IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

A Review of Recent Developments in BLDC Motor Control Systems for EV

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Doi : https://doi.org/10.56975/ijcrt.v14i7.310005

Abstract. This research reviews the transformative role of Artificial Intelligence (AI) in enhancing the control, diagnostic, and estimation frameworks of Brush-less DC (BLDC) motors within electric vehicle (EV) and fuel cell electric vehicle (FCEV) environments. Traditional Proportional-Integral (PI) controllers often fail to maintain stability under the high nonlinearity, parameter variations, and load disturbances inherent in modern propulsion systems. To address these limitations, this paper examines advanced AI methodologies, including Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Deep Reinforcement Learning (DRL), and Deep Transfer Learning (DTL). These tools are utilized for real-time parameter tuning, sensorless position estimation, and predictive maintenance through Remaining Useful Life (RUL) forecasting. Experimental and simulation results across the reviewed literature consistently demonstrate that AI-integrated systems significantly reduce settling time, eliminate overshoot, and minimize torque ripple. Ultimately, the integration of AI acts as a "virtual sensing" and "intelligent decision-making" layer that optimizes energy efficiency and extends the operational lifespan of EV powertrains.

Keywords— BLDC motor, ANFIS, sensorless control, Electric Vehicles.

Introduction

The global transition toward sustainable transportation has positioned the Electric Vehicle (EV) and Fuel Cell Electric Vehicle (FCEV) as critical solutions for reducing carbon emissions. At the heart of these vehicles lies the Brushless DC (BLDC) motor, favored for its high power density, high efficiency, and low maintenance requirements. However, the dynamic environment of an EV characterized by frequent acceleration, regenerative braking, and varying road conditions imposes significant challenges on motor control systems. For decades, Proportional-Integral-Derivative (PID) controllers have been the industry standard due to their simplicity. Despite their ubiquity, they possess inherent drawbacks. Classical PID is designed for linear systems and struggles to adapt to the nonlinear dynamics of BLDC motors and fuel cell voltage fluctuations. Fixed gains (Kp, Ki, Kd) cannot account for real-time changes in motor resistance or temperature, often leading to significant overshoot and slow recovery from load disturbances. Traditional control requires physical sensors (e.g., Hall Effect sensors) that increase system cost, volume, and vulnerability to environmental noise.

I. THE AI-DRIVEN PARADIGM SHIFT

To overcome these barriers, researchers have turned to Artificial Intelligence (AI) to create self-evolving and adaptive control architectures. AI tools serve several pivotal roles:

A. *Intelligent Tuning*: Metaheuristic algorithms like Particle Swarm Optimization (PSO) and Snake Optimization (SOA) are employed to find optimal controller settings that minimize tracking error.
B. *Hybrid Intelligence:* Systems like ANFIS combine the human-like reasoning of Fuzzy Logic with the learning capabilities of Neural Networks to handle system uncertainties.
C. *Virtual Sensing:* Artificial Neural Networks (ANN) enable sensorless control by estimating rotor position and temperature from terminal voltages, effectively acting as "soft sensors".
D. *Autonomous Learning:* Reinforcement Learning (RL) allows controllers to learn optimal policies through continuous interaction with the motor environment, eliminating the need for manual re-tuning.

This review explores how these AI tools are revolutionizing the EV landscape, moving from static mathematical models toward robust, data-driven systems capable of ensuring high-precision motion control and long-term system reliability.

II. COMPREHENSIVE REVIEW OF METHODOLOGIES

The development and experimental validation of an optimized PI-ANFIS controller designed for the speed control of a Brushless DC (BLDC) motor within a Fuel Cell Electric Vehicle (FCEV) framework is demonstrated [1]. The experimental setup features a clean energy powertrain centered on a Nexa Ballard 1.2 kW fuel cell power module, which converts hydrogen into electrical current to act as the source as shown in Fig.1 The power is managed through a multi-stage conversion process, utilizing a unidirectional buck-boost converter to stabilize the voltage at 24 V and a bidirectional boost converter to reach the 48 V traction bus. The propulsion is provided by a three-phase Brushless DC (BLDC) motor, which is driven by a DC-to-AC inverter utilizing Pulse Width Modulation (PWM) for precise speed and voltage control. To ensure accurate commutation and monitoring, the system integrates Hall Effect sensors for rotor position detection alongside a comprehensive sensor suite for real-time measurements. All control logic and experimental validation are executed through a high-performance dSPACE MicroLabBox (DS1202) controller board.

