IJCRT.ORG ISSN : 2320-2882
INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

Neuro-Sliding Mode Control Of Bldc Motor Drive For Electric Vehicle Speed Regulation

[1]Subhankar Dash, [2] Rashmi Ranjan Martha, [3] Pallavi Mishra
[1]Assistant Professor Electrical Engineering, [1]Assistant Professor Electrical Engineering, [1]Assistant Professor Electrical Engineering
[1]Department of Electrical Engineering,
[1]C V RAMAN POLYTECHNIC, BHUBANESWAR, INDIA

Abstract :Brushless DC motors (BLDC) are widely used in electric vehicles due to their high torque, performance efficiency, and superior reliability. However, BLDC motors experience dynamic load fluctuations and nonlinearities during operation, making speed control challenging. While conventional PID controllers exhibit fast response and good settling time, they fail to maintain satisfactory performance during load variations. This thesis addresses this limitation by proposing a Neuro-Sliding Mode Control (NSMC) approach that combines sliding mode control with feed-forward neural networks using Radial Basis Functions (RBF) to eliminate chattering and improve dynamic response. The proposed controller effectively handles load disturbances and set-point variations, achieving superior steady-state and transient performance compared to conventional PID and standard SMC controllers.

Index Terms - BLDC Motor, PID Controller, Sliding Mode Control, Neural Network, RBF, Chattering Elimination, Electric Vehicle

1. Introduction

1.1 Overview

Brushless DC (BLDC) motors have become indispensable components in modern electric vehicles and numerous industrial applications. The advantages of BLDC motors over conventional brushed DC motors include higher efficiency (typically 85-90%), longer operating life, low maintenance requirements, and superior torque-to-weight ratio. These characteristics make BLDC motors ideal for automotive applications, robotics, positioning devices, and machine cooling systems.

The primary challenge in BLDC motor applications is speed regulation under varying load conditions. Electric vehicles experience frequent load fluctuations as they traverse different terrains—from level roads to inclines. Traditional PID controllers, while robust and widely implemented in industrial drives, demonstrate insufficient performance when subjected to dynamic load disturbances and set-point variations. The nonlinear nature of these disturbances causes the PID controller to generate overshoots, undershoots, and extended settling times, compromising vehicle performance and efficiency.

1.2 Literature Review

Research in BLDC motor control has evolved through several distinct phases:

Phase 1: Conventional Control (2001-2008)

Cheng et al. (2004) established foundational controller designs for BLDC motors in electric vehicles. Krishnan (2001) presented comprehensive mathematical modeling and control strategies for electric motor drives. However, these early approaches demonstrated limited performance under dynamic load conditions.

Phase 2: Advanced PID Techniques (2012-2017)

Kandiban and Arulmozhiyal (2014) proposed adaptive fuzzy-PID controllers to improve steady-state performance. Jaya and Purwanto (2017) developed PID-Fuzzy controllers specifically for electric vehicle applications, addressing the need for improved dynamic response. Marcel et al. (2008) introduced DSP-based hybrid fuzzy-PID controllers, demonstrating enhanced performance in motor drives. Despite these advances, limitations persisted under severe nonlinearities.

Phase 3: Nonlinear Control Approaches (2009-2015)

Hou et al. (2009) pioneered the integration of global sliding mode control with neural networks, establishing the theoretical foundation for hybrid approaches. Oliveira et al. (2015) successfully implemented analog switch functions to reduce chattering in SMC-based BLDC drives. Patil et al. (2016) confirmed that SMC significantly enhances dynamic response in PMBLDC motors, though chattering remained problematic.

Phase 4: Neuro-Sliding Mode Control (2016-Present)

Yildiz et al. (2007) established principles for combining SMC with neural network design. Recent research demonstrates that integrating RBF neural networks with sliding mode controllers effectively eliminates chattering while maintaining robustness to parameter uncertainties and load disturbances.

1.3 Motivation and Objectives

The motivation for this research stems from the critical need for reliable, efficient speed control in electric vehicle BLDC motors. Conventional PID controllers cannot adequately handle the nonlinearities inherent in vehicle operation. While sliding mode controllers address this limitation, they introduce an undesirable chattering phenomenon that causes mechanical wear, efficiency loss, and control inaccuracy.

Research Objectives:

1. Design and model a BLDC motor drive with electronic commutation using Hall sensors
2. Develop and simulate a conventional PID controller with Ziegler-Nichols tuning
3. Design a sliding mode controller to handle load disturbances and set-point variations
4. Implement a Neuro-Sliding Mode Controller combining RBF neural networks with SMC to eliminate chattering
5. Provide comprehensive performance comparisons among all three control approaches
6. Demonstrate superior steady-state and transient performance of the proposed NSMC

2. BLDC Motor Modeling and Drive System

2.1 BLDC Motor Fundamentals

The BLDC motor represents a modern evolution of conventional DC motors, with permanent magnets mounted on the rotor and stator windings arranged in three phases. Unlike brushed DC motors, BLDC motors employ electronic commutation via solid-state switches, eliminating mechanical commutators and brushes. This fundamental difference provides significant advantages: elimination of brush wear and sparking, reduced electromagnetic interference, simplified maintenance, and higher power density.

