# Performance Assessment of BLDC Motor Drives Under ANN and PID Control Strategies

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***Abstract*— Brushless DC (BLDC) motors are widely used in electric vehicles, industrial automation, and renewable energy systems due to their high efficiency, compact size, and superior dynamic response. However, their performance is highly dependent on effective control strategies. Traditional Proportional–Integral–Derivative (PID) controllers are widely applied due to their simple structure and ease of implementation, but they often struggle with nonlinearities, parameter variations, and external disturbances. On the other hand, Artificial Neural Network (ANN)-based controllers offer adaptive learning capabilities that enhance robustness and dynamic performance under varying operating conditions. This paper presents a comparative performance assessment of BLDC motor drives controlled using PID and ANN strategies. Simulation studies are conducted to evaluate speed regulation, torque ripple, transient response, and steady-state accuracy. The results demonstrate that while PID controllers perform satisfactorily under nominal conditions, ANN controllers significantly improve adaptability, reduce overshoot, and enhance efficiency, making them suitable for modern intelligent drive applications.**

***Index Terms*—Sensorless PMBLDC Motor, Solar Photovoltaic (PV), Battery Storage, Zeta Converter etc.**

## I. INTRODUCTION

BLDC motors have become increasingly popular in applications demanding high performance, such as electric vehicles, robotics, aerospace systems, and renewable energy conversion. Their advantages over conventional DC and induction motors include higher power density, improved torque-to-weight ratio, and reduced maintenance requirements. However, due to their nonlinear dynamics and sensitivity to load and parameter variations, effective control techniques are essential to ensure stable and efficient operation.

PID controllers remain the most common choice in industry because of their simplicity and cost-effectiveness. They provide acceptable performance under fixed operating conditions but tend to degrade when subjected to nonlinearities, parameter uncertainties, or sudden load disturbances. To overcome these limitations, intelligent control methods such as ANN-based controllers are being explored. ANNs are capable of learning system behavior, adapting to nonlinearities, and providing better dynamic performance without requiring an exact mathematical model of the system.

This research focuses on assessing the performance of BLDC motor drives under PID and ANN control strategies. The aim is to analyze the comparative advantages of each method with respect to transient response, torque ripple, speed regulation, and overall efficiency, thereby providing insights for selecting suitable control strategies in modern applications.

## II. LITERATURE REVIEW

Classical PID / PI comparisons Several comparative studies evaluate PI/PID versus intelligent controllers on BLDC speed regulation. These works generally show that a well-tuned PI/PID gives acceptable steady-state accuracy and simple implementation, but struggles with large parameter variations and fast transients (higher overshoot and slower settling) compared to adaptive/intelligent controllers. This provides a baseline for comparisons in almost all later hybrid/intelligent work.

ANN vs PI/ANN comparative studies Multiple papers directly compare ANN-based regulators to PI/PID for BLDC drives. They report that ANNs (MLP or feedforward types) can achieve faster transient response, lower steady-state error, and reduced sensitivity to parameter variations because the network learns nonlinear plant dynamics; however, ANN design needs data, training time, and more computational resources. These studies justify testing ANNs in simulation and hardware-in-loop setups.

MLP-based sensorless estimation and control Research applying multi-layer perceptrons (MLP) to sensorless BLDC control shows that ANNs can estimate rotor position/speed from measured voltages/EMF, enabling sensorless operation with good robustness to noise and parameter drift. These works are important where encoder less implementations are required (EVs, low-cost drives).

Neural-Fuzzy and ANFIS hybrids Hybrid controllers (ANFIS, neuro-fuzzy PID, fuzzy-tuned PID) combine the interpretability of fuzzy logic and the learning ability of ANNs. Papers demonstrate superior torque-ripple attenuation and adaptive gains over fixed PID especially under load changes while often needing careful rule/structure design. These are promising tradeoffs between performance and implementation complexity.