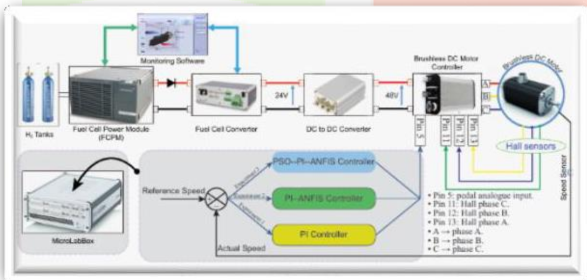

Fig. 1. Schematic diagram of the BLDC control system in an FCEV application (adapted from ref.1)

Here, (Artificial Intelligence) AI is utilized to enhance the performance of classical controllers, which often struggle with load disturbances and parameter variations.

A. *Adaptive Neuro-Fuzzy Inference System (ANFIS)*

ANFIS combines the transparent reasoning of Fuzzy Logic with the learning capabilities of Neural Networks.

- Function: It is used to adjust the gains (K_p and K_i) of a proportional-integral (PI) controller online.
- Architecture: The system uses a five-layer Sugeno-type model. It processes inputs (speed error and its integral) through fuzzification, rule, normalization, defuzzification, and output layers to determine the optimal controller gains.

B. *Particle Swarm Optimization (PSO)*

PSO is a metaheuristic algorithm used to further refine the AI model.

- Application: PSO is utilized to fine-tune the scaling gains of the PI-ANFIS controller.
- Goal: To minimize the Integral of Time-weighted Absolute Error (ITAE), ensuring the fastest response with the least oscillation.The study compared three techniques: Classical PI, PI-ANFIS, and PSO-PI-ANFIS table 1. Shows comparison.

Table 1. Comparison between Classical PI, PI-ANFIS, and PSO-PI-ANFIS

Feature	***Classical PI***	***PI-ANFIS***	***PSO-PI-ANFIS***
Tracking Accuracy	Moderate	High	Superior
Overshoot	Present	Reduced	Eliminated
Current Ripples	Significant	Moderate	Minimal
Load Disturbance	Slow recovery	Stable	Robust & Smooth

By optimizing motor control, the AI reduces peak current demands during sudden load changes, potentially extending the fuel cell's lifespan or it reduced stress on Fuel cell. The PSO-PI-ANFIS model maintains a stable 48 V DC bus voltage and accurately follows reference speeds even under heavy load torque (upto 9Nm). The experimental results confirms that these AI models are accurate and computationally fast enough for practical vehicle applications. The design and performance comparison of Proportional-Integral (PI) and Adaptive Neuro-Fuzzy Inference System (ANFIS) controllers for Brushless DC (BLDC) motor-driven electric vehicles is explored [2]. Fig.2 shows the Assembly of the projected sensorless hybrid controller.

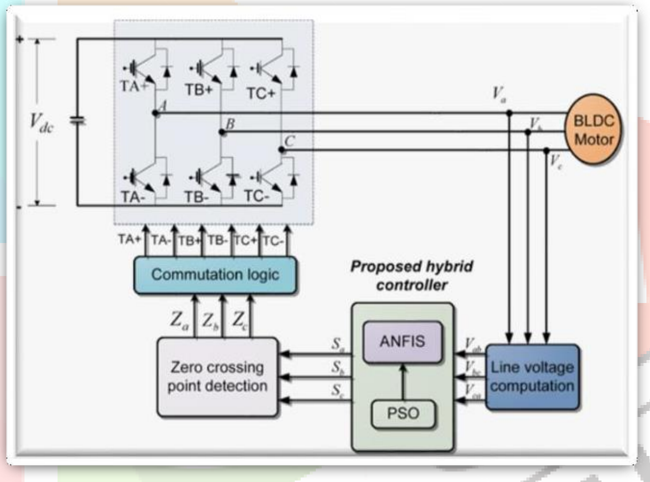

Fig.2. Assembly of the projected sensorless hybrid controller. (adapted from ref.2)