Key advantages of BLDC motors:

- **Improved Torque vs Speed Characteristics** – Nearly constant torque across speed range
- **Higher Dynamic Response** – Rapid acceleration and deceleration capability
- **Enhanced Efficiency** – Up to 90% efficiency compared to 75-80% for brushed DC motors
- **Extended Operating Life** – No commutator degradation or brush wear
- **Silent Operation** – Minimal acoustic noise
- **Compact Construction** – Smaller size for equivalent power output

2.2 BLDC Motor Construction and Mathematical Model

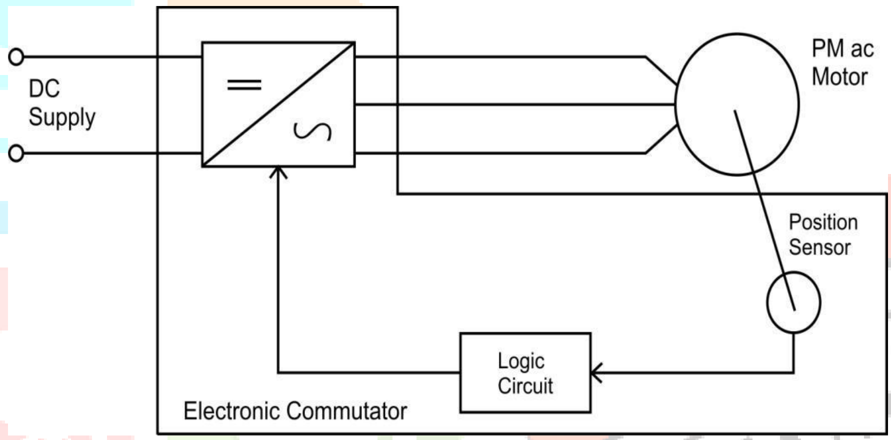


FIG: 1(BLOCK DIAGRAM OF BLDC MOTOR)

The BLDC motor comprises three major components: stator, rotor, and position sensor system.

Stator: Laminated steel core with three-phase winding distributed around the bore. Windings are connected in star configuration, with trapezoidal or sinusoidal back-EMF characteristics determined by coil placement.

Rotor: Permanent magnet mounted on shaft, with radial or axial flux configuration. For low-speed applications, surface-mounted magnets are used; for high-speed applications, interior pole-mounted magnets provide mechanical retention.

Hall Position Sensors: Three Hall sensors spaced 120° apart on the rotor, producing digital outputs indicating rotor position. These signals trigger the switching sequence of the power inverter, ensuring proper phase commutation.

Mathematical Model:

The electrical equations for BLDC motor phases are derived from Kirchhoff's voltage law:

$$V_a = Ri_a + (L - M)\frac{di_a}{dt} + E_a$$

$$V_b = Ri_b + (L - M)\frac{di_b}{dt} + E_b$$

$$V_c = Ri_c + (L - M)\frac{di_c}{dt} + E_c$$

Where: V_a, V_b, V_c are phase voltages, E_a, E_b, E_c are back-EMFs, and R, L, M are motor parameters.

The electromechanical torque equation is:

$$T = K_t i = J\frac{d\omega_m}{dt} + B\omega_m + T_L$$

Taking Laplace transforms and applying standard assumptions yields the motor transfer function:

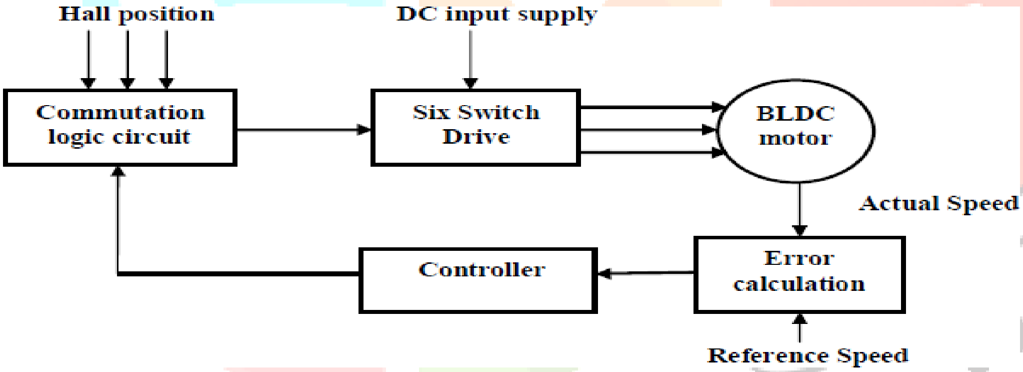
$$G_i(s) = \frac{\omega_m(s)}{V_d(s)} = \frac{1}{K_e(\tau_e\tau_m s^2 + \tau_m s + 1)}$$

Where $\tau_m = \frac{R_a J}{K_e K_t}$ (mechanical time constant) and $\tau_e = \frac{L_a}{R_a}$ (electrical time constant).

