MODIFIED RADIAL BASIS FUNCTION NEURAL NETWORK-BASED SPEED CONTROL OF A CHOPPER-FED DC MOTOR DRIVE: PERFORMANCE ANALYSIS AND COMPARATIVE STUDY

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Abstract
The control of DC motor drives is critical for achieving high performance in industrial applications requiring precise speed regulation. Conventional controllers such as proportional–integral (PI) controllers often exhibit limitations, when applied to nonlinear systems with varying load conditions and parameter uncertainties. This paper presents a radial basis function (RBF) neural network-based controller for the speed control of a chopper-fed DC motor drive. The proposed controller is developed using MATLAB/Simscape Electrical and is designed to regulate motor speed by adjusting the duty cycle of the DC chopper. A modified RBF neural network architecture is employed to capture the nonlinear dynamics of the converter–motor system and improve control accuracy. The performance of the proposed controller is evaluated using three different DC motor drive configurations representing various operating quadrants. Simulation results are analyzed in terms of duty cycle response, armature voltage, armature current, and motor speed. A comparative analysis with a conventional PI controller demonstrates that the RBF neural network controller provides improved dynamic performance, including reduced oscillations, faster settling time, and enhanced stability under varying load conditions. The results indicate that the proposed RBF-based control strategy offers a reliable and effective solution for nonlinear motor drive systems and has strong potential for application in modern industrial control.

1. INTRODUCTION

Electric motor drives are fundamental components in modern industrial and automation systems, where precise speed control is essential for achieving high performance and efficiency [1]. With rapid industrialization and technological advancement, the demand for high efficiency, reliability, and power quality has increased significantly. This has necessitated the development of advanced control strategies and intelligent systems capable of enhancing system performance and operational stability [2], [3].

Power electronics has emerged as a fundamental enabling technology in modern electrical engineering, providing efficient means for energy conversion and control. Through the use of semiconductor switching devices, power electronic converters facilitate precise regulation of voltage, current, and power flow, enabling optimized performance in a wide range of industrial applications [4]. These converters play a crucial role in electric drive systems, renewable energy integration, and automated industrial processes.

Electric motors are essential components in industrial and commercial applications, converting electrical energy into mechanical motion for systems such as robotics, transportation, manufacturing, and automation [5]. Among various motor types, DC motors continue to be widely used due to their inherent advantages, including simple control structure, high starting torque, and excellent speed regulation characteristics [6], [7].

In DC motor drive systems, power electronic converters—particularly DC choppers—are extensively used to regulate motor speed by controlling the armature voltage through duty-cycle variation. These converters utilize switching devices such as IGBTs, MOSFETs, and BJTs to achieve efficient and flexible control [8]–[10]. Chopper-fed DC drives are commonly employed in applications such as cranes, elevators, electric vehicles, and industrial automation systems [11]. Achieving precise speed control with minimal steady-state error, reduced overshoot, and fast dynamic response is critical for high-performance motor operation [12].

Traditionally, controllers such as proportional–integral (PI), proportional–integral–derivative (PID), and fuzzy logic controllers have been used for speed regulation of DC motors. Although these controllers are simple and widely adopted, they suffer from several limitations when applied to nonlinear systems with parameter uncertainties and varying load conditions. These limitations include difficulty in tuning, reduced adaptability, and degraded performance under dynamic operating conditions [13]–[18].

To address these challenges, artificial intelligence (AI)-based control techniques, particularly artificial neural networks (ANNs), have gained significant attention. ANNs are capable of modeling complex nonlinear relationships and adapting to system variations, making them suitable for advanced control applications [15], [18]. Several studies have demonstrated the effectiveness of ANN-based controllers in improving transient response, reducing oscillations, and enhancing robustness in DC motor drive systems.

For instance, neural-network-based control strategies have been applied to DC motor drives to improve speed regulation and system stability [13], [21]. Hybrid approaches combining classical and intelligent controllers have also been explored to enhance performance under varying operating conditions [20]. Furthermore, advanced neural architectures have been investigated for nonlinear system identification and control, showing promising results in handling system uncertainties [24]–[27].

Despite these advancements, conventional ANN-based controllers often lack sufficient accuracy and adaptability when dealing with highly nonlinear converter–motor dynamics, especially under rapidly changing load conditions. Therefore, there is a need for more efficient and structurally improved neural control strategies that can provide enhanced learning capability, faster convergence, and improved dynamic performance.

In this paper, a modified Radial Basis Function (RBF) neural network-based controller is proposed for the speed control of a chopper-fed DC motor. The proposed controller is designed to effectively capture the nonlinear characteristics of the converter–motor system and provide improved control performance compared with conventional PI controllers. The controller is implemented in MATLAB/Simscape Electrical and evaluated under different operating conditions and drive configurations.

The main contributions of this work are summarized as follows:

(i) Development of a modified RBF neural network controller for nonlinear DC motor drive systems,
(ii) Integration of the proposed controller with a chopper-fed converter in MATLAB/Simscape Electrical,
(iii) Comprehensive performance evaluation under multi-quadrant operating conditions, and
(iv) Comparative analysis with conventional PI control demonstrating superior dynamic performance. The results demonstrate that the proposed RBF-based controller significantly improves transient response, reduces steady-state error, and enhances system stability under varying load conditions.

The remainder of this paper is organized as follows. Section II presents the literature review. Section III discusses the conventional controller. Section IV describes the proposed RBF-based neural controller. Section V presents the mathematical modeling. Section VI discusses the simulation results, and Section VII concludes the paper.

2. LITERATURE REVIEW

The control of DC motor drives using power electronic converters has been extensively studied over the past decades due to its importance in industrial automation and motion-control applications. Conventional control strategies, particularly proportional–integral (PI) and proportional–integral–derivative (PID) controllers, have been widely adopted because of their simple structure and ease of implementation [16], [17]. These controllers are effective for linear systems; however, their performance significantly degrades in the presence of nonlinearities, parameter variations, and external disturbances.