The research [2] developed a sensorless PMBLDC motor controller. The PMBLDC motor’s back EMF ZCPs are the basis for the sensorless control technique’s design. The suggested method estimates the ZCPs of back EMFs of a phase from the line voltages of the PMBLDC motor drive. The training rule of the suggested ANFIS control structure is improved in this case using the PSO method. The ANFIS controller’s back propagation error is reduced by the PSO approach. The estimated better value is based on the smallest error value. The study focused on enhancing the dynamic performance of a 5-kW, 48-V BLDC motor used in EV applications. Following results were obtained.

- Performance Metrics: The ANFIS controller significantly outperformed the PI controller by reducing rise time, settling time, and peak overshoot.
- Operational Stability: ANFIS provided a more stable response during rapid acceleration and deceleration (speed reversal), which is critical for smooth EV operation in heavy traffic or emergency braking scenarios.
- Efficiency: The ANFIS controller achieved a settling time of 0.036 s, compared to 0.065 s for the PI controller, representing a substantial improvement in system stabilization.

In the context of this research, AI specifically fuzzy logic and neural networks serves as an advanced alternative to traditional linear controllers, Such as

A. Handling Nonlinearity and Variability

— PI Limitations. : Standard PI controllers are linear and typically restricted to a single operating point. They struggle with the nonlinear nature of EVs, where speeds and loads vary constantly.

— AI Adaptability: AI-based controllers like ANFIS are better suited for variable speed operation because they do not require a rigid mathematical model of the system.

B Hybrid Intelligence (ANFIS)

ANFIS acts as a hybrid solution by combining the strengths of two AI domains.
— Fuzzy Logic: It handles imprecision and undefined variables using linguistic rules rather than precise numbers.
— Artificial Neural Networks (ANN): It identifies relationships between inputs and outputs through learning algorithms, allowing the controller to "understand" and adapt to system behaviors over time.

C. Energy Management and Optimization

Beyond motor speed regulation, the paper highlights AI's broader role in the EV ecosystem:
— Efficiency Gains: AI algorithms have been shown to increase Internal Combustion Engine (ICE) efficiency by 17% and reduce energy consumption in Plug-in Hybrid EVs by nearly 30%.
— Optimization: Techniques like Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) are used to optimize parameters such as State of Charge (SOC) and power demand to enhance fuel economy and battery autonomy.
A comparative study of Proportional-Integral (PI) and Adaptive Neuro-Fuzzy Inference System (ANFIS) controllers for regulating the speed of a 5-kW Brushless DC (BLDC) motor in electric vehicle (EV) applications is done [3]. The study focused on improving the dynamic performance of EVs during frequent acceleration and deceleration. While PI controllers are popular due to their simplicity, they often struggle with the nonlinearities and variable speed operations inherent in EV powertrains. The researchers designed an ANFIS-based controller to address these limitations, evaluating performance through MATLAB/Simulink. Table 2 and Table 3 gives Speed and Toque response in Time domain specifications. From both tables it is confirmed that the ANFIS-based system produced a comparatively lower amount of torque ripple than the PI system. The PI controller exhibited a peak overshoot of approximately 26.1%, whereas the ANFIS controller demonstrated zero overshoot, indicating superior stability. ANFIS consistently expedited motor acceleration across all tested speeds. The studies shown that the AI is widely used in other EV areas, such as using Artificial Neural Networks (ANN) and ANFIS for Energy Management Systems (EMS) to reduce energy consumption and improve fuel efficiency in hybrid vehicles.