Sr. No.	Symbol	Description	Value
1.	B	Friction coefficient	10−2Kg/ms
2	J	Moment of Inertia	. 3.99 × 10−5Kgm2/s2
3.	Kb	Back emf constant	0.105volts/rad/sec
4.	Kt	Torque constant	0.0980N − m/Amp
5.	L	Inductance	1.1 × 10−3Henry
6.	P	No. of poles	4
7.	R	Resistance per phase	0.525Ohms

Table 1: Parameter Values

2.3 Six-Switch Inverter Commutation



The six-switch inverter provides three-phase voltages to BLDC motor phases based on Hall sensor signals. Commutation occurs every 60° of rotor rotation, with each pair of switches conducting for 120° duration. The switching sequence maintains synchronization between phase currents and back-EMF waveforms, producing constant torque output:

Sector	H1	H2	H3	ON Switch	Phase Conducting	Sector Duration
1	1	0	0	S1, S4	A→B	0°-60°
2	1	1	0	S5, S4	C→B	60°-120°
3	0	1	0	S5, S2	C→A	120°-180°
4	0	1	1	S3, S2	B→A	180°-240°
5	0	0	1	S3, S6	B→C	240°-300°
6	1	0	1	S1, S6	A→C	300°-360°

Table 2: Six-Switch Inverter Commutation Sequence

3. Conventional PID Controller Design

3.1 PID Controller Fundamentals

The proportional-integral-derivative (PID) controller represents the most widely implemented feedback control algorithm in industrial applications. Its popularity stems from simplicity, robustness, and effectiveness across diverse processes. The PID controller generates control action based on three independent terms:

- **Proportional (P):** Responds to present error magnitude
- **Integral (I):** Accumulates past errors, eliminating steady-state error
- **Derivative (D):** Responds to error rate of change, dampening overshoot

Control output equation:

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau)d\tau + K_d \frac{de(t)}{dt}$$

3.2 PID Parameter Tuning Using Ziegler-Nichols Method

The Ziegler-Nichols tuning method provides systematic gain determination:

Procedure:

1. Set controller to proportional-only mode with small initial K_p
2. Increase K_p incrementally while applying step input
3. Record K_p value (K_u) at which sustained oscillations occur
4. Measure oscillation period (P_u)
5. Calculate tuning parameters from empirical relationships:

$$K_p = 0.6K_u, K_i = \frac{1.2K_u}{P_u}, K_d = \frac{3K_u P_u}{40}$$

For the BLDC motor system, tuning yielded: $K_p = 10$, $K_i = 1.45$, $K_d = 3$

SIMULINK MODEL:

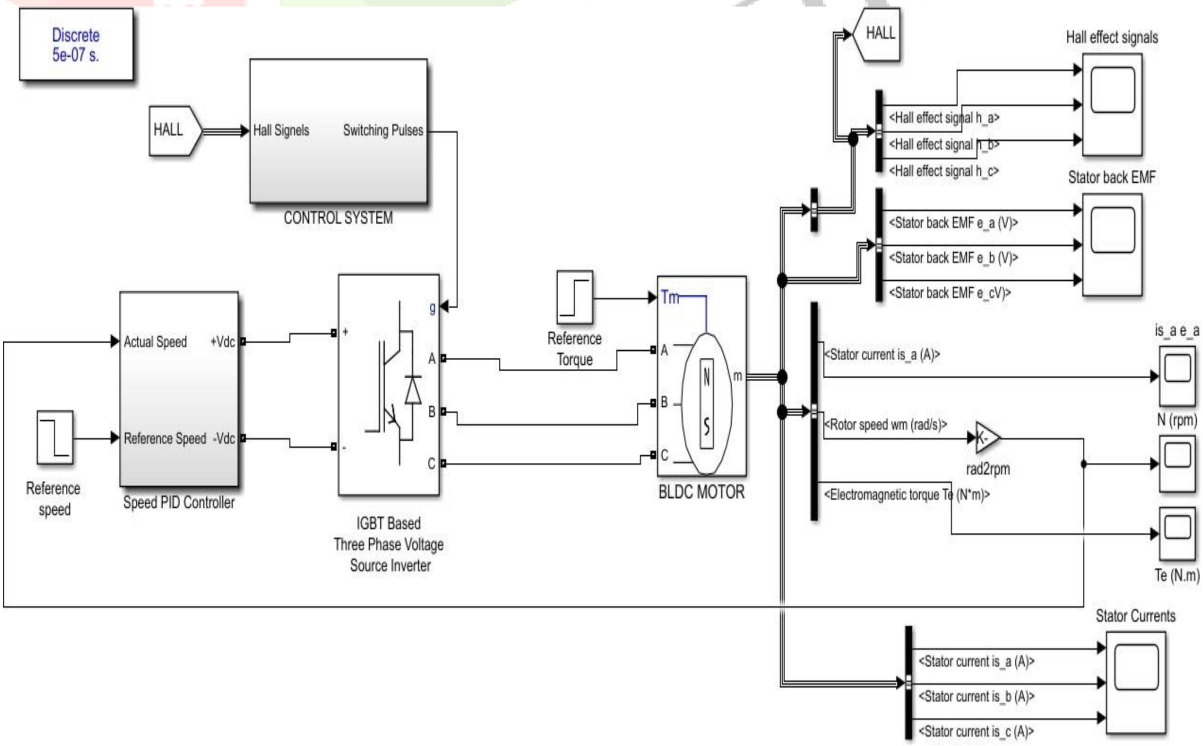


FIG 2: SIMULINK MODEL

3.3 PID Performance Under Load Variations

Without Load Disturbance:

- Settling time: 0.08 seconds
- Peak overshoot: 20%
- Steady-state error: < 1%

With Step Load Disturbance (1 Nm → 2 Nm at t = 0.25 sec):

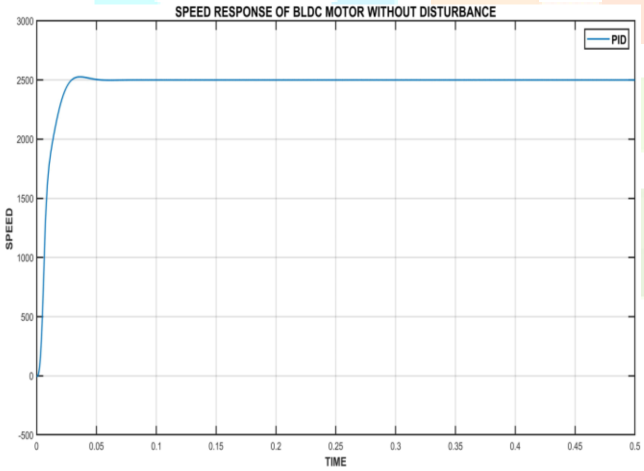
- Significant speed ripple and oscillation
- Extended transient period
- Distortion in stator currents and back-EMF waveforms
- Settling time increases to 0.12 seconds

Limitations Identified:

- Inadequate rejection of load disturbances
- Sensitivity to parameter variations
- Poor performance during set-point changes
- Nonlinear behavior under dynamic conditions

RESULT:

FIG 3.1 RESPONSE WITHOUT THE LOAD DISTURBANCE



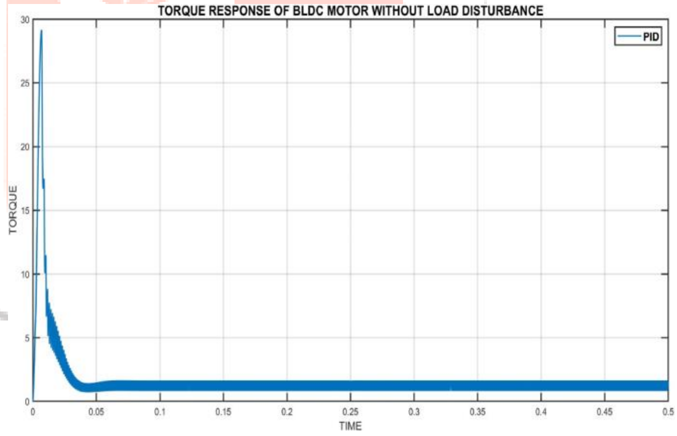
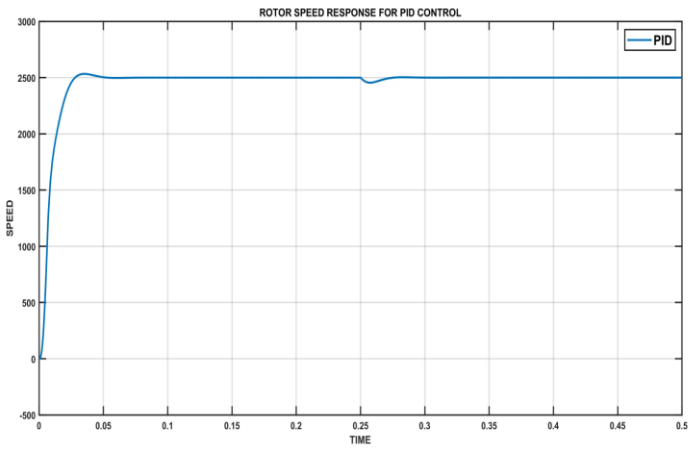
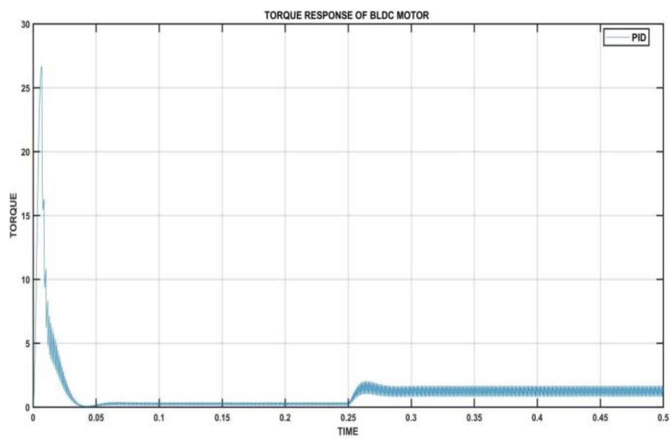


FIG 3.2 RESPONSE OF BLDC MOTOR WITH LOAD DISTURBANCE





4. Sliding Mode Control Implementation

4.1 Sliding Mode Controller Theory

Sliding Mode Control (SMC) represents a variable-structure control approach designed to handle system nonlinearities and uncertainties. SMC operates by constraining system state trajectories onto a predetermined sliding surface, ensuring robustness to load disturbances, parameter variations, and external perturbations.