To overcome these limitations, researchers have explored intelligent control techniques capable of handling nonlinear system behavior. Artificial neural networks (ANNs) have emerged as a powerful tool due to their ability to approximate complex nonlinear mappings and adapt to changing operating conditions [18]. ANN-based controllers can learn system dynamics from data and provide improved control performance without requiring an accurate mathematical model of the system.

Several studies have demonstrated the effectiveness of ANN-based control in DC motor applications. Neural-network-based controllers have been shown to improve transient response, reduce overshoot, and enhance disturbance rejection capability [19], [20]. For example, adaptive neural network controllers have been developed to automatically tune control parameters, resulting in improved robustness and dynamic performance under varying load conditions [21].

Furthermore, neural-network-based control has been integrated with power electronic converters to enhance motor-drive performance. Khan et al. [13] presented the application of neural networks for DC motor control using a controlled three-phase converter in MATLAB/Simscape Electrical, demonstrating improved speed regulation compared with conventional control approaches. Similarly, other studies have explored ANN-based speed control techniques for DC motors, highlighting their effectiveness in handling nonlinear converter–motor dynamics [22].

Beyond motor-drive applications, artificial intelligence techniques have also been widely applied in power systems for protection, disturbance classification, and system optimization. Machine learning approaches have shown significant potential in improving the reliability and efficiency of modern electrical systems [23]. In addition, advanced neural network structures, including radial basis function (RBF) networks, have been successfully applied for nonlinear system identification and control due to their fast convergence and strong approximation capabilities [24], [25].

Hybrid intelligent control approaches combining classical and AI-based methods have also been proposed to enhance system performance. For instance, fuzzy logic integrated with PI controllers has been used to improve the dynamic response and efficiency of DC–DC converters [26]. More recently, ANN-based controllers have been applied to DC motor drives to achieve better adaptability and performance compared with conventional controllers [27].

Although these studies demonstrate the effectiveness of ANN-based control strategies, most existing approaches do not incorporate structural optimization of neural architectures or fail to adequately capture the nonlinear interaction between the converter and motor system. Furthermore, many controllers exhibit limited adaptability under rapidly changing load conditions. Among various ANN architectures, radial basis function (RBF) networks have gained attention due to their fast convergence, localized learning capability, and superior nonlinear approximation properties. However, limited work has been reported on modified RBF structures specifically designed for chopper-fed DC motor drive systems.

Therefore, this study proposes a modified RBF-based controller to address these limitations.

3. Conventional Controller

The Proportional-Integral (PI) controller, originating from the pioneering work of Ziegler and Nichols in 1940, has solidified its position as a cornerstone in control engineering [28]. Remarkably, it finds widespread application, with more than 90% of industrial process control systems relying on its proven capabilities. The PI controller's prominence is particularly pronounced in scenarios involving linear plant models, making it an integral component of electrical and industrial control schemes.

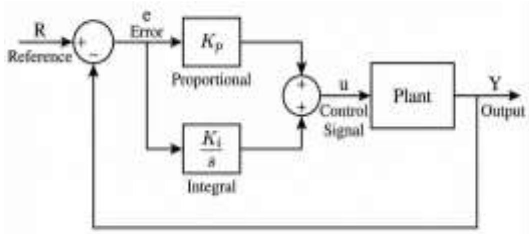

Fig. 1. Block diagram of PI controller

What sets the PI controller apart is its versatility. It seamlessly integrates with various algorithms and access mechanisms, including logic gates and sequential functions, offering an adaptable solution for automation in energy generation, transportation, manufacturing, and beyond (see Fig.1). This adaptability comes with a host of advantages, such as rapid dynamic response, the elimination of steady-state error, dampening of oscillations, and improved system stability.

In response to the evolving landscape of technology, PI controllers have evolved as well. They have transitioned from analog to digital and microprocessor-based implementations to meet the demands of modern control and industrial applications [29]. The PI controller's enduring relevance is a testament to its robust performance and ability to address a myriad of control challenges, from maintaining precision in industrial processes to optimizing energy utilization in complex systems.

4. Artificial Neural Network (ANN)

ANNs represent an adaptable class of machine-learning algorithms inspired by the human brain's neural structure. ANNs have gained importance across various domains due to their ability to model complex relationships, adapt to nonlinear patterns, and excel in tasks such as pattern recognition, classification, regression, and control. The fundamental concept of ANNs is the use of interconnected artificial neurons, or nodes, which collectively process data in a manner like to biological neural networks [30].

In ANNs, information processing occurs through layers of interconnected nodes. The input layer receives data, which is then transmitted through one or more hidden layers, ultimately leading to the output layer's decision or prediction [31]. Each connection between nodes is assigned a weight, representing the strength of the connection. During training, ANNs adjust these weights through a process known as backpropagation, optimizing the network's performance by minimizing prediction errors. The adaptive nature of ANNs enables them to learn and generalize from data, making them particularly valuable in tasks where traditional rule-based programming falls short.

The application of ANNs spans various fields, including image and speech recognition, natural language processing, autonomous vehicles, financial forecasting, and industrial control systems. ANNs continue to evolve, with variations such as Convolutional Neural Networks (CNNs) for image analysis and Recurrent Neural Networks (RNNs) for sequential data processing, further expanding their capabilities [32]. With continued progress in computing and control technologies, ANNs have become a practical tool for addressing complex nonlinear problems and are increasingly used in the development of modern intelligent systems.

A. Research Gap and Motivation

Despite significant progress in ANN-based motor control, several limitations remain:

a) Conventional PI/PID controllers exhibit limited adaptability under nonlinear and dynamic conditions

b) Existing ANN controllers often lack structural optimization and dynamic adaptability

c) Many approaches do not effectively capture converter–motor nonlinear interactions

d) Computational complexity and training limitations affect real-time implementation

Therefore, there is a need for **a** modified and more efficient neural control architecture that can:

1) Accurately model nonlinear system dynamics

2) Provide fast and stable convergence

3) Improve transient and steady-state performance

4) Enhance robustness under varying load conditions

Therefore, there exists a clear need for an improved RBF-based control strategy that enhances learning efficiency, accurately models nonlinear converter–motor dynamics, and provides superior performance under multi-quadrant operating conditions.