Table 2. Speed Response Time-Domain Parameters

Specification	***PI Controller***	***ANFIS Controller***	***Improvem ent with ANFIS***
Rise Time (s)	0.0091 s	0.008 s	≈ 12%
Settling Time (s)	0.065 s	0.036 s	≈ 44.6%
Peak Overshoot (%)	26.1 %	0 %	Eliminated
Steady-State Error	≈ 0 rpm	≈ 0 rpm	Same
Speed Dip during Load Change (rpm)	Higher	Lower	Reduced
Speed Recovery Time (s)	Higher	Lower	Faster recovery
Stability at Speed Reversal	Moderate	High	Improved
Specification	PI Controller	ANFIS Controller	Improve me nt with ANFIS
Rise Time (s)	0.0091 s	0.008 s	↓ ≈ 12%

Table 3. Torque Response Time domain parameters

Specification	***PI Controller***	***ANFIS Controller***	***Observation***
Starting Peak Torque	≈ 36 Nm	≈ 36 Nm	Same initial value
Torque Overshoot	High	Low	Reduced oscillations
Torque Ripple (steady state)	High	Low	Smoother torque
Torque settling time(s)	Higher	Lower	Faster stabilization
Torque Behavior during Speed Reversal	Oscillatory	Smooth	Improved damping

A method for position and speed estimation of Brushless DC (BLDC) motors without the use of physical sensors, relying instead on Artificial Neural Networks (ANN) and terminal phase voltages is presented [4]. The proposed method is developed with multilayer ANNs. The fundamental part of the method estimated the rotor position and the rotor speed estimation was based on the position results, as shown in Fig.3. The study addresses the limitations of traditional sensors such as increased cost, size, and potential for failure in stressful environments by developing a sensorless drive system. Approaches such as the Extended Kalman Filter (EKF), although its speed estimation performance was slightly inferior to ome advanced methods.

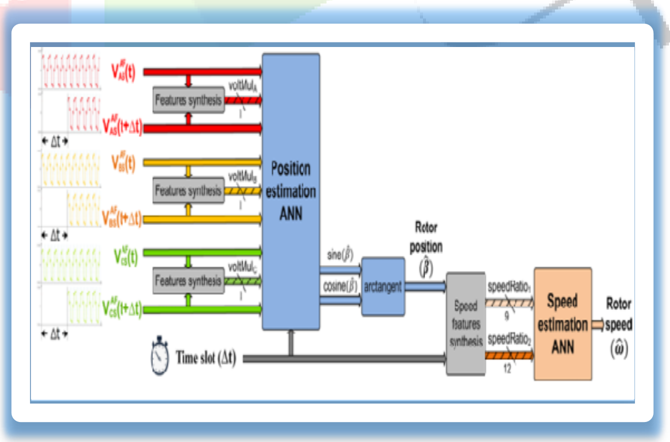

Fig. 3. Block diagram of the ANN-based estimation algorithm (adapted from ref.4)

The core of the proposed sensorless system is based on AI, specifically Artificial Neural Networks (ANN), which were chosen for their ability to learn complex nonlinear functions with high accuracy and fault tolerance.

A. *Position Estimation*

- Topology: A three-layer Multilayer Perceptron (MLP) with a cascade topology (10 input nodes, 5 hidden nodes, and 2 output nodes) is used.

- Function: It learns the mapping between input features (terminal phase voltages and timestamps) and the sine/cosine components of the rotor's rotational angle.
- Learning: The Backpropagation algorithm is employed to optimize network weights based on labeled data from an external encoder used during the training phase.

B. Speed Estimation

- Topology: A second three-layer MLP-ANN is used, featuring 21 input nodes and 10 hidden nodes as shown in Fig.3.
- Function: It estimates speed by processing "SpeedRatio" features derived from position differentials and timestamps within specific acquisition windows.
- Role: Unlike simple observers, the ANN acts as a filter to identify cycle variations and detect periodic speed changes while managing instantaneous deviations.