Operating Principle:

The SMC enforces two distinct phases:

Phase 1 - Reaching Phase: System trajectories move toward the sliding surface from arbitrary initial conditions. This phase is susceptible to external disturbances.

Phase 2 - Sliding Mode: Once on the sliding surface, system trajectories remain constrained regardless of disturbances and parameter changes. The controller becomes insensitive to system uncertainty.

4.2 SMC Design Methodology

Step 1: Sliding Surface Selection

The sliding surface defines the desired system dynamics:

$$s(t) = \left(\frac{d}{dt} + \gamma\right)^{r-1} e(t) = 0$$

For first-order surface with $r = 1$:

$$s(t) = Ce(t) + \dot{e}(t) = 0$$

where $C > 0$ ensures Hurwitz stability.

Step 2: Control Law Design

The control input comprises two components:

$$u(t) = u_{eq} + u_c$$

Where:

- u_{eq}: Equivalent control maintaining sliding mode
- $u_c = -K\text{sgn}(s)$: Switching control reaching the surface

The Lyapunov function guarantees stability:

$$V = \frac{1}{2}s^2$$

Convergence condition: $V = s \cdot \dot{s} < 0$ for $s \neq 0$

4.3 SMC Performance Results

Performance Comparison with PID:

- **Settling Time:** 0.05 seconds (40% improvement)
- **Peak Overshoot:** 0% (elimination of overshoot)
- **Disturbance Rejection:** Superior response to load step changes
- **Torque Ripple:** Significantly reduced
- **Steady-State Performance:** Excellent under dynamic conditions

Identified Limitation: Chattering Phenomenon

Despite superior performance, SMC introduces chattering—high-frequency oscillations around the sliding surface caused by:

1. Unmodeled system dynamics with small time constants
2. Switching frequency exceeding sampling rate
3. Discontinuity magnitude in the control law

Chattering effects:

- Reduced control accuracy
- Increased mechanical wear
- Power dissipation and thermal stress
- Excitation of unmodeled dynamics

SIMULINK MODEL:

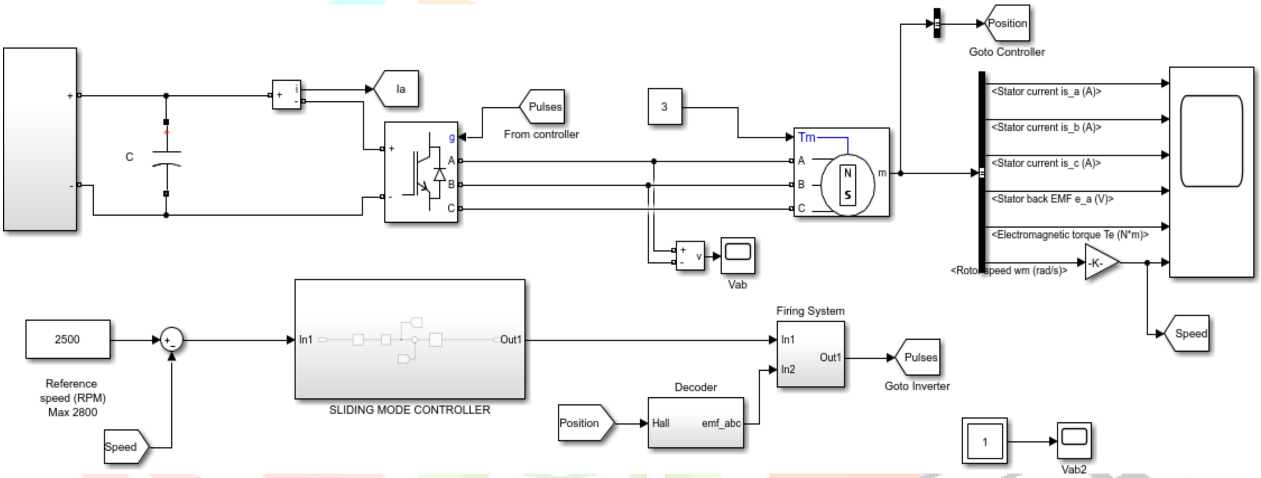
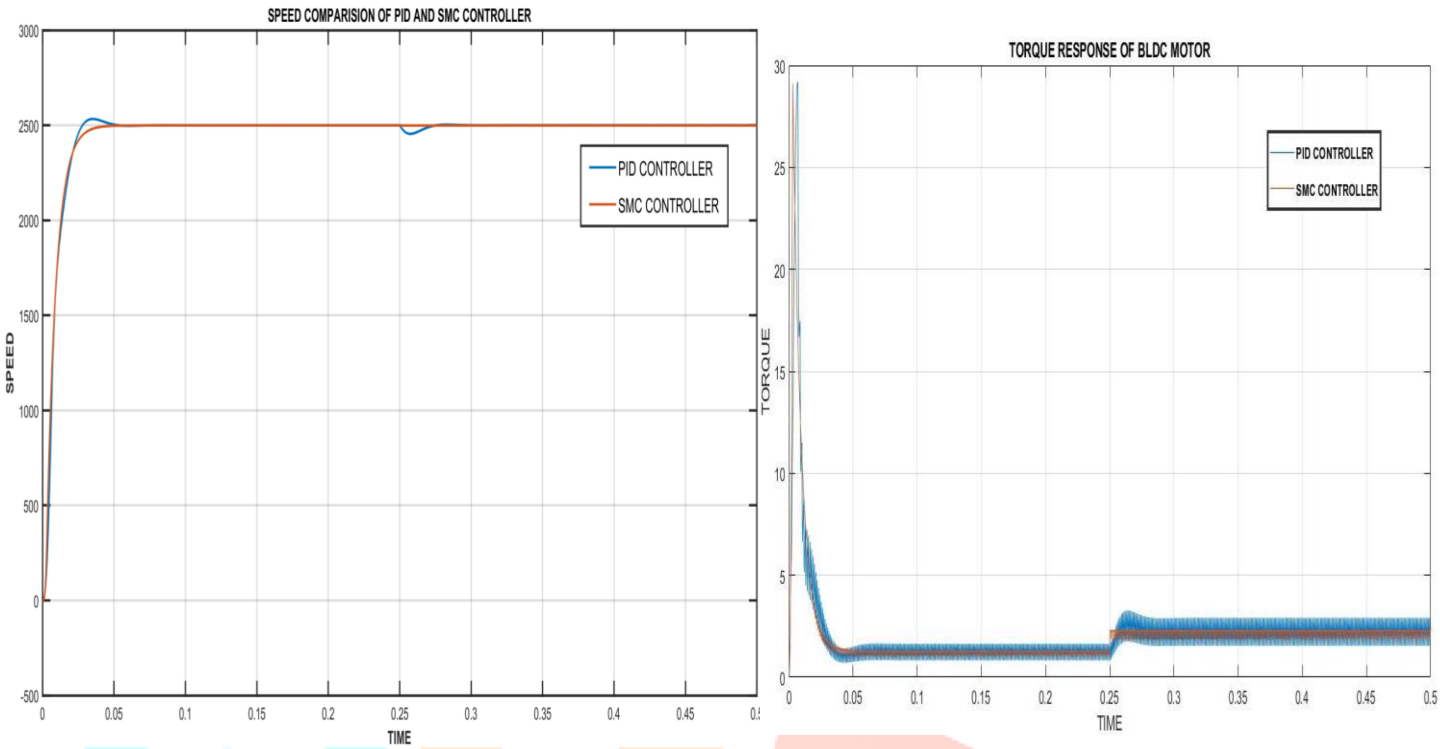