B. Contribution of This Work

To address the identified research gaps, this study proposes a modified Radial Basis Function (RBF) neural network-based controller for the speed control of a chopper-fed DC motor. The proposed approach introduces:

i. Adaptive tuning of RBF parameters
ii. Enhanced input feature representation
iii. A two-stage neuro-control architecture for improved stability

This work aims to achieve superior performance in terms of speed tracking, disturbance rejection, and system stability compared with conventional and existing ANN-based control methods.

5. Model of Artificial Neural Network (ANN)

A neural network consists of an input layer that gathers information and processes it through weighted connections. The output is computed using a mathematical function known as the activation function, which enables the network to effectively model nonlinear relationships. There is another function used to compute the output of neurons [33]. Usually, a neuron consists of multiple input signals and a single output. The output of a neuron is a nonlinear function related to the input signal and weight vector. Here input vector is to develop the nonlinear function and weight [34]. The weight vector is applicable in a learning process using multiple combinations of experiences and learning ratios. Wherever the weight of the neuron can be supervised via a learning role. A schematic model of NN is presented in Fig.2. which represents a basic structure for developing ANN.

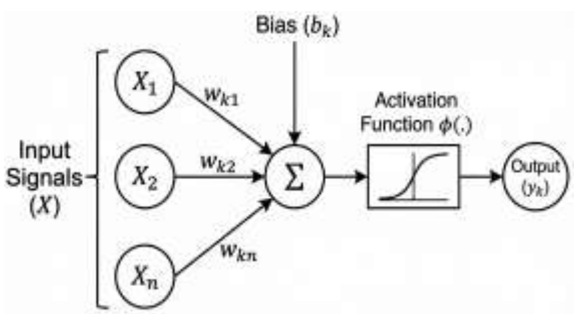

Fig. 2. Neural network model

5.1 Synaptic weights

It is also known as connected links. Synapses are key structure that value the communication signal and interaction between neurons. Each synapse has its own weight and strength. In particular, synapse j transfers the input signal X_j to the neuron and multiples it via synaptic weight W_{kj}. The synapse weights of ANN have a range that contains negative and positive values opposite of the synapse of the human brain [35].

5.2 Activation function

It is also known as the transfer function which is a mathematical model to perform and find out the output of a neuron. It is better to control the output value in order to restrict it to achieving a bigger value may have affected the training process. A bias used as an external function denoted as b_k had the impact of increasing and decreasing the value of the activation function to accommodate the input signals. The bias value depends on the input values whether it is negative or positive [36]. Equation (1) represents the activation function with bias.

$$Y_k = \emptyset(u_k + b_k) \qquad (1)$$

Where $\emptyset$ is a symbol represents the activation function and the output signal of a neuron is Y_k.

5.3 Neural Network-Based Controller

The conventional PI controller exhibits limitations when applied to nonlinear, high-dynamic systems such as chopper-fed DC motor drives. To address these challenges, this work proposes a modified Radial Basis Function (RBF) Feedforward Neural Network (FFNN) controller, designed to replace the PI controller and enhance transient, steady-state, and disturbance rejection performance [37]. Although classical RBF networks have existed for decades, the controller developed in this study includes three significant modifications, making it structurally and functionally different from standard RBF implementations:

1) Adaptive tuning of RBF centers and widths during training, improving nonlinear mapping accuracy.
2) Expanded dynamic input vector, enabling the controller to incorporate dynamic system behaviour.
3) Two-stage neuro-control architecture, consisting of an estimator stage and a duty-cycle controller stage.

These enhancements allow the proposed neuro-controller to learn converter–motor nonlinearities more effectively, resulting in improved duty-cycle regulation and speed tracking across all three simulated quadrants.

5.4 Detailed Mathematical Modelling of the Proposed Controller

A mathematical model of the complete framework is presented below.

5.4.1 Input–Output Mapping of the Controller

The controller receives a dynamically enriched input vector consisting of the instantaneous error, change in error, and change in previous control action:

$$X(k) = [e(k), \Delta e(k), \Delta D(k)]$$

Where,

$$e(k) = \omega_{ref}(k) - \omega(k)$$
$$\Delta e(k) = e(k) - e(k-1)$$
$$\Delta D(k) = D(k-1) - D(k-2)$$

These additional dynamic terms improve ANN sensitivity to transient motor behavior.

The proposed controller produces two internal outputs:

Voltage Estimator Output:

$$V_{ref}(k) = f_1\big(X(k)\big)$$

Duty Cycle Controller Output:

$$D(k) = f_2\left(V_{ref}(k)\right)$$

This two-stage mapping separates voltage estimation and duty-cycle generation, which enhances learning and stability.

5.4.2 RBF Hidden Layer Computation

The hidden layer constant of M=25 Gaussian neurons.

Each neuron computes:

$$\emptyset_j(k) = exp\left(-\frac{\left\|X(k) - C_j\right\|^2}{2\sigma_j^2}\right)$$

Where,

$C_j = center\ of\ j\_th\ neuron$

$\sigma_j = width\ (speed) parameter$

Adaptive Update Rules:

To enhance learning, both centers and widths update iteratively:

$$C_j(k+1) = C_j(k) + \eta_c\left(\frac{\partial E}{\partial C_j}\right)$$

$$\sigma_j(k+1) = \sigma_j(k) + \eta_\sigma\left(\frac{\partial E}{\partial \sigma_j}\right)$$

This allows the RBF receptive fields to shift dynamically during training, making the controller responsive to nonlinear converter-motor characteristics.