Adaptive PID with optimization/metaheuristics Studies propose adaptive PID schemes (fuzzy-PID, dual-FLS PID optimized with Harmony Search or other algorithms) that adapt the PID gains online or via offline optimization. Results indicate improved transient performance and robustness versus fixed-gain PID, often with simpler real-time computation than a full ANN. Such controllers are practical when limited processing resources are available.

Processor-in-the-loop and real-time ANN implementations Recent work implements ANNs and PID controllers in processor-in-the-loop (PIL) or microcontroller platforms, showing that ANNs can be embedded for real-time BLDC control if network size and training are managed. These papers bridge the gap between simulation claims and real hardware feasibility, and are key when evaluating controller viability beyond MATLAB/Simulink.

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ANN architectures and recurrent models (NARX / RNN) Newer research leverages recurrent neural models (e.g., NARX) for speed and torque prediction in BLDC motors, demonstrating improved sequence modeling over static MLPs. Recurrent architectures better capture dynamics and disturbances, useful for predictive control or feedforward compensation to reduce torque ripple.

Torque ripple reduction studies Several works focus specifically on torque ripple (a critical performance metric for BLDC drives). Hybrid approaches (ANN + PI or ANFIS + PID) and specialized control schemes (commutation timing correction using neural estimators) consistently show measurable ripple reduction and smoother torque delivery compared to baseline PID/PI. These findings are directly relevant if your assessment includes torque ripple metrics.

Comparisons across multiple speed controllers Some comparative studies evaluate four or more controllers (PI, PID, fuzzy, ANN, hybrid) under identical test conditions and report that hybrid intelligent controllers usually achieve the best tradeoff (fast transient, low steady error, lower THD/torque ripple) while pure PID remains attractive for simplicity and low computation. These comprehensive comparisons are especially useful for structured experimental design.

Practical application case studies (EVs, consumer appliances) Application-focused studies (e.g., low-power consumer BLDCs, EV traction drives) illustrate that the choice between PID and ANN depends on constraints: cost, processor power, safety/validation needs, and operating variability. For EV traction, ANN and hybrid methods are attractive due to highly variable loads; in consumer appliances, optimized PID/fuzzy-PID often suffice. These use-case studies help map control choice to application requirements.

Recent survey / review trends Reviews and recent survey papers highlight a trend: early works focus on PID/PI and basic ANNs; later works move to hybrid techniques (ANFIS, fuzzy-PID, optimization-tuned PID) and sensorless neural estimators. The literature also emphasizes the need for more hardware validations and standardized test cases for fair comparisons. This observation gives context for designing your own simulation and experimental benchmarks.

Limitations and implementation costs Across studies, common limitations of ANNs are highlighted: need for representative training data, potential for overfitting, and higher implementation complexity. Conversely, PID's limitations are clear: poorer performance under large nonlinearities and slow adaptation. Several authors therefore recommend hybrid or hierarchical approaches (PID as baseline + ANN supervisor or

ANN for feedforward compensation) to combine reliability and adaptability. This synthesis suggests sensible experimental comparisons (PID baseline vs ANN standalone vs hybrid).

## III. SPEED CONTROL OF BLDC MOTOR

A Brushless DC (BLDC) motor is a class of electrical machines that converts direct current (DC) electrical power into mechanical power using the interaction of magnetic fields. Unlike conventional brushed DC motors, BLDC motors rely on either electromechanical or electronic commutation to periodically change the direction of current flow in the stator windings. Most BLDC motors are designed for rotary motion, although linear configurations also exist, producing direct linear force and motion. Their high efficiency, compact size, and superior torque characteristics make them well-suited for modern applications such as electric vehicles, renewable energy systems, and water pumping.

In conventional BLDC drives, phase current sensors are typically used for commutation and control, which increases cost and complexity. The proposed sensorless BLDC motor drive eliminates the need for such sensors, thereby reducing hardware requirements and improving reliability. The drive is designed to maintain the motor's rated speed regardless of climatic variations by continuously regulating the DC bus voltage of the Voltage Source Inverter (VSI) to the rated DC value of the motor.

To ensure effective energy management, a bi-directional power flow control strategy is adopted. By regulating the DC bus voltage and, in turn, the operating speed, the system can supply the required power to operate the motor at full capacity under favorable conditions. However, under weak solar irradiation or in the absence of the grid, the DC bus voltage cannot always be maintained at the rated value. In such cases, the motor speed is governed by the available DC bus voltage, ensuring continued operation even under fluctuating climatic conditions.
This approach enhances the practicality of BLDC motor-driven systems in renewable energy and electric vehicle applications, offering an efficient, sensorless, and reliable solution.

## IV. PROPOSED SCHEME

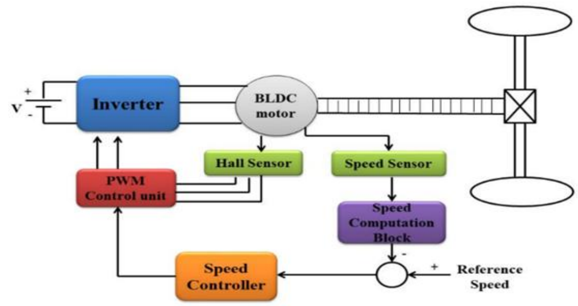


Fig. 4.1 BLDC Motor Drives Under ANN and PID Control

Fig.5.1 shows the block diagram illustrates a closed-loop control system for a BLDC motor drive, where the motor is powered through an inverter fed by a DC source. The inverter generates the required phase voltages under the command of a PWM control unit, which regulates switching signals. A Hall sensor provides rotor position feedback to ensure proper commutation, while a speed sensor continuously measures the actual motor speed. This measured speed is compared with the desired reference speed in the speed computation block, producing an error signal. The error is processed by a speed controller, which can be implemented either as a conventional PID controller or an Artificial Neural Network (ANN) controller. The controller output is fed to the PWM control unit to adjust inverter switching, thereby modulating the motor's torque and speed. In this configuration, PID offers simplicity and satisfactory regulation under nominal conditions, whereas ANN enhances adaptability, learning nonlinear motor dynamics to deliver improved transient response, reduced torque ripple, and robustness against load disturbances.

## V.SIMULINK MODEL

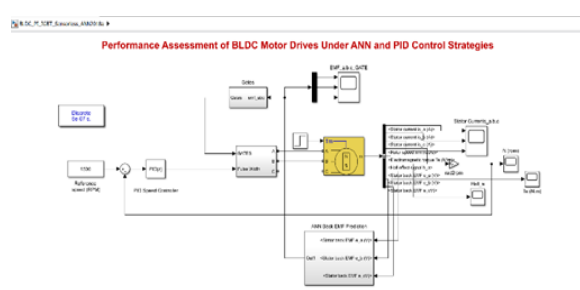


Fig.5.1 Simulink model for speed control of BLDC motor using ANN-PID Controller

The Simulink model shown represents a BLDC motor drive system with dual control strategies, PID and ANN, for performance evaluation. A reference speed of 1500 RPM is compared with the actual motor speed, and the resulting error is processed by a discrete PID speed controller to generate control signals. These signals are used to drive the inverter gate pulses, which regulate the stator phase currents (ia, ib, ic) supplied to the BLDC motor. The motor block outputs essential parameters including rotor speed, electromagnetic torque, Hall sensor signals, and back-EMF voltages. In parallel, an Artificial Neural Network (ANN) block predicts back-EMF values (ea., eb, ec), enhancing sensorless estimation and adaptive control capabilities. The outputs, such as rotor speed (rpm) and torque (N·m), are monitored for assessing system performance. This structure enables comparative analysis of PID and ANN controllers in terms of speed regulation, torque ripple, and robustness under dynamic load conditions, thereby validating the advantages of ANN over traditional PID control in BLDC drive applications