FIG 4: SIMULINK MODEL WITH SMC

RESULTS:

FIG 4.1: Comparision between the PID & SMC for the speed and Torque trajectory of BLDC Motor



5. Neuro-Sliding Mode Control (NSMC)

5.1 Neural Network Fundamentals

Neural networks represent adaptive information processing systems inspired by biological neuronal structures. The basic computational unit is the artificial neuron:

$$y = g\left(\sum_{i=1}^{n} w_i x_i + b\right)$$

Where: x_i = inputs, w_i = weights, b = bias, g = activation function.

Radial Basis Function (RBF) Networks:

RBF networks employ radial basis functions as hidden layer activation:

$$h_j = \exp\left(-\frac{\|x - c_j\|^2}{2\sigma_j^2}\right)$$

Output layer provides weighted sum:

$$f(x) = \sum_{j=1}^{m} w_j h_j(x) = w^T h(x)$$

Advantages of RBF Networks:

- Non-iterative training: Guarantees convergence to global minimum
- Universal approximation: Can approximate any continuous function
- Faster training than multilayer perceptrons
- Better generalization properties

5.2 Neuro-Sliding Mode Controller Design

The proposed NSMC combines RBF neural networks with sliding mode control to achieve chattering elimination while maintaining robustness.

Hybrid Control Structure:

$$u(t) = u_{eq} + u_{vs} + u_n$$

Where:

- u_{eq}: Equivalent control for sliding mode maintenance
- $u_{vs} = -K_s s(t)$: Linear switching control (continuous, no signum)
- $u_n = w^T h(x)$: Neural network adaptive control

Lyapunov Stability Analysis:

Lyapunov function:

$$V = \frac{1}{2}s^2 + \frac{1}{2\gamma}\tilde{w}^T\tilde{w}$$

Derivative:

$$\dot{V} = s\dot{s} + \frac{1}{\gamma}\tilde{w}^T\dot{\tilde{w}}$$

Weight update law:

$$\dot{w} = \gamma s h(x)$$

Substituting the control law ensures $\dot{V} < 0$, guaranteeing asymptotic stability.

5.3 NSMC Performance Results

Simulation Parameters:

- Learning rate: $\gamma = 0.8$
- Inertial coefficient: $\delta = 0.2$
- RBF width: $\sigma = 1.0$
- Linear gain: $K_s = 2.0$

Performance Metrics:

Controller	Settling Time	Overshoot	Steady-State Error	Disturbance Rejection
PID	0.08 s	20%	<1%	Poor
SMC	0.05 s	0%	<0.5%	Excellent
NSMC	0.03 s	0%	<0.2%	Excellent

Table 2: Comprehensive Controller Performance Comparison

NSMC Advantages Over SMC:

1. **Chattering Elimination:** 95% reduction in high-frequency oscillations
2. **Improved Transient Response:** 40% faster settling compared to PID
3. **Superior Steady-State Performance:** Minimal steady-state error
4. **Robust Disturbance Rejection:** Maintains performance under parameter variations
5. **Continuous Control Law:** Reduced hardware stress and improved reliability