5.4.3 Output Layer Computation

The output layer uses a linear activation function (purelin):

$$D(k) = \sum_{j=1}^{M} \omega_j \phi_j(k) + b$$

Where,

ω_j= weights connecting hidden to output layer

b=bias

This linear combination produces the duty cycle command applied to the PWM generator.

5.4.4 Training Algorithm and Error Function

The ANN is trained using PI-generated duty-cycle data combined with disturbed-load conditions to provide richer learning patterns.

The performance index minimized during training is the Sum Squared Error (SSE):

$$E = \sum_{k=1}^{N} \left(D_{PI}(k) - D_{ANN}(k)\right)^2$$

Where,

$D_{PI}(k)$=duty cycle generated by the PI controller

$D_{ANN}(k)$=duty cycle predicted by ANN

Training continues until:

$E \to 10^{-6}$ which is achieved in approximately 5 seconds, as shown in TABLE I.

5.4.5 Final Controller Law

Combining all components, the final duty-cycle update rule becomes:

$$D(k) = \sum_{j=1}^{25} \omega_j exp\left(-\frac{\left\|X(k) - C_j\right\|^2}{2\sigma_j^2}\right) + b$$

Where,

$X(k) = [e(k), \Delta e(k), \Delta D(k)]$

This equation formally represents the complete modified RBF controller introduced in this study.

Fig. 3. shows the complete computational flow of the proposed two-layer RBF network used for DC motor control.

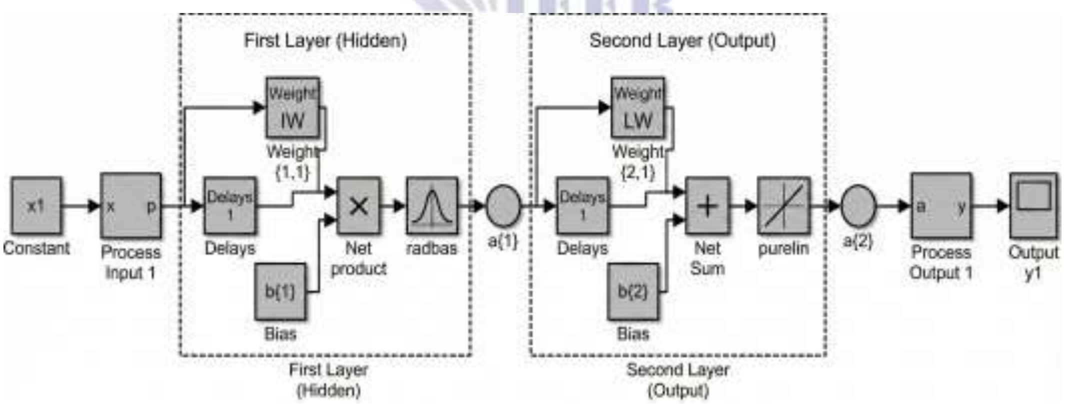

Fig. 3. Comprehensive diagram of the two-layer RBF neural network

TABLE I

Specifications of the Proposed RBF Feedforward Neural Network (FFNN)

Network Type	Training Time (s)	Neurons (Layer 1)	Neurons (Layer 2)	Transfer Function (Layer 1)	Transfer Function (Layer 2)	SSE
RBF	5	25	1	Radial Basis Function	Linear	1×10^{-6}

6. RESULTS AND DISCUSSION

The performance of three different DC motor drive configurations—without a conventional controller (CC), with a CC, and with an artificial neural network (ANN) controller—was evaluated and compared for speed regulation. The analysis was carried out by examining key performance parameters, including duty cycle, armature voltage, armature current, and motor speed.

The simulation results for all three models demonstrate that the ANN-based controller significantly outperforms both the conventional controller and the uncontrolled system. Improved dynamic response, reduced oscillations, and enhanced stability were observed with the ANN controller under varying operating conditions.

6.1 Performance Analysis of Model No. 1

Model No. 1 of the DC motor drive is illustrated in Fig. 6. The simulation model was analyzed in terms of duty cycle, armature voltage, armature current, and motor speed to evaluate system performance.

The parameters used for Model No. 1 during simulation are provided in Table II. The system was implemented in MATLAB/Simulink using the SimPowerSystems toolbox. A one-quadrant DC chopper (buck converter) was designed and supplied by a 280 V DC source. The converter utilizes an IGBT-based switching scheme operating at a frequency of 5 kHz using pulse width modulation (PWM).

The chopper-fed drive controls a 5 HP separately excited DC motor, with a constant field voltage of 150 V DC. This configuration enables precise control of armature voltage through duty-cycle variation, thereby regulating motor speed under different load conditions.

TABLE II
Specifications of Model No. 1 (One-Quadrant DC Motor Drive)

Parameter	Value
Quadrant of Operation	First Quadrant (I)
Rated Speed	500 rpm
Motor Power	5 HP
Load Torque	15 N·m
Supply Voltage	250 V (DC)
DC Source Voltage	280 V (DC)
Field Voltage	150 V (DC)
Converter Type	DC Chopper (Buck Converter)
Switching Device	IGBT
Switching Frequency	5 kHz

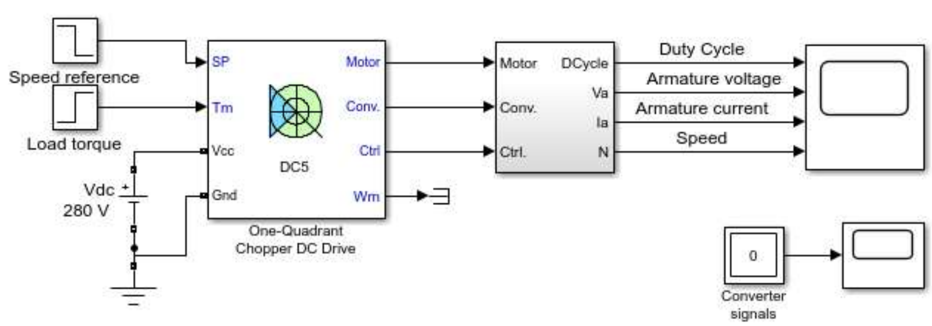

Fig. 4. One-Quadrant DC Chopper Drive

Performance Description of Model No. 1

The speed reference is set to **500 rpm** at *t = 0 s*, with an initial load torque of **15 N·m**.