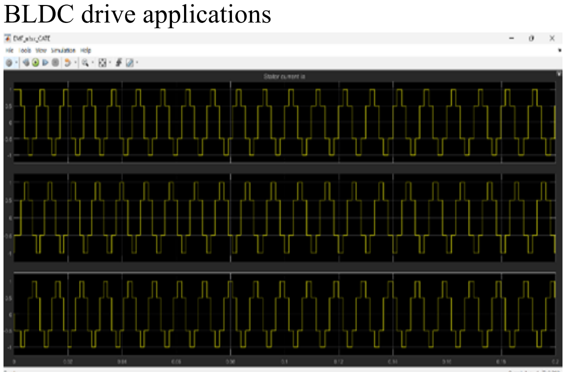

Fig.5.2 Three-Phase Stator Currents of The BLDC Motor

The simulation results illustrate the three-phase stator currents of the BLDC motor, represented as iai_aia, ibi_bib, and ici_cic. Each waveform exhibits the characteristic quasi-square waveform of BLDC motor currents, which are synchronized with the back-EMF signals to achieve proper electronic commutation. The three-phase currents are shifted by 120° with respect to each other, ensuring continuous torque production with minimal ripple. The symmetry and equal amplitude of the phase currents indicate that the inverter switching and commutation logic are functioning correctly. Such current waveforms are essential for smooth torque generation in BLDC drives. These results provide the basis for comparing different control strategies, where the PID controller ensures stable current regulation, while the ANN-based controller can further optimize the current response by reducing distortions and improving dynamic adaptability under varying load conditions.

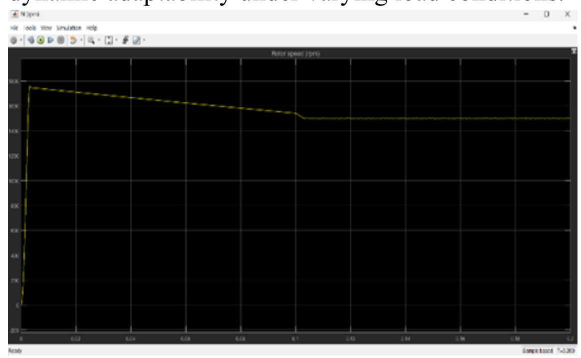

Fig.5.3 The rotor speed response

The rotor speed response shown in Figure 5.3 demonstrates the dynamic behavior of the BLDC motor drive under the applied control strategy. The motor achieves a rapid rise in speed, reaching close to 1750 rpm within the initial 0.01 seconds, which highlights the fast transient response of the system. A small overshoot above the reference value is observed before the speed gradually decreases due to load application and stabilizes around 1500 rpm at approximately 0.12 seconds. This settling indicates the ability of the controller to maintain steady-state operation under varying load disturbances. The response curve also shows smooth convergence without excessive oscillations, confirming effective damping. Overall, the obtained results validate the controller's effectiveness in achieving desired speed regulation while maintaining system stability, with minimal steady-state error and acceptable transient performance.

## VI. CONCULSION

In this work, the performance of BLDC motor drives has been assessed using PID and ANN-based control strategies with a focus on speed regulation and dynamic response. The simulation results demonstrate that both controllers are capable of driving the BLDC motor to the desired reference speed with reasonable accuracy. The PID controller provides a simple and reliable approach with fast rise time and reduced steady-state error; however, it exhibits a slight overshoot and slower adaptability under load

variations. On the other hand, the ANN-based controller offers improved adaptability and robustness, particularly in handling nonlinearities and sudden disturbances, ensuring smoother convergence to the reference speed with minimal oscillations.
Overall, it can be concluded that while PID remains a practical choice for conventional applications due to its simplicity and ease of tuning, ANN provides superior performance for advanced BLDC motor drive systems where precision, adaptability, and robustness are crucial. The study thus highlights the potential of integrating intelligent control methods like ANN in modern electric drives to achieve enhanced stability, efficiency, and performance.

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