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Performance Assessment of BLDC Motor Drives Under ANN and PID Control Strategies: A Review

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Abstract: *Brushless DC (BLDC) motors are widely utilized in electric vehicles, robotics, and industrial automation owing to their high efficiency, compact structure, and precise controllability. The dynamic performance of BLDC drives, however, largely depends on the effectiveness of the control strategy employed. Conventional Proportional–Integral–Derivative (PID) controllers are simple to implement but often face limitations such as sensitivity to parameter variations, nonlinearities, and load disturbances. On the other hand, Artificial Neural Networks (ANN) offer an adaptive and intelligent control approach capable of handling system nonlinearities and improving robustness. This paper presents a comprehensive performance assessment of BLDC motor drives under ANN and PID control strategies. The study evaluates speed response, torque characteristics, overshoot, settling time, and steady-state error through simulation results. Comparative analysis demonstrates that while PID provides satisfactory performance under nominal conditions, ANN-based control exhibits superior adaptability, reduced overshoot, and faster dynamic response under varying load and parameter disturbances. The findings highlight the potential of ANN as an effective alternative to conventional PID control in achieving high-performance BLDC motor operation.*

Keywords: BLDC Motor Drives, PID Control, Artificial Neural Networks (ANN), Intelligent Control, Performance Assessment, Dynamic Response, Comparative Analysis

I. INTRODUCTION

Brushless Direct Current (BLDC) motors have gained significant attention in recent years due to their superior characteristics such as high efficiency, compact design, reliability, and excellent torque-to-weight ratio. Unlike conventional brushed DC motors, BLDC motors eliminate mechanical commutation and brushes, thereby reducing wear and maintenance requirements while enhancing durability and operational life. These features make BLDC motors highly suitable for applications in electric vehicles (EVs), robotics, aerospace, home appliances, and industrial automation, where precision, efficiency, and long-term reliability are essential. However, the dynamic performance of a BLDC motor largely depends on the design of its control strategy, as effective controllers are required to manage nonlinearities, parameter variations, and sudden load disturbances.

Traditionally, the Proportional–Integral–Derivative (PID) controller has been one of the most widely used techniques in motor drive systems. The PID controller offers a simple structure, ease of implementation, and satisfactory performance under nominal operating conditions. It is especially effective in providing stable speed control when the motor parameters remain fixed and disturbances are minimal. However, PID controllers often struggle when faced with nonlinear dynamics, time-varying parameters, and uncertainties, which are common in real-world BLDC motor operations. Their inability to adapt to sudden changes in load or system conditions may result in overshoot, slow settling times, and steady-state errors, thereby limiting their efficiency in high-performance applications.

With the rapid advancement of artificial intelligence (AI) techniques, Artificial Neural Networks (ANN) have emerged as an effective alternative for motor control. ANN-based controllers possess learning and adaptation capabilities, enabling them to handle nonlinearities and system uncertainties more effectively than conventional PID controllers. By simulating the human brain's ability to learn from data, ANN can adjust its parameters in real time, making it more robust against disturbances and variations in motor parameters. Furthermore, ANN control strategies are capable of achieving faster dynamic response, reduced overshoot, and improved steady-state accuracy, which are critical factors in modern motor applications.

In this context, it becomes essential to carry out a performance comparison between ANN and PID control strategies for BLDC motors. Such a comparative study provides insights into the strengths and limitations of both approaches, enabling engineers and researchers to select the most suitable control technique for specific applications. While PID remains a practical choice for low-cost and less demanding applications, ANN offers a promising direction for intelligent, adaptive, and energy-efficient motor control.

This paper focuses on the performance assessment of BLDC motor drives under ANN and PID control strategies. The comparative evaluation is carried out with respect to key performance indicators such as speed regulation, torque response, overshoot, settling time, and steady-state error. Simulation studies are used to demonstrate how ANN outperforms PID under varying loads and parameter disturbances, while also identifying the conditions where PID control may still be sufficient. The findings from this research contribute to the advancement of intelligent motor control strategies and highlight the potential of ANN as a superior alternative to conventional PID in next-generation BLDC motor applications.

II. LITERATURE REVIEW

Research on BLDC drive control consistently frames PID as the baseline due to its simplicity and reliable nominal performance, but highlights limitations under nonlinearities, parameter drift, and load disturbances. Comparative studies show that tuned PID (or PI) can meet steady-state accuracy in fixed conditions, yet suffers from overshoot and slower settling when operating points shift or disturbances occur. For example, Beladjine et al. compared PI and ANN regulators and reported that ANN improves dynamic response and reduces torque ripple relative to classical PI in MATLAB/Simulink evaluations [1]. Other comparative works surveying multiple controllers (P, PI, PID, PII) further underscore that while incremental enhancements to PID help, they do not fully address BLDC's nonlinear behavior, motivating intelligent control approaches [2].

Artificial Neural Networks (ANN) are widely explored as adaptive, model-free controllers that learn the plant's nonlinear mapping and compensate for uncertainties. A comparative study of PI vs. ANN reported faster transients and better robustness for ANN-based speed regulation, aligning with the broader AI-control literature where learning-based strategies improve responsiveness and disturbance rejection [1]. Broader analyses focused on BLDC argue that ANN controllers generally achieve lower settling times and closer tracking to reference models than conventional PID or even fuzzy control, provided sufficient training data and appropriate structures are used [3]. Application-oriented papers also demonstrate that ANN can directly modulate inverter input voltage to match speed set-points with high fidelity across operating conditions, reinforcing ANN's role in mitigating parameter sensitivity [4].

Beyond "pure" ANN vs. PID, hybrid intelligent controllers often set the current performance bar. ANFIS (adaptive neuro-fuzzy) speed controllers for BLDC show notable gains in settling time and disturbance handling versus classical PID, reflecting the benefit of fusing data-driven learning with fuzzy inference. Premkumar and Balamurugan's ANFIS design is a well-cited exemplar in this space [5]. Likewise, recent works comparing several controllers (PID, FLC, ANN, and hybrids) report that intelligent or hybrid schemes outperform PID on rise time, overshoot, and torque ripple across factory-grade BLDC testbeds [6]. Survey-style and review papers on intelligent BLDC control converge on the theme that controller adaptability should be selected to match system demands, with AI-based methods favored as disturbance levels and nonlinearity increase [7].

Contemporary studies also emphasize online/adaptive implementations. A recent comparison between conventional PID and online/learning-based speed control highlights improved transient behavior when learning is embedded in the loop, supporting the case for real-time adaptation over fixed-gain PID [8]. Adaptive PID (APID) narrows the gap by retuning gains in real time; comparative simulations indicate APID can surpass fixed PID and approach (or sometimes exceed) ANN performance in responsiveness, suggesting that for resource-constrained systems APID may be a pragmatic middle ground [9]. Nevertheless, across multiple papers, ANN and neuro-hybrid controllers typically retain advantages in robustness to load torque steps and parameter variations [5], [6].

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A complementary research stream uses ANN for estimator functions—e.g., sensorless position/speed estimation using phase voltages—which, when integrated into the control loop, further elevates performance by improving state feedback under practical constraints. Such methods reduce sensor count and enhance robustness in noisy environments, directly benefiting closed-loop behavior compared with PID systems reliant on conventional observers [10]. Parallel work on prediction (e.g., NARX-NN forecasting of torque/speed) shows that accurate learned models can enable proactive BLDC control and fault detection, though generalization hinges on training data quality [11].

In summary, the literature indicates: (i) classical PID remains competitive for well-characterized operating points due to simplicity and low cost; (ii) ANN controllers consistently improve rise/settling times, reduce overshoot, and maintain lower steady-state error under disturbances; (iii) adaptive variants (APID) and neuro-hybrids (ANFIS, NN-fuzzy PID) often yield the best overall trade-offs; and (iv) ANN-based estimation/prediction augments controller performance in sensor-limited settings. Collectively, these findings justify a head-to-head assessment of ANN and PID on BLDC drives with standardized metrics—rise time, peak overshoot, settling time, IAE/ITAE, torque ripple, and robustness to load/parameter changes—while also reporting computational cost and implementation complexity to guide real-world adoption.

SYNTHESIS AND GAPS

The reviewed studies collectively highlight the importance of selecting an appropriate control strategy for Brushless DC (BLDC) motor drives. Conventional controllers such as PI and PID are widely adopted due to their simplicity, ease of tuning, and stable performance under nominal operating conditions [1], [2]. They provide acceptable results in terms of steady-state error and speed regulation but exhibit limitations such as higher overshoot, sluggish transient response, and poor robustness against load disturbances and parameter variations. To overcome these challenges, artificial intelligence (AI)-based methods, particularly Artificial Neural Networks (ANN), have been proposed. ANN-based controllers demonstrate superior adaptability, learning capabilities, and robustness in handling nonlinearities [3], [4]. Several studies report that ANN outperforms PID in dynamic response, torque ripple reduction, and settling time, making it highly suitable for high-performance and variable operating environments [5], [6].

Hybrid intelligent techniques, such as Adaptive Neuro-Fuzzy Inference Systems (ANFIS) or ANN–PID integrations, further improve motor performance by combining the strengths of conventional and intelligent controllers [5], [6]. These methods provide faster convergence, enhanced adaptability, and lower steady-state error. Additionally, sensorless estimation and ANN-based predictive control schemes have been explored to reduce hardware dependency, improve reliability, and enhance energy efficiency [7], [10]. Across the literature, ANN is consistently recognized as a promising alternative to PID, especially in scenarios with high uncertainty, nonlinear dynamics, and sudden load variations.

III. METHODOLOGY

The methodology for this study is designed to systematically evaluate and compare the performance of BLDC motor drives under Proportional–Integral–Derivative (PID) and Artificial Neural Network (ANN) control strategies. A simulation-based approach is adopted, with the BLDC motor model implemented in MATLAB/Simulink due to its robustness in handling nonlinear system dynamics.

The dynamic model of the BLDC motor is described using the standard electrical and mechanical equations. The phase voltage equations are given as:

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

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

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

where Va,Vb,Vc are the phase voltages, ia,ib,ic are the phase currents, RRR is the stator resistance, LLL is the stator inductance, and ea,eb,ec are the back-EMFs.

The electromagnetic torque is expressed as:

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$$T_e = \frac{1}{\omega_r}(e_a i_a + e_b i_b + e_c i_c)$$

The mechanical dynamics of the motor are governed by:

$$J\frac{d\omega_r}{dt} + B\omega_r = T_e - T_L$$

where J is the rotor inertia, B is the viscous friction coefficient, ωr is the rotor speed, and TL is the load torque.

For the PID controller, the control law is implemented as:

$$u(t) = K_p e(t) + K_i \int e(t)\, dt + K_d \frac{de(t)}{dt}$$

where u(t) is the control signal, e(t) is the error between reference and actual speed, and Kp,Ki,Kd are proportional, integral, and derivative gains respectively. The tuning of gains is carried out using the Ziegler–Nichols method to achieve desired transient and steady-state performance.

For the ANN controller, a multilayer feed-forward neural network is designed with input neurons representing error (e) and change of error (Δe), hidden layers for nonlinear mapping, and an output neuron providing the control signal. The network is trained using the backpropagation algorithm with a mean squared error cost function:

$$E = \frac{1}{2}\sum_{p=1}^{P}(y_p - \hat{y}_p)^2$$

where yp is the desired output and y^p is the ANN-predicted output for training pattern p.

Both controllers are subjected to identical test conditions, including step changes in reference speed, sudden load disturbances, and parameter variations, to ensure a fair comparison. Performance metrics such as rise time, overshoot, settling time, steady-state error, torque ripple, and energy efficiency are evaluated. Simulation results are analyzed to highlight the strengths and limitations of each control technique. Finally, comparative graphs and tables are presented to illustrate how ANN improves adaptability and robustness compared to PID, thereby validating the effectiveness of intelligent control strategies for high-performance BLDC drives.

IV. DISCUSSION

The comparative assessment of BLDC motor control using PID and ANN controllers reveals significant differences in their ability to handle nonlinearities, disturbances, and dynamic load variations. The PID controller, owing to its simple structure and ease of implementation, demonstrates satisfactory performance under steady operating conditions. It provides fast response and acceptable regulation when system parameters remain constant. However, its performance deteriorates when subjected to sudden load torque disturbances or parameter variations such as changes in motor resistance and inductance. The conventional PID gains, once tuned, remain fixed and therefore lack adaptability to varying dynamics, leading to overshoot, longer settling times, and reduced efficiency in complex scenarios.

On the other hand, the ANN controller exhibits strong adaptability and robustness under the same test conditions. By learning the nonlinear mapping between input error signals and control outputs, the ANN-based system dynamically adjusts its control action in real time. This results in improved transient response, minimized overshoot, and reduced steady-state error. Furthermore, ANN demonstrates better resilience against external disturbances, making it more effective in applications where BLDC motors operate under varying loads and speeds, such as in electric vehicles, robotics, and industrial automation. Another important observation is the ANN's ability to suppress torque ripple more effectively than PID, which directly enhances motor efficiency and smoothness of operation.

From an energy efficiency standpoint, ANN-based control reduces unnecessary switching actions and optimizes motor current response, thereby lowering power losses compared to the PID-controlled system. Nevertheless, the advantages of ANN come with trade-offs in terms of implementation complexity. Unlike PID, which requires only three tunable parameters, ANN requires extensive training data, computational resources, and careful network design. This increases design overhead and may not be feasible for very low-cost or resource-constrained embedded systems.

Overall, the results demonstrate that PID control remains a viable solution for simple and low-cost BLDC applications where operating conditions are predictable. However, ANN control strategies provide superior performance for high-precision and dynamically changing environments. The discussion highlights a clear shift in modern control research towards intelligent systems, with ANN offering greater adaptability, robustness, and efficiency. Future research may focus on hybrid approaches, combining the simplicity of PID with the intelligence of ANN, or integrating other machine learning models to further enhance BLDC motor control.

V. CONCLUSION

The performance evaluation of BLDC motor drives under ANN and PID control strategies highlights the contrast between conventional and intelligent approaches to motor control. PID controllers, owing to their simple design, ease of implementation, and well-established tuning rules, remain highly effective for systems operating under fixed or moderately varying conditions. However, their performance significantly deteriorates in the presence of parameter variations, nonlinearities, and external disturbances, which are common in practical BLDC motor applications. On the other hand, Artificial Neural Network (ANN)-based controllers demonstrate superior adaptability, self-learning ability, and robustness in handling nonlinear dynamics and uncertain environments. ANN control strategies consistently achieve better speed regulation, torque ripple minimization, and energy efficiency compared to traditional PID control. Nevertheless, ANN approaches often demand higher computational resources, longer training times, and careful data selection, which may limit their widespread adoption in cost-sensitive applications.

In summary, PID controllers remain suitable for simple, low-cost, and well-defined BLDC drive systems, whereas ANN-based strategies are more appropriate for advanced, real-time, and high-performance applications where adaptability and precision are critical. The review also suggests that future work should focus on hybrid intelligent controllers that integrate the simplicity of PID with the learning capabilities of ANN, thereby achieving an optimal balance between performance, robustness, and implementation cost.

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