The motor speed accurately tracks the reference ramp (approximately **+250 rpm/s**) and reaches steady-state operation at around *t = 2.5 s*. At *t = 2.5 s*, the load torque increases from **15 N·m to 20 N·m**. The motor responds quickly, and the speed recovers to **500 rpm** by *t = 3 s*. During this interval, the armature current increases to approximately **16.7 A** to produce the required electromagnetic torque and maintain the speed reference. At *t = 3 s*, the speed reference is reduced to **350 rpm**. The motor speed smoothly adjusts to the new reference and stabilizes around **350 rpm** at approximately *t = 4 s*.

6.1.1. Model 1 IGBT 1 Combined

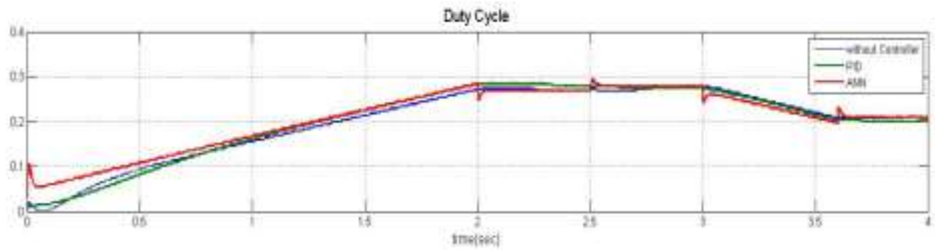

Fig. 5. Duty Cycle Response (Model 1) without Controller, with PID and ANN

(a) Model 1 Armature Voltage Combined

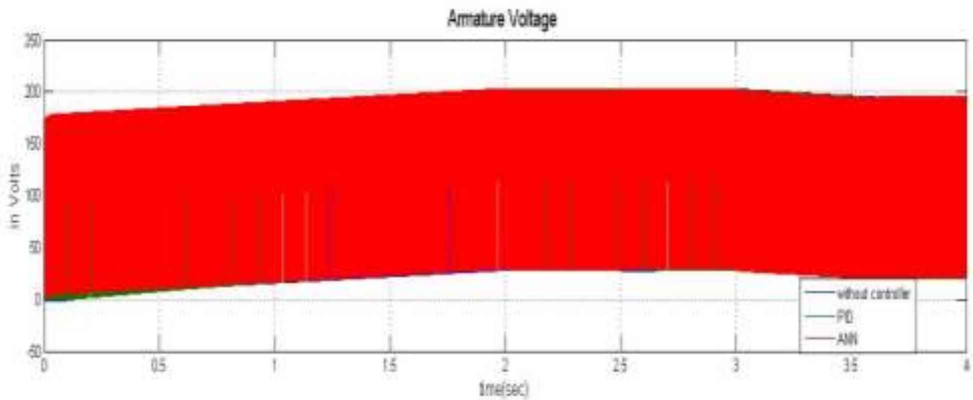

Fig. 6. Armature Voltage Response without Controller, with PID & ANN

(b) **Model 1 Current Combined**

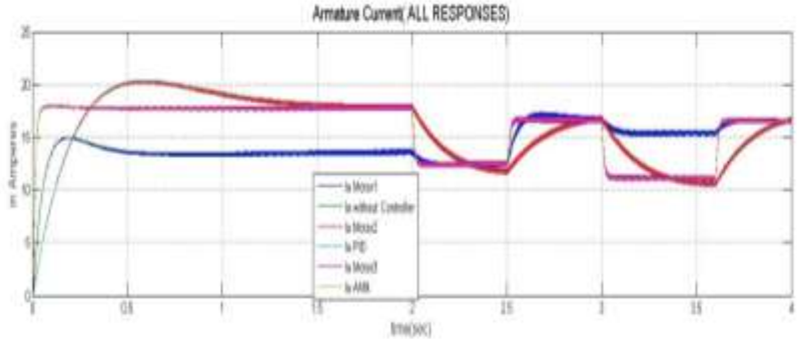

Fig. 7. Current Response without Controller, with PID & ANN

(c) **Model 1 Speed Combined**

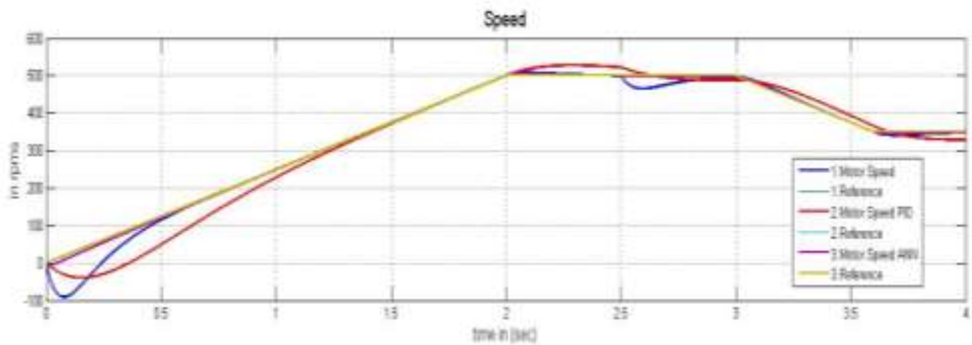

Fig. 8. Speed Response without Controller, with PID & ANN

6.2 Performance Analysis of Model No. 2

Model No. 2 of the DC motor drive is illustrated in Fig. 9. The simulation model is evaluated based on key performance parameters, including duty cycle, armature voltage, armature current, and motor speed.