C. Computational Efficiency

- Hardware Integration: The AI models are designed with a simple topology to ensure they can be deployed on low-cost hardware like FPGAs.
- Nonlinear Mapping: The use of tan-sigmoid activation functions in hidden layers allows the AI to handle multidimensional mapping problems more effectively than traditional linear models.

A novel (Snake Optimization Algorithm) SOA-DTL (Deep Transfer Learning)-RL (Reinforcement Learning) adaptive cascade PI controller designed to improve speed and current regulation in Brushless DC (BLDC) motors is proposed [5], particularly for electric vehicle and industrial applications. Fig.4 shows the General structure of the test system using BLDC and the controller. A cascade PI controller is designed with transfer learning (TL)-based tuning to control the speed and current at the same time. The TL mechanism maximizes the inner and outer control loop, and adaptive selection of gain can be made to achieve better dynamic response. Such cascade structure increases the decoupling of the control objectives, decreases the sensitivity to disturbances, and provides accurate regulation of motor dynamics leading to a higher stability, faster adaptation, and better overall performance of the motor under changing operating conditions. Secondly, the deep neural network (DNN) that is applied in the TL framework is optimally adjusted to adaptive PI gains. The DNN has better generalization, convergence, and robust ness of adapting to different operating conditions, which is achieved by optimizing the architecture, hyper parameters, and the activation functions as shown in Fig.5 Thirdly, the TL is combined with reinforcement learning (RL) which adds to the adaptive gain-tuning mechanism and enables the controller to self-learn and dynamically optimize PI parameters without the necessity of manual re-tuning. Additionally, The SOA optimizes TL initial parameters Meta heuristically, to guarantee optimal initialization, quicker convergence, and to avoid negative transfer effects. Finally, a Typhoon HIL setup is used to validate the controller in real-time, showing better transient response, lesser steady state error and greater disturbance rejection, validating the robustness and practicality of the controller in industrial BLDC motor applications.

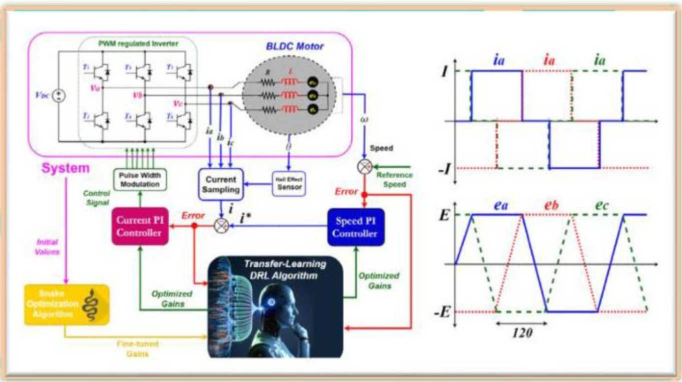

Fig.4 General Structure of the test system using BLDC and the controller (adapted from ref.5).

The proposed controller addresses the limitations of traditional fixed-gain PI controllers, such as poor performance under system variations and load fluctuations.

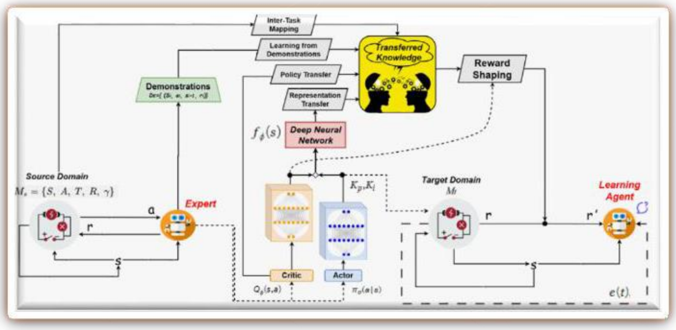

Fig. 5. An overview of the DTL approach organized by the format of transferred knowledge (adapted from ref.5)