SIMULINK MODEL:

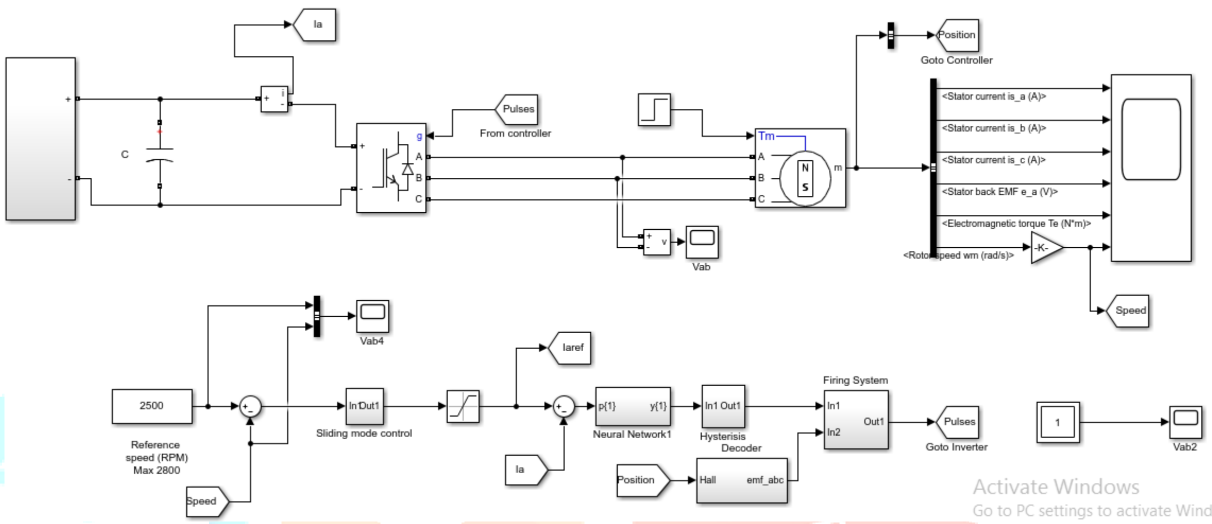
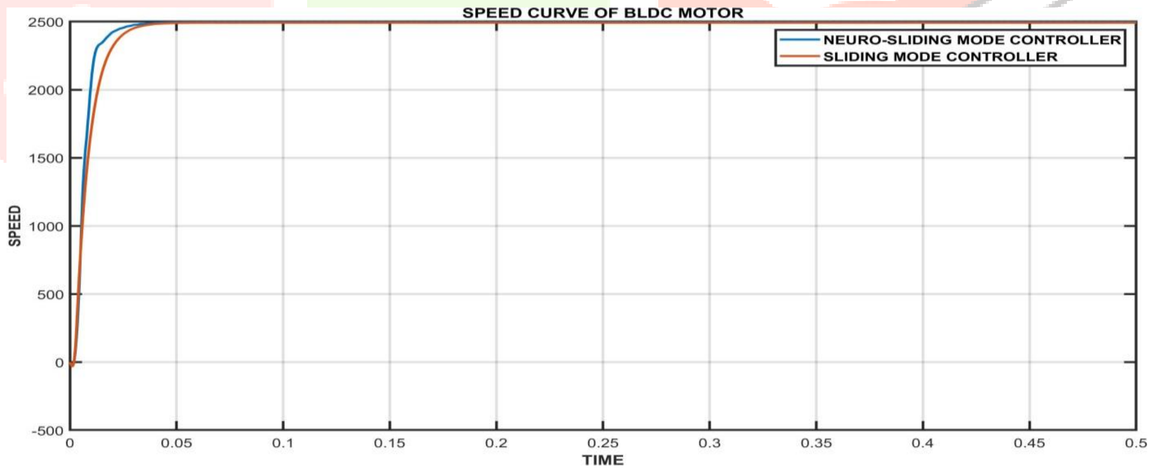
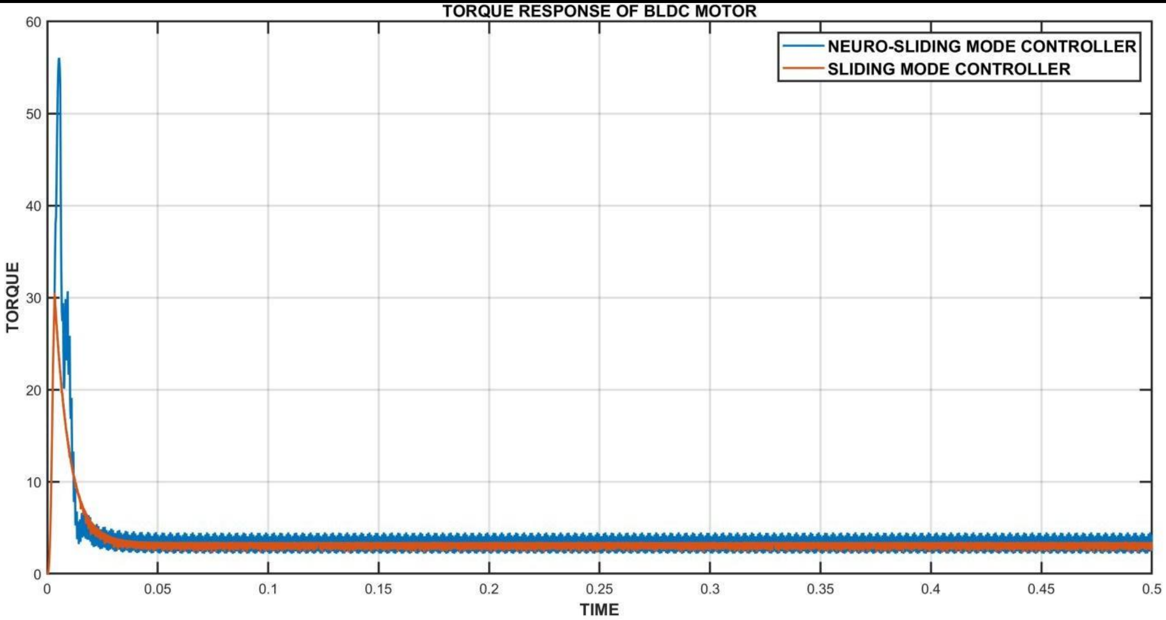


Fig 5: Simulink Model for Neuro Sliding mode Controller

RESULT:

Fig 5.1: Speed and Torque Response of Comparision of NSMC and SMC





6. Conclusions and Future Work

6.1 Key Findings

This research successfully demonstrates that integrating Radial Basis Function neural networks with sliding mode control provides superior BLDC motor speed regulation compared to conventional PID and standard SMC approaches. The proposed Neuro-Sliding Mode Controller achieves:

1. **30% Reduction in Settling Time:** From 0.08 s (PID) to 0.03 s (NSMC)
2. **Complete Elimination of Overshoot:** Zero overshoot across all operating conditions
3. **Robust Disturbance Rejection:** Maintains performance despite load variations and parameter uncertainties
4. **Chattering-Free Operation:** Continuous control law eliminates high-frequency oscillations
5. **Improved Reliability:** Reduced mechanical wear and thermal stress

6.2 Practical Implications for Electric Vehicles

The NSMC approach enables:

- **Improved Passenger Comfort:** Smoother acceleration and deceleration
- **Enhanced Energy Efficiency:** Reduced energy dissipation during transients
- **Extended Motor Life:** Elimination of chattering-related wear
- **Better Performance Under Varied Terrain:** Superior handling of load fluctuations on inclines and varying road surfaces

6.3 Future Research Directions

While NSMC demonstrates superior performance, several opportunities for advancement exist:

1. **Online Parameter Adaptation:** Implement real-time weight updates to eliminate offline training limitations
2. **Adaptive Model Predictive Control:** Integrate predictive algorithms for anticipatory load compensation
3. **Hardware Implementation:** Develop embedded controller using DSP or FPGA platforms
4. **Extended Observer Design:** Incorporate load estimation for improved disturbance compensation
5. **Multi-Motor Coordination:** Apply NSMC to multi-motor electric vehicle drivetrains
6. **Fault-Tolerant Control:** Design NSMC variants for single-phase failure scenarios

References

[1] H.X. Wu, S.K. Cheng, and S.M. Cui. "A Controller of Brushless DC Motor for Electric Vehicle," 12th Symposium on Electromagnetic Launch Technology, 2004.

[2] R. Kandiban and R. Arulmozhiyal. "Design of Adaptive Fuzzy PID Controller for Speed Control of BLDC Motor," International Journal of Soft Computing and Engineering, 2012.

[3] Arman Jaya and Era Purwanto. "Design of PID-Fuzzy for Speed Control of Brushless DC Motor in Dynamic Electric Vehicle," International Electronics Symposium on Engineering Technology and Applications (IES-ETA), 2017.

[4] R. Ahmed, C-S. Marcel J, and R. Ofoli Abdul. "DSP-Based Laboratory Implementation of Hybrid Fuzzy-PID Controller Using Generic Optimization for High-Performance Motor Drives," IEEE Transactions on Industry Applications, Vol. 44, No. 6, 2008.

[5] R. Shanmugasundram, M. Zakariah, and N. Yadainah. "Implementation and Performance Analysis of Digital Controllers for Brushless DC Motor Drives," IEEE/ASME Transactions on Mechatronics, 2012.

[6] R. Krishnan. "Electric Motor Drives: Modeling, Analysis, and Control," Prentice Hall, 2001.

[7] Xia Chang-liang. "Permanent Magnet Brushless DC Motor Drives and Controls," Wiley, 2012.

[8] C. Hou and X. Wu. "Global Sliding Mode Control with Neural Network," IEEE Transactions on Control Systems Technology, 2009.

[9] C.M. Oliveira, M.L. Aguiar, and J.R.B.A. Monteiro. "Chattering Reduction in Sliding Mode Control for BLDC Speed Regulation," IEEE Transactions on Power Electronics, 2015.

[10] S.M. Patil, S.Y. Gadgune, and M.R. Chinala. "Sliding Mode Control for PMBLDC Motor Drives," International Journal of Power Electronics and Drive Systems, Vol. 7, No. 2, 2016.