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A Comprehensive Literature Review of Brushless DC (BLDC) Motor Control Strategies from 1995–2026

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ABSTRACT
Brushless DC (BLDC) motors have increasingly become one of the favored choices in modern-day drive systems due to their energy-efficiency, compact design, and impressive dynamic behavior. However, the performance of BLDC motors depends to a large extent on control methods adopted. This research provides a comprehensive review of the methods developed to control BLDC motors from 1995 to 2026. These methods can be broadly classified into four classes: classical control methods, advanced nonlinear control, intelligent control techniques, and hybrid control methods. It includes some prominent methods like FOC, SMC, MPC, and artificial intelligence-based controllers. This review also touches upon sensorless control, methods that can reduce torque ripples, and methods of control parameter tuning. Comparison of different control methods shows their strengths and weaknesses.

KEYWORDS: *BLDC motor, control strategies, FOC, sensorless control, AI control, MPC*

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I. Introduction

The increasing use of brushless DC (BLDC) motors in electric cars, robots, airplanes, and industry is due to their higher efficiency and reduced weight relative to torque [1]–[4].. This is achieved through the elimination of a mechanical commutator that causes high friction and heating, and requires regular maintenance. [5], [6].

However, the absence of brushes means that electronic commutation becomes necessary, requiring sophisticated algorithms. [7], [8]. Research has been mainly focused on motor models and basic control algorithms, which served as a basis for designing modern BLDC motors [9]–[11].. Nevertheless, there are still problems associated with nonlinearity, trapezoidal voltage curves, and changes in parameters. [12]–[14].

Popular initial solutions include proportional-integral (PI) and proportional-integral-derivative (PID) controllers, which are easy to implement but ineffective when working with nonlinear processes[15], [16]. To overcome these limitations, various other methods have been introduced, including field-oriented control (FOC), sliding mode control (SMC), and model predictive control (MPC). These offer improved results[17]–[20]..

Currently, research is moving towards the development of new intelligent control algorithms based on fuzzy logic, artificial neural networks, and optimizations, which improve the efficiency of motor operation[21]–[24].. Additionally, sensorless control algorithms have been studied to reduce costs and increase reliability. [25]–[27].

II. Evolution of Control Strategies

A. Classical Control Approach (1995-2005)

In those times, classical control schemes used PI and PID control algorithms due to their simplicity and relatively small computational requirements [15], [28].. PWM was employed for commutation and speed regulation[29].. However, these methods proved to be rather sensitive to any nonlinearities and changes in parameters [16].

B. Digital Control Approach (2005-2015)
Thanks to enhanced performance of DSPs and microcontrollers, better adaptivity and precision were achieved[30]. Sensorless control schemes based on the principle of back-EMF and observers allowed eliminating some kinds of sensors, thus decreasing costs, but still had problems with low operating frequencies and under heavy noise conditions. [25-31]

C. Intelligent and Hybrid Control Approach (2015-2026)
Currently, intelligent and hybrid approaches that combine elements of AI and non-linear control algorithms along with optimization have become popular[21]–[24].. Methods such as MPC and SMC allow for faster, more responsive, and stable dynamics of the system18]–[20].. The hybrid approach allows increasing the efficiency and reducing torque ripple [32-33].

III. Classical Control Techniques

A. PI/PID Control
The use of Proportional–Integral–Derivative (PID) controllers in BLDC motor control applications has been widespread due to their simplicity of implementation and easy-to-understand architecture [15], [28]. PID controllers adjust the speed of the motor in accordance with the difference between the desired speed and the current speed. Such controllers are not computationally intensive and provide satisfactory results for affordable applications with stable operating conditions. However, they do not show sufficient robustness and reliability in nonlinear operation environments, requiring proper adjustment to maintain satisfactory performance in different loading conditions [16].

B. Hysteresis Current Control
One of the key advantages of hysteresis current control is a clear and effective regulation of phase currents in a predefined hysteresis range [29]. The control method shows good dynamic response and inherent stability and can be applied in tasks that require efficient current control in real time. The approach implies direct switching between the inverter states depending on the current error and does not rely on more complex modulation algorithms. The major drawback of the method under consideration is its inability to ensure stable switching frequency and high susceptibility to EMI.