It utilizes a cascade structure that separates fast inner current dynamics from slower outer speed dynamics, enhancing stability and disturbance rejection The effectiveness of this framework was validated through Hardware-in-the-Loop (HIL) testing on the Typhoon HIL 606 platform, demonstrating superior performance in response time, energy efficiency, and robustness compared to standard PI and PSO-optimized controllers. Here, AI serves as the "intelligent core" of the controller, moving away from static models toward a self-learning system. It includes:

A. *Real-Time Adaptation (Reinforcement Learning)*

- Dynamic Tuning: The RL agent acts as an online optimizer that adjusts K_p and K_i gains without manual intervention.
- Self-Learning: By utilizing a reward function that penalizes tracking errors and excessive control effort, the AI learns optimal control policies through continuous interaction with the motor environment.

B. *Knowledge Transfer (Deep Transfer Learning)*

- Efficiency: AI allows the controller to "transfer" expertise from a source domain (simulated environments) to a target domain (real-world hardware).
- Training Acceleration: This eliminates the need to train the controller from scratch, mitigating the "lengthy training time" issue typical of standard RL.

C. *Pattern Recognition & Generalization (DNN)*

- Feature Extraction: Deep Neural Networks (specifically a 16-8 hidden layer structure) are used to map complex, nonlinear system states to precise control actions.
- Generalization: The DNN enables the controller to handle unmolded disturbances and noisy sensor data more effectively than classical logic.

D. *Optimization (Snake Optimization)*

- Safe Initialization: Inspired by biological behaviors, the SOA algorithm ensures the AI starts with a stable foundation, avoiding the "negative transfer" or "random start" risks that can lead to system instability.

A deep learning-based framework for estimating the Remaining Useful Life (RUL) of Brushless DC (BLDC) motors is presented [6] which is, specifically focusing on stator-related faults. The study addresses the challenge of real-time health state estimation in BLDC motors, which are prone to failures due to complex operating conditions and overloading. The research focused on two prevalent stator anomalies such as Inter-turn Faults (ITF) and Winding Short-circuit (WSC). Instead of traditional vibration signals, which can be insensitive to incipient stator faults, the authors used a generator output voltage from a coupled motor-generator setup as the degradation parameter. A 3-phase Average Value Rectifier (AVR) with a smoothing capacitor converts the generator's AC output into a DC health index that is resistant to environmental noise and heat. The study utilizes a Long Short-Term Memory (LSTM) network enhanced with an Attention Mechanism to capture nonlinear degradation trends and predict the motor's lifecycle. A brief overview of the proposed prognostics framework is illustrated in Fig. 1

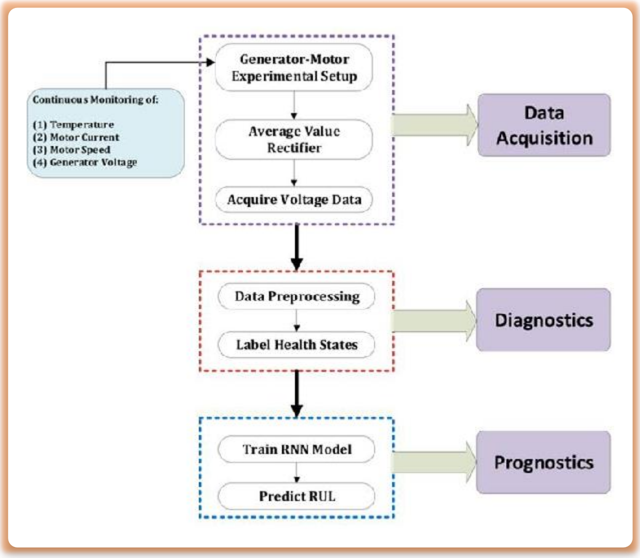

Fig. 6. Proposed prognostics framework of BLDC motor subjected to stator-related faults (adapted from ref.6)

The study addressed the challenge of real-time health state estimation in BLDC motors, which are prone to failures due to complex operating conditions and overloading.

➢ Stator Faults: The research focuses on two prevalent stator anomalies those are Inter-turn Faults (ITF) and Winding Short-circuit (WSC).
➢ Novel Health Indicator: Instead of traditional vibration signals, which can be insensitive to incipient stator faults, the authors use the generator output voltage from a coupled motor-generator setup as the degradation parameter.
➢ Data Processing: A 3-phase Average Value Rectifier (AVR) with a smoothing capacitor converts the generator's AC output into a DC health index that is resistant to environmental noise and heat.
➢ Core Model: The study utilizes a Long Short-Term Memory (LSTM) network enhanced with an Attention Mechanism to capture nonlinear degradation trends and predict the motor's lifecycle.

AI serves as the predictive engine for translating technical degradation data into actionable maintenance insights.

A. Advanced Sequence Modeling

- RNN/LSTM: Recurrent Neural Networks (RNNs) are employed for their ability to handle time-series data. LSTMs are specifically used to manage long-term dependencies and avoid the "vanishing gradient" problem during training.
- Trend Prediction: AI models learn the intrinsic characteristics of voltage degradation over the motor's lifecycle to forecast when a system will reach its end-of-life (EOL).

B. Attention Mechanism

- Feature Weighting: The AI uses an attention layer to assign quantitative weights to specific time steps.
- Handling Nonlinearity: This allows the model to "focus" on critical inconsistent changes in the degradation data, significantly improving prediction accuracy for complex faults like WSC compared to standard LSTMs.

C. Fault Diagnosis and Health Monitoring

- Pattern Recognition: AI-driven Motor Current Signature Analysis (MCSA) identifies fault characteristics, such as peaks in the harmonics of the motor current, which signify a violation of Kirchhoff's Current Law due to stator irregularities.
- Real-time Estimation: The framework enables on-the-fly condition monitoring, allowing for maintenance before a catastrophic breakdown occurs

Paper [7] presented a stabilized speed regulation control method for brushless DC motors (BLDCM) in electric vehicles using a deep reinforcement learning (DRL) approach. In this research, Artificial Intelligence (specifically Machine Learning) acts as an intelligent optimizer rather than just a static program. RL (Reinforcement Learning) is defined as a self-supervised learning method where an "agent" learns to make decisions by interacting with an environment.

AI plays a vital role in Motor Control

- Adaptive Tuning: Unlike traditional PID where parameters are fixed or manually adjusted, the AI (DDPG agent) continuously observes the system's state and adjusts parameters in real-time to find the optimal configuration.
- Handling Complexity: The AI is used to overcome the nonlinear characteristics of the motor that standard mathematical models may not capture perfectly.
- Performance Optimization: AI serves as the "decision-making layer" that identifies the best "strategy" for motion control, leading to a more stable and responsive electric vehicle drive system.

The review paper [8] provides an extensive categorization and analysis of techniques used to eliminate mechanical sensors in Electric Vehicle (EV) propulsion systems. By replacing physical sensors with "soft sensors," manufacturers can reduce system costs, minimize motor volume, and enhance reliability against electromagnetic interference and temperature fluctuations.

The following sections summarize the core strategies and the evolving role of Artificial Intelligence (AI) in this field as detailed in the review. The paper categorizes estimation approaches based on the operational speed range of the motor.

A) Zero and Low-Speed Methods

At standstill or low speeds, the motor's Back-Electromotive Force (EMF) is too small to detect. Control strategies instead rely on the physical properties of the motor:

- High-Frequency (HF) Injection: This is the most effective method for zero-speed operation. It involves injecting a continuous HF carrier signal (rotating or pulsating) and analyzing the resulting current response.
- Carrier Frequency Component: Uses the PWM inverter's own carrier signal to extract position data, requiring less additional hardware.

B) Medium and High-Speