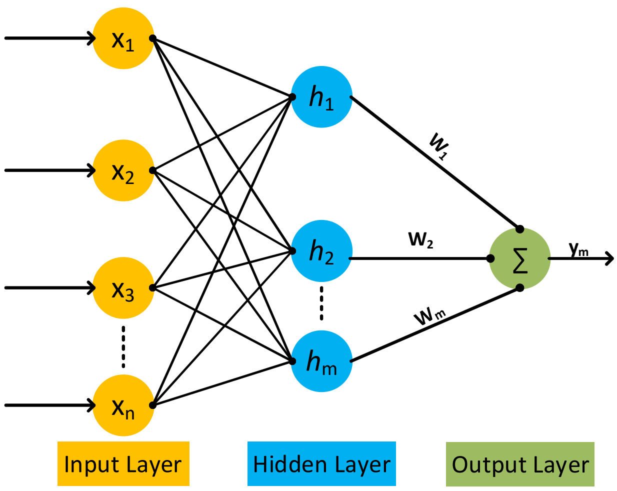


Fig. 4. RBF neural network structure

$$h_j = e^{\left(-\frac{\|x-c_j\|^2}{\sigma_j^2}\right)}, j = 1,2, \dots m \tag{5}$$

Where

$\|x - C_j\|^2$: Euclidean norm

C_j: Centre vector of the j_{th} hidden layer neuron node

σ_j: Width of the j_{th} hidden layer neuron node

h_j: Output of the j_{th} node of the hidden layer

The network parameters (C_j, σ_j, w_j) are trained using gradient descent approach, which results in small but steady adjustments to each parameter. The error issued by the system-managed variables is utilised to adjust the network's settings. These modifications make the RBF network more efficient, enhance its generalisation capability and verify that it truly matches the actual distribution of the underlying data [22]–[24]. The gradient descent method updates the three network parameters as shown in Eq (6) [22]. RBF neural network has been considered to be the best choice in terms of reliability, preciseness, durability, number of samples, effectiveness, and ease.

$$\begin{cases} E_1 = \frac{1}{2}\left(y(t) - y_m(t)\right)^2 \\ \Delta w_j(t) = -\eta \frac{\partial E_1}{\partial w_j} = \eta\left(y(t) - y_m(t)\right) h_j \\ w_j(t) = w_j(t-1) + \Delta w_j(t) + a\left[w_j(t-1) - w_j(t-2)\right] \\ \Delta b_j = -\eta \frac{\partial E_1}{\partial b_j} = \eta\left(y(t) - y_m(t)\right) w_j h_j \frac{\|x-c_j\|^2}{\sigma_j^3} \\ b_j(t) = b_j(t-1) + \Delta b_j + a\left[b_j(t-1) - b_j(t-2)\right] \\ \Delta c_{ij} = -\eta \frac{\partial E_1}{\partial c_{ij}} = \eta\left(y(t) - y_m(t)\right) w_j h_j \frac{x_j - c_{ji}}{b_j^2} \\ c_{ji}(t) = c_{ji}(t-1) + \Delta c_{ji} + a\left[t-1) - c_{ji}(t-2)\right] \\ y_m = \sum \left(w_j * e^{\left(-\frac{\|x-c_j\|^2}{\sigma_j^2}\right)}\right) \end{cases} \tag{6}$$

Where

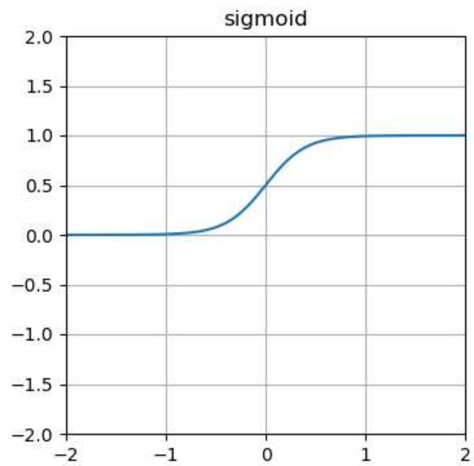
E_1: Network identification performance index

y(t): The output of the system at a specific time t

w_j : Output layer weight vector

η: Rate of learning. Typically, a value within the range of 0 to 1 is picked in order to guarantee the achievement of convergence of the iterative algorithm.

a: Momentum coefficient. Typically selected within the range of 0 to 1



(i)

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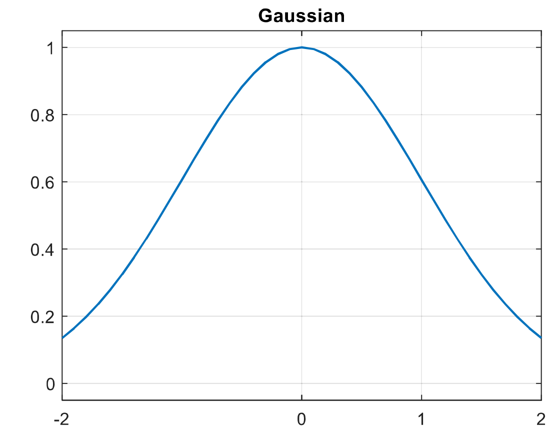

(ii)

Fig. 5. Different activation functions: (i) Sigmoid, (ii) Gaussian [25]

IV. Simulation Results

A simulation model for a BLDC motor controller has been designed using MATLAB/Simulink environment in order to assess the outcomes of the outlined control approach. The study utilised a conventional PI controller and an online RBF neural network for the simulation. Table II outlines the set of parameters used in simulation for designing BLDC.

Table II. Parameters of simulation

Parameters	Value
Number of poles	4
Back EMF waveform	Trapezoidal
Stator phase resistance (Ω)	2.8750
Stator phase inductance (H)	8.5e-3
Flux linkage	0.175
Back EMF flat area (°)	120
K_p	1
K_i	318.4
Controlled Voltage Source	100 V DC

The simulated design of the BLDC motor's speed output can be seen in Figure 6. By comparing the behaviour of both controller conventional PI & online RBF controller, the following were considered during the design of BLDC:

- Reference speed of 3000 RPM
- Constant torque

Figures 7 & 8 display the simulation results of the conventional PI and online RBF controller's impact on the speed response of a BLDC motor design. The results indicate that the PI controller exhibits a prompt speed response of 3000 RPM, attaining stability in a shorter duration of 0.027 seconds in contrast to the online RBF approach, which necessitates 0.039 seconds. Based solely on the provided data, it can be contended that the PI controller exhibits superior performance in achieving a swifter speed response.

Nevertheless, it is crucial to contemplate supplementary variables and assess the efficacy of the regulators from a more comprehensive standpoint. The following are several factors to consider:

- Complexity and adaptability: Online RBF approach is an adaptive control strategy that is capable of dynamically modifying its parameters in response to real-time data. The system exhibits adaptability to dynamic changes, which may enhance its resilience and versatility in managing diverse operational circumstances or disruptions. In contrast, the PI controller requires manual tuning and may not adapt as effectively to dynamic changes.
- System reliability and stability: Increasing the speed with which a system can respond does not always improve its performance. It is essential for control systems to be stable and durable. Even if the online RBF approach is slightly slower to obtain the steady speed response, it may exhibit greater stability and robustness features, guaranteeing smoother operation and less susceptibility to noise or external disturbances.

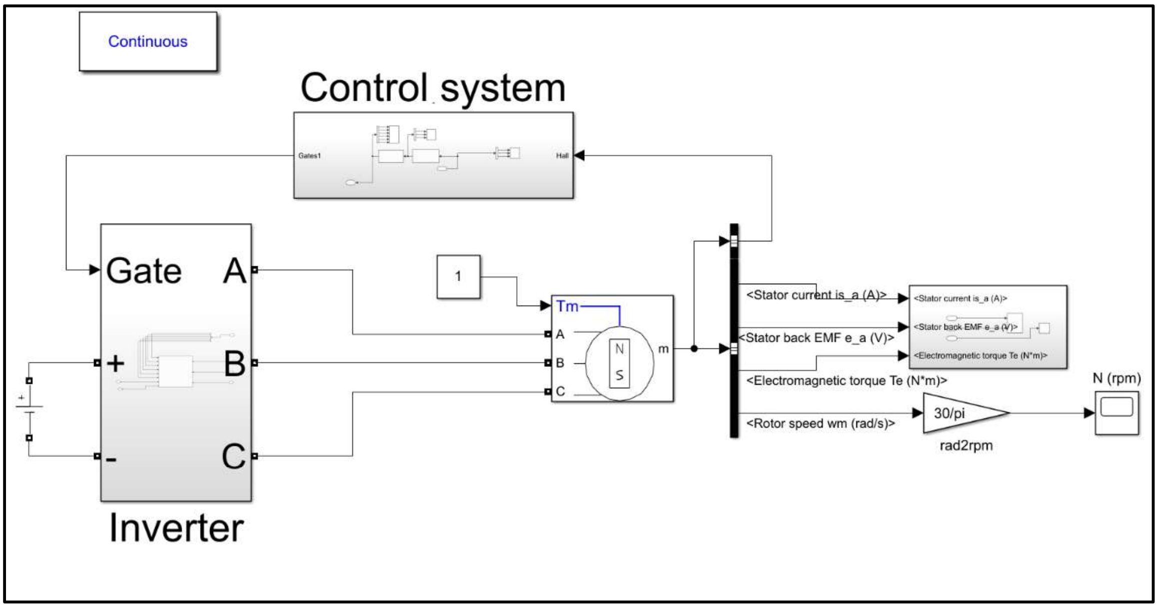

Fig. 6. Simulink BLDC motor model

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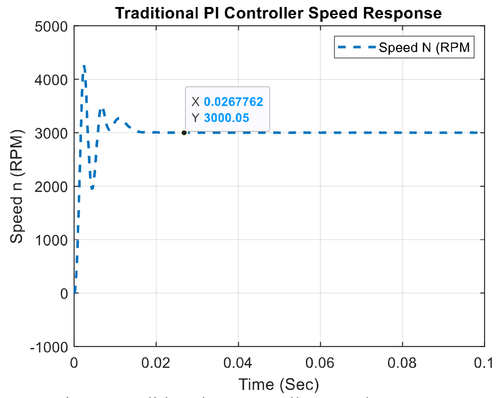

Fig. 7. Traditional PI controller speed response

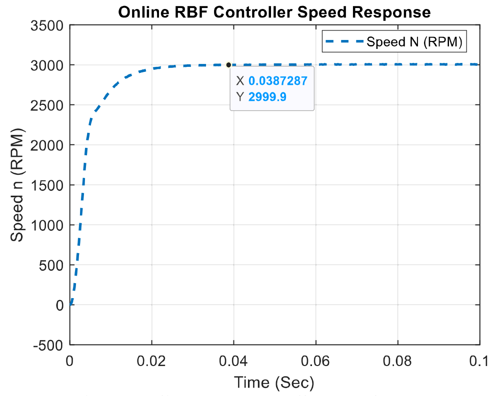

Fig. 8. Online RBF controller speed response

V. CONCLUSIONS

The study examined the differences between traditional PI control and online RBF theory in terms of their performance on a BLDC motor. The results indicate that the online RBF control outperforms the traditional PI control when subjected to constant reference speed. The PI speed control that was designed exhibits favourable response characteristics. Nevertheless, the response characteristics of the online RBF controller are significantly superior The effectiveness of the system can be attributed to its capacity to manage nonlinearities, accommodate parameter fluctuations and unpredictability and exhibit resilience to model mismatches.

The study concentrates on control method performance. However, computational complexity, real-time constraints, and hardware limits were not properly addressed. These practical issues should be examined in future research to assess the practicality and implementation challenges of using the proposed control approaches in real-world applications.

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