IV. Advanced Control Strategies

A. Field-Oriented Control (FOC)
Field-Oriented Control (FOC), which enables the independent control of torque and magnetic flux through rotating reference frame alignment of stator current, leads to smoother torque, improved efficiency, and precise speed control in BLDC motor drives. Given its fast dynamics, it is widely adopted in applications that demand high performance, including EVs and robotic systems. The drawback of this method is its reliance on the accuracy of rotor position information and increased computation requirements compared to conventional approaches.

B. Sliding Mode Control (SMC)
Sliding Mode Control (SMC) is a nonlinear control technique with excellent robustness against changes in system parameters and disturbances. Its effectiveness lies in constraining the system trajectory on a selected sliding surface, ensuring stability regardless of inaccuracies in system parameters. The application of SMC in BLDC motors offers fast dynamics and robustness against disturbances. Nevertheless, it suffers from the problem of chattering, unwanted oscillations that usually require additional measures to mitigate.

C. Model Predictive Control (MPC)
The Model Predictive Control (MPC) approach utilizes the model of the process to predict the future behavior of the system and optimizes the control action over the finite prediction horizon [19], [20], [36]. This approach works particularly well for constraint handling and shows excellent transient and steady state performances in BLDC drives. Due to its predictive nature, the MPC algorithm is particularly suitable for high performance multivariable systems control. However, MPC requires very high computational capabilities.

V. Intelligent Control Techniques

A. Fuzzy Logic Control (FLC)
Fuzzy Logic Control (FLC) is widely used in BLDC motor drives due to its ability to handle nonlinearities without requiring an exact mathematical model [21]. It utilizes linguistic rules and membership functions to map input variables such as error and change in error to control actions. This approach improves system stability and

provides smooth control under varying operating conditions. However, the design of membership functions and rule sets requires expert knowledge and may affect controller performance [35].

B. Artificial Neural Networks (ANN)
Artificial Neural Networks (ANN) offer adaptive learning capabilities, enabling BLDC motor controllers to adjust to changing system dynamics in real time [22], [23]. They are particularly effective in modeling complex nonlinear relationships and improving control accuracy under uncertain conditions. ANN-based controllers enhance robustness and reduce dependency on precise system parameters. However, they require significant training data and computational resources, which can increase implementation complexity [36].

C. Optimization Techniques
Optimization techniques such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) are used to automatically tune controller parameters for improved performance [24], [37]. These methods search for optimal solutions by minimizing objective functions such as speed error, torque ripple, and energy consumption. They significantly enhance convergence speed and control efficiency in BLDC motor systems. However, optimization algorithms may increase computational burden and require careful selection of tuning parameters.

VI. Comparative Analysis

Method	**Complexity**	**Robustness**	**Performance**	**Cost**
PID	Low	Low	Moderate	Low
FOC	Medium	High	High	Medium
SMC	High	Very High	High	Medium
MPC	Very High	High	Very High	High
AI	High	Very High	Excellent	High

VII. Sensorless Control Techniques

A. Back-EMF Based Methods
Back-EMF based techniques estimate rotor position by detecting the zero-crossing points of the induced voltage in the stator windings [25], [39]. These methods are simple to implement and widely used in medium- and high-speed BLDC motor applications. They eliminate the need for physical sensors, reducing system cost and improving reliability. However, their performance degrades at low speeds due to weak back-EMF signals and increased noise sensitivity [27].

B. Observer-Based Techniques
Observer-based methods, such as sliding mode observers and Luenberger observers, estimate rotor position and speed using mathematical models of the motor [31], [38]. These techniques provide better accuracy and robustness compared to simple back-EMF methods. They are effective in handling parameter variations and disturbances in BLDC systems. However, accurate modeling and tuning of observer parameters are required for optimal performance.

C. Kalman Filter-Based Estimation
Kalman filter techniques use statistical estimation methods to predict and correct rotor position and speed in real time [26]. They offer high accuracy and noise rejection capabilities, making them suitable for precision applications. Extended and Unscented Kalman Filters are commonly used for nonlinear BLDC motor systems. Despite their advantages, these methods involve high computational complexity and require careful parameter initialization.

D. AI-Based Sensorless Techniques
Artificial intelligence-based sensorless methods use neural networks and fuzzy logic to estimate rotor position without relying on precise mathematical models [23], [36]. These techniques improve estimation accuracy under

nonlinear and uncertain conditions. They are particularly effective at low speeds where conventional methods struggle. However, they require extensive training data and computational resources, which can increase system complexity.

VIII. Hybrid Control Strategies

A. FOC with AI Optimization

The idea involves using Field Oriented Control (FOC) technology together with PSO or GA optimization techniques to optimize the control parameters and enhance overall control performance [17], [37]. An AI-based system is employed to modify control parameters during operation for maximum efficiency under varying operating loads. This results in less steady-state error and smooth torque regulation compared to conventional FOC systems. However, incorporating such optimization techniques increases the computational burden and complexity.

B. MPC with Neural Networks

Use of Model Predictive Control (MPC) together with Artificial Neural Networks (ANNs) enhances prediction capability by modeling system behavior [19], [36]. The artificial neural network is used in MPC to estimate how the system behaves without the need for accurate mathematical models. The use of ANNs in MPC improves transient response and reduces control errors in BLDC drives, but the process requires significant computational power and extensive training of neural networks.

C. Sliding Mode Control with Adaptive Techniques

Sliding Mode Control (SMC) technology, when used with adaptive techniques, minimizes chatter effects while maintaining robustness [18], [35]. Adaptive techniques are used in real time to adjust control parameters based on system behavior, thereby enhancing performance under varying conditions. Developing adaptive techniques that converge appropriately can be quite complex.

D. Fuzzy Logic with PID Control

Fuzzy logic combined with PID control enhances system performance by dynamically tuning PID gains based on operating conditions [21]. The fuzzy system adjusts controller parameters using linguistic rules, improving response speed and stability. This hybrid approach is effective in handling nonlinearities and uncertainties in BLDC motors. However, it requires careful design of membership functions and rule sets.

E. Sensorless Control with Intelligent Estimation

Hybrid sensorless methods combine observer-based techniques with AI algorithms for improved rotor position estimation [23], [38]. Neural networks and fuzzy systems enhance estimation accuracy, particularly at low speeds. This approach reduces reliance on physical sensors while maintaining high performance. However, increased computational complexity and data requirements remain challenges.

F. Optimization-Based Hybrid Controllers

Optimization-based hybrid controllers use algorithms such as PSO and GA to tune control parameters in real time [24], [37]. These methods improve convergence speed and overall system efficiency by minimizing error functions. They are particularly useful in complex nonlinear BLDC motor systems. However, they may increase computational load and require careful parameter selection.

G. Multi-Objective Hybrid Control Frameworks

Multi-objective hybrid control strategies optimize multiple performance metrics such as efficiency, torque ripple, and energy consumption simultaneously [32], [33]. These frameworks use advanced optimization techniques to balance trade-offs between conflicting objectives. They are increasingly used in high-performance and electric vehicle applications. However, their implementation complexity and computational demands are significant.

IX. Torque Ripple Reduction Techniques

A. Harmonic Current Injection

Harmonic current injection reduces torque ripples through compensation of nonideal back-EMF waveforms and commutation effects. Torque will be generated in a smoother manner through the deliberate addition of well-placed harmonic currents into the motor's stator winding. This technique is commonly employed in BLDC drives [24], [28].

B. Pulse Width Modulation (PWM) Optimization
Advanced PWM algorithms including Space Vector PWM and sinusoidal PWM improve the pattern of switching operations while minimizing harmonic content in the current waveform. Effective PWM strategies help mitigate torque pulsations as well as increasing the overall efficiency of the system. The selection of an optimum switching frequency also plays a role [29], [30].

C. Advanced Control Strategies
Torque ripples can be effectively reduced by utilizing advanced control algorithms such as FOC, SMC, and MPC, which provide superior current regulation along with increased performance. Such control schemes deliver efficient torque control and show great promise in modern BLDC applications [19]-[23].

D. Current Shaping Techniques
Current shaping involves manipulating the waveform of the stator current to resemble the desired back-EMF shape of the motor. As a consequence, torque ripples induced by misalignments become negligible, and the operation becomes much smoother. With proper profiling, efficiency rises dramatically, especially for accurate processes [24], [37].

E. Optimization-Oriented Techniques
In these techniques, the optimization process is carried out using advanced algorithms such as particle swarm optimization (PSO) and genetic algorithm (GA). These techniques enable the achievement of optimal working points and minimizing torque ripples, which is extremely important for complex nonlinear systems [27], [41].

F. Direct Torque Control (DTC)
DTC uses a different strategy since its approach does not require the use of any transformation to control electromagnetic torque and flux. This technique is capable of providing high dynamic responses and reducing torque ripples through optimization. However, there must be some limitation in the variations in switching frequency [48], [22].

G. Sensorless Ripple Reduction Strategies
The future-oriented sensorless strategy incorporates ripple reduction in position estimation. Observer-based methods and Kalman filters significantly enhance the accuracy and minimize torque ripples [43], [44].

D. Current Shaping Techniques
Current shaping modifies the stator current waveform to better match the ideal back-EMF profile of the motor. This reduces mismatch-induced torque pulsations and enhances smooth operation. Optimal current profiling significantly improves performance in precision applications [24], [37].

E. Optimization-Based Techniques
Metaheuristic algorithms such as PSO and GA are used to optimize controller parameters and switching strategies. These methods improve convergence to optimal operating conditions and minimize torque ripple effectively. They are particularly useful in complex nonlinear systems [27], [41].

F. Direct Torque Control (DTC)
DTC directly controls electromagnetic torque and flux without requiring coordinate transformations. It offers fast dynamic response and reduced torque ripple when properly optimized. However, switching frequency variations must be managed carefully [48], [22].

G. Sensorless-Based Ripple Minimization
Advanced sensorless techniques incorporate ripple minimization within position estimation algorithms. Observer-based methods and Kalman filtering improve accuracy and reduce torque fluctuations. These approaches enhance both performance and reliability [43], [44].

X. Challenges in BLDC Motor Control

A. Nonlinear System Dynamics
BLDC motors exhibit inherent nonlinear behavior due to switching operations, magnetic saturation, and back-EMF characteristics. These nonlinearities complicate controller design and reduce the effectiveness of classical linear control methods. Advanced nonlinear and adaptive control techniques are required to address these challenges [19], [32].

B. Parameter Variations and Uncertainty
Motor parameters such as resistance, inductance, and inertia vary with temperature, load, and operating conditions. These variations can degrade controller performance and lead to instability if not properly compensated. Robust and adaptive control strategies are essential to handle such uncertainties effectively [31], [35].

C. Torque Ripple and Acoustic Noise
Torque ripple is one of the factors that contribute to the disruption of smoothness during operation, which leads to vibrations and noise. The main causes include the phenomenon of commutation, harmonic currents, and distortions in the waveform of the back electromotive force (BEMF). In order to minimize torque ripple, sophisticated methods should be employed [24], [28], [37].

D. High Computational Complexity
Model predictive control, artificial intelligence-based control, and hybrid control require considerable computational resources. Their execution in real-time applications could pose difficulties for embedded systems with low computational capacity. This problem needs to be solved by developing innovative techniques [20], [23].

E. Sensorless Control Shortcomings.
Despite its ability to reduce costs and increase reliability, sensorless control fails to function properly during very low speed or zero-speed operation since accurate rotor position estimation is hindered by poor back-EMF generation. For enhanced control accuracy, advanced observer models and AI-based estimates are essential [42] – 44].

F. Controller Parameters Fine-Tuning
Modern control systems have multiple parameters that need to be adjusted to ensure maximum efficiency. Manually adjusting parameters is time-consuming and might fail to cope with different operating conditions. Automation of control systems via PSO and GA optimization has been growing popular lately [27], [41].

G. Thermal Issues and Decreased Efficiency
High-speed operation and power losses make the motor generate heat, decreasing its overall efficiency and lifespan. Control methods that are poorly selected lead to increased switching losses and increased thermal effects. It is necessary to use more efficient control methods [24], [37].

H. Real-Time Embedded System Implementation
Implementing advanced control methods in real-time embedded systems such as DSPs and FPGAs comes with its difficulties, including limited memory and computing capabilities. Proper hardware and software design and integration are required to implement new algorithms successfully [31], [20].

XI. Future Research Directions

Future research is focused on the following:

A. Adaptive Control through AI
AI would take center stage in future BLDC drives to enable dynamic adjustment to varying operating conditions. Using AI methods such as deep learning and reinforcement learning would lead to improved controller performance in scenarios where an accurate model is not available. This results in higher robustness, efficiency, and fault tolerance [26], [33], [34].

B. Digital Twin
The adoption of digital twin technology will facilitate the creation of dynamic real-world virtual counterparts for BLDC motor configurations in order to monitor and control the latter. The twin could help predict performance and diagnose faults, among other advantages, before any modifications are made physically. This would enhance reliability while minimizing costs associated with maintenance [36].

C. Intelligent Motor Systems via IoT
Introducing IoT technology in the mix will pave the way for remote monitoring, diagnostics, and control of BLDC motors. IoT technology will support predictive maintenance and energy management with many applications in industrial automation and smart grids [32], [36].

D. Enhanced Sensorless Control at Slow Speeds

Achieving robust operation of the sensorless control scheme under conditions of slow or zero motor speed continues to be a key research challenge. In future studies, the focus will be more on efficient estimation schemes based on AI and hybrid observers to increase control accuracy [42]–[44].

E. Methods of Real-Time Optimization

In terms of future prospects, one can expect the development of control schemes with a combination of real-time optimization techniques for adjusting control parameters dynamically. This should lead to an increased convergence rate and control accuracy by utilizing PSO, GA, and hybrid algorithms [27], [41].

F. Sustainable Control

With sustainability becoming the core trend, there will be much attention paid to reducing energy consumption and increasing efficiency. This is related to the development of advanced control schemes that ensure low losses, low torque ripples, and minimal temperature rise in electric drives [24], [37].

G. Fault-tolerant and Self-healing Control Systems

The next generation of BLDC control systems will comprise fault detection, diagnosis, and healing. The use of AI-based diagnostics will make it possible to predict and solve faults automatically, improving system reliability and minimizing downtime [33], [38].

H. Hardware Acceleration and Embedding

Due to increasing computational requirements, future research will seek to implement advanced control schemes using FPGA, DSP, and embedded architectures. This will pave the way for implementing high performance control schemes such as MPC and AI-based controls on embedded systems [20], [23].

XII. Conclusion

In the paper presents an overview of BLDC motor control technologies is provided in the period from 1995 to 2026. Initially, PI and PID controllers were rather primitive and could not address nonlinear conditions. However, moving toward digital and sensorless technologies helped improve efficiency and reliability. Field-Oriented Control (FOC), Sliding Mode Control (SMC), and Model Predictive Control (MPC) have become key approaches which provided enhanced dynamic performance and accuracy. Application of intelligent controllers such as ANN, FLC, and optimization methods allowed for adaptive behavior and self-tuning of parameters. Finally, hybrid approaches helped achieve even higher efficiency and minimize torque ripple. Even though sensorless algorithms made it possible to reduce expenses, they continue to face difficulties associated with low-speed operations. Overall, further research will likely be aimed at more sophisticated and advanced control systems that rely on artificial intelligence, IoT and self-optimization mechanisms.

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