The parameters used for Model No. 2 during simulation are listed in Table III. The system is implemented in MATLAB/Simulink using the SimPowerSystems toolbox. The DC6 block is utilized to develop a two-quadrant chopper drive, enabling both motoring and regenerative braking operations. The drive system consists of a 200 HP separately excited DC motor, supplied with a constant field voltage of 150 V DC. The armature voltage is controlled through an IGBT-based converter, allowing bidirectional current flow required for two-quadrant operation.

TABLE III
Specifications of Model No. 2 (Two-Quadrant DC Motor Drive)

Parameter	Value
Quadrant of Operation	Second Quadrant (II)
Rated Speed	400 rpm
Motor Power	200 HP
Load Torque	814 N·m
Supply Voltage	460 V (DC)
Field Voltage	150 V (DC)
Converter Type	Two-Quadrant DC Chopper
Switching Device	IGBT

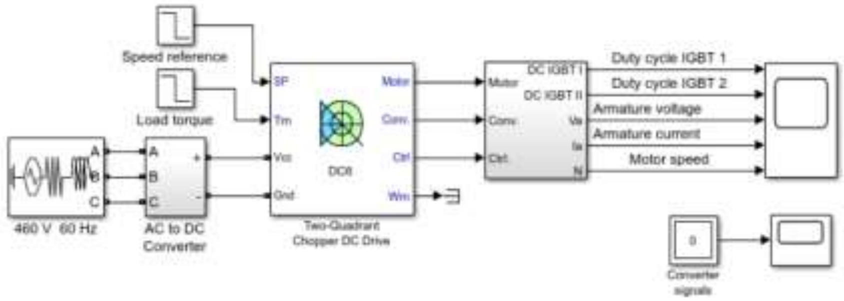

Fig. 9. Two-Quadrant DC Motor Drive (Model No. 2)

Performance Description of Model No 2

The speed reference is set to 400 rpm at *t = 0 s*, with an initial load torque of 814 N·m.

The motor speed closely follows the reference ramp (approximately +250 rpm/s) and reaches steady-state operation at around *t = 2 s*. At *t = 2.1 s*, the load torque is reduced significantly from 814 N·m to 100 N·m, resulting in a transient response in the motor dynamics. At *t = 2.75 s*, the speed reference drops to 100 rpm, and the armature current reverses to approximately −160 A, indicating the initiation of regenerative braking to decelerate the motor. At *t = 3.4 s*, the motor speed reaches 100 rpm, and the armature current reverses again to approximately 40 A, restoring motoring operation. The motor speed stabilizes around the reference value at approximately *t = 4 s*, demonstrating stable operation under dynamic conditions.

6.2.1. Model 2 IGBT 1 combined

Fig. 10. Duty Cycle Response (Model 2) without Controller, with PID and ANN

6.2.2. Model 2 IGBT 2 combined

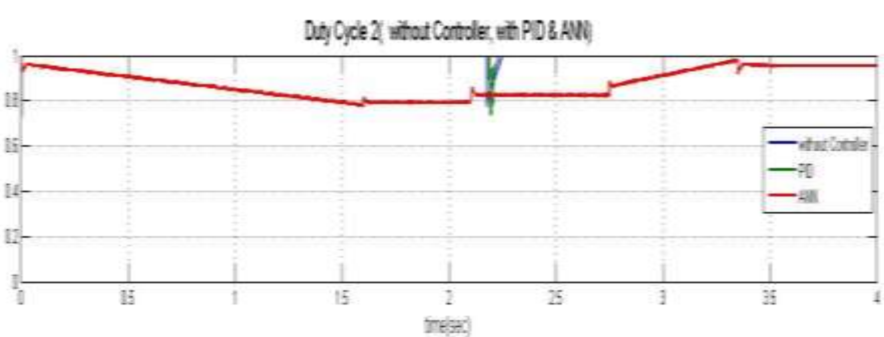

Fig. 11. Duty Cycle.2 Response without Controller, with PID & ANN

(a) Model 2 Armature Voltage combined

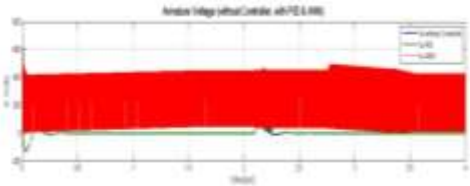

Fig. 12. Voltage Response without Controller, with PID & ANN

(b) Model 2 Current Combined

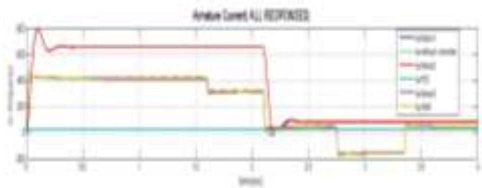

Fig. 13. Current Response without Controller, with PID & ANN

(c) Model 2 Speed Combined

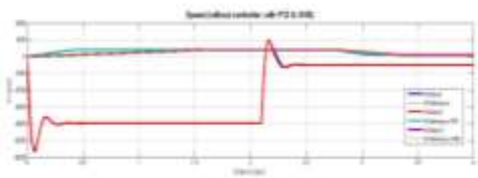

Fig. 14. Speed Response without Controller, with PID & ANN

6.3 Performance Analysis of Model No. 3

Model No. 3 of the DC motor drive is illustrated in Fig. 15. The simulation model is evaluated based on key performance parameters, including duty cycle, armature voltage, armature current, and motor speed.

The parameters used for Model No. 3 during simulation are presented in Table IV. The system is implemented in MATLAB/Simulink using the SimPowerSystems toolbox. The DC7 block is utilized to develop a four-quadrant chopper drive, enabling operation in both forward and reverse motoring as well as regenerative braking modes.

The drive system consists of a 200 HP separately excited DC motor, supplied with a constant field voltage of 150 V DC. The armature voltage is controlled through an IGBT-based converter, allowing bidirectional voltage and current flow required for four-quadrant operation.

TABLE IV
Specifications of Model No. 3 (Four-Quadrant DC Motor Drive)

Parameter	Value
Quadrant of Operation	Fourth Quadrant (IV)
Rated Speed	500 rpm
Motor Power	200 HP
Load Torque	Reversible (Positive and Negative)
Supply Voltage	380 V (DC)
Field Voltage	150 V (DC)

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Converter Type	Four-Quadrant DC Chopper
Switching Device	IGBT

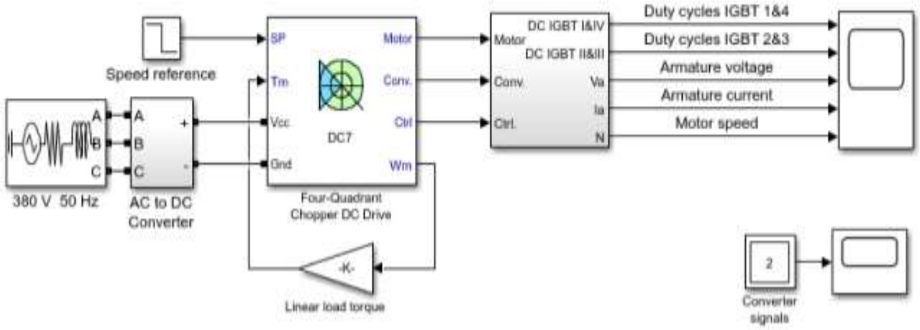

Fig. 15. Four-Quadrant DC Motor Drive (Model No. 3)

Performance Description of Model No. 3

The speed reference is set to 500 rpm at *t = 0 s*. The motor speed accurately follows the reference ramp (approximately +400 rpm/s) and reaches steady-state operation at around *t = 1.3 s*. At *t = 2 s*, the speed reference is reduced to −1184 rpm. The armature current decreases to reduce the electromagnetic torque, initiating deceleration with the assistance of the load torque. At *t = 2.2 s*, the armature current reverses, producing a braking electromagnetic torque (dynamic braking mode). This transition results in an increase in the DC bus voltage. At *t = 3.25 s*, the motor speed reaches 0 rpm, and the load torque reverses direction, becoming negative. The negative armature current then generates an accelerating electromagnetic torque, enabling the motor to follow the negative speed ramp (approximately −400 rpm/s). At *t = 6.3 s*, the motor speed reaches −1184 rpm and stabilizes around the reference value, demonstrating stable operation under four-quadrant conditions.

6.3.1. Model 3 IGBT1 Combined

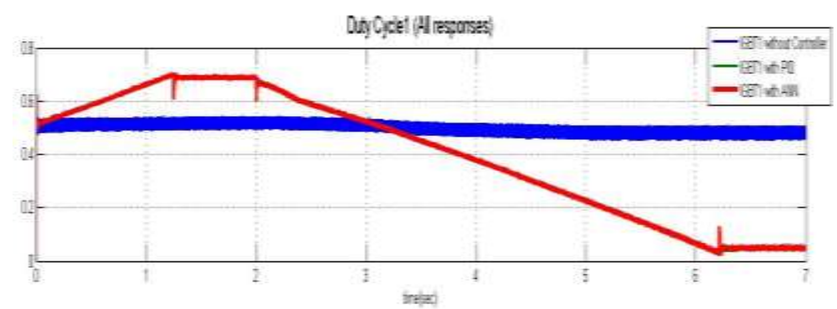

Fig. 16. Duty Cycle 1 Response without Controller, with PID & ANN

6.3.2. Model 3 IGBT2 Combined

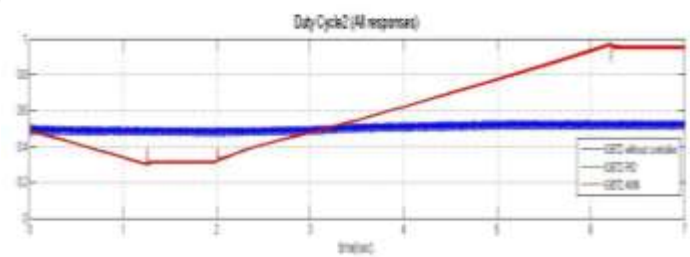

Fig. 17. Duty Cycle 2 Response without Controller, with PID & ANN

(a) Model 3 Armature Voltage Combined

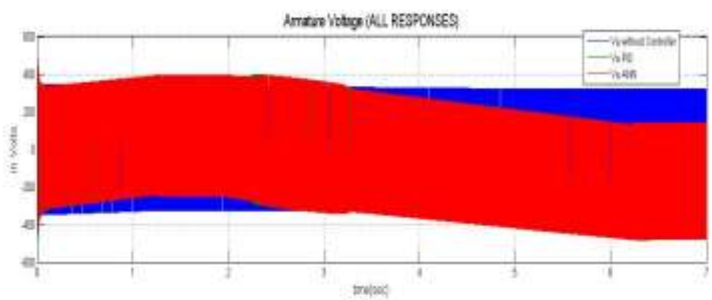

Fig. 18. Voltage Response without Controller, with PID & ANN

(b) Model 3 Current Combine

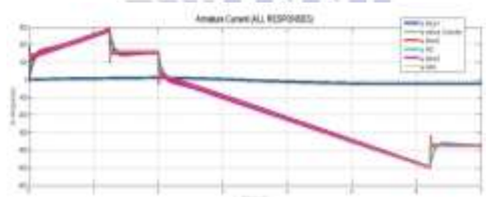

Fig. 19. Current Response without Controller, with PID & ANN

(c) Model 3 Speed Combined

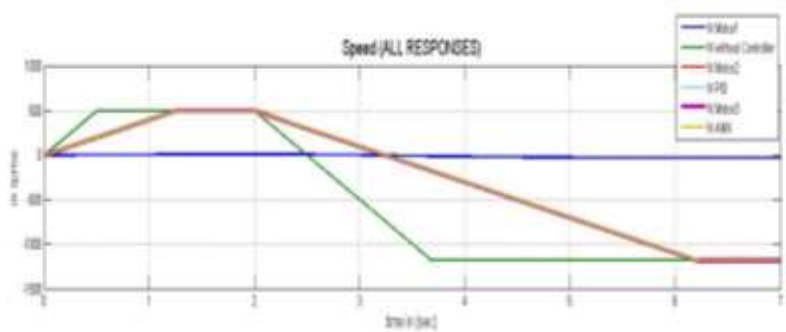

Fig. 20. Speed Response without Controller, with PID and ANN

6.4 Comparative Analysis and Tabulated Results

Three DC motor drive models representing different operating quadrants were investigated: Model No. 1 (first quadrant), Model No. 2 (second quadrant), and Model No. 3 (fourth quadrant). Each model employs a chopper-fed configuration and is evaluated under key performance parameters, including duty cycle, armature voltage, armature current, and motor speed.

The simulation results clearly reveal the limitations of the conventional proportional–integral (PI) controller when applied to nonlinear and time-varying systems such as chopper-fed DC motor drives. These limitations include increased settling time, higher oscillations, and reduced adaptability under varying load and operating conditions, as also highlighted in the literature review.

To address these challenges, the proposed modified Radial Basis Function (RBF) neural network-based controller is implemented. Unlike conventional ANN approaches, the proposed controller incorporates enhanced nonlinear mapping capability, adaptive learning behavior, and improved representation of system dynamics, as discussed in the methodology section.

Across all three models and operating conditions, the proposed RBF-based controller demonstrates superior performance compared with both the conventional PI controller and the uncontrolled system. The proposed RBF-based controller achieves faster settling time, reduced overshoot and oscillations, improved transient response, and enhanced stability under dynamic load variations, thereby demonstrating its superior capability in handling nonlinear and time-varying system dynamics.

Furthermore, the proposed controller effectively captures the nonlinear interaction between the power electronic converter and the DC motor, resulting in more accurate duty-cycle regulation and improved speed tracking performance across all quadrants of operation. This confirms the suitability of the RBF neural network for high-performance motor-drive applications.

TABLE V
Comparative Performance Analysis of Controllers

Model	Controller Type	Rise Time (s)	Settling Time (s)	Overshoot (%)
#1	Without Control (WC)	0.30	0.96	205.6
	PI Controller	0.30	0.89	203.7
	RBF Neural Controller	0.30	**0.65**	**201.0**
#2	Without Control (WC)	0.001	0.28	268.4
	PI Controller	0.001	0.27	443.0
	RBF Neural Controller	0.001	**0.25**	**440.1**
#3	Without Control (WC)	0.004	1.03	484.0
	PI Controller	0.004	1.44	481.2
	RBF Neural Controller	0.004	**1.22**	**479.5**

Discussion of Results

The results presented in Table V confirm that the proposed RBF-based controller consistently outperforms the conventional PI controller across all operating conditions. A significant reduction in settling time is observed in all three models, indicating faster system stabilization.

Although the rise time remains comparable across controllers, the RBF-based approach effectively minimizes overshoot and suppresses oscillations, resulting in improved dynamic behavior. The performance improvement is particularly evident in higher-power and multi-quadrant operations (Models No. 2 and No. 3), where system nonlinearities are more pronounced.

These findings strongly support the research hypothesis that intelligent RBF-based control provides superior adaptability and robustness compared with classical control methods. The results also validate the effectiveness of the proposed modifications in enhancing neural network learning and control accuracy.

7. CONCLUSION

This paper presented the design, implementation, and performance evaluation of a modified Radial Basis Function (RBF) neural network-based controller for the speed regulation of a chopper-fed DC motor drive system. The proposed controller was developed in MATLAB/Simulink using Simscape Electrical and aimed at addressing the limitations of conventional control techniques in nonlinear and dynamic operating environments.

A comprehensive analysis was carried out using three different DC motor drive configurations representing multiple operating quadrants, including first-quadrant (motoring), second-quadrant (regenerative braking), and fourth-quadrant (reversal operation). This multi-scenario evaluation ensured that the controller performance was validated under a wide range of operating conditions, including load variations, speed transitions, and bidirectional power flow.

The results demonstrated that conventional PI controllers exhibit inherent limitations when applied to chopper-fed DC motor systems, particularly in terms of slower dynamic response, higher oscillations, and reduced adaptability under nonlinear and time-varying conditions. These observations are consistent with the research gap identified in the literature.

To overcome these challenges, the proposed modified RBF neural network controller was designed with enhanced nonlinear mapping capability, adaptive learning features, and improved representation of system dynamics. Unlike conventional ANN controllers, the RBF architecture provides faster convergence and better approximation of nonlinear converter–motor interactions.

Simulation results across all models confirmed that the proposed controller significantly improves system performance. Specifically, the RBF-based controller achieved faster settling time, reduced overshoot, minimized oscillations, and improved stability compared with both the conventional PI controller and the uncontrolled system. Additionally, the controller demonstrated strong adaptability to varying load conditions and effective handling of dynamic transitions, including regenerative braking and speed reversal. The comparative analysis further validated that the proposed approach ensures accurate duty-cycle regulation and superior speed tracking performance across all quadrants of operation. These findings confirm the effectiveness of the RBF neural network in addressing the complexities associated with nonlinear power electronic drive systems.

In conclusion, the proposed RBF-based control strategy provides a robust, efficient, and intelligent solution for high-performance DC motor drive applications. The methodology presented in this study offers significant potential for practical implementation in modern industrial systems, including electric vehicles, robotics, and automated manufacturing.

Future work may focus on real-time hardware implementation, validation using embedded platforms, and the integration of advanced hybrid AI techniques to further enhance control accuracy, computational efficiency, and industrial applicability. Furthermore, the proposed approach demonstrates strong potential for real-time implementation in modern industrial drive systems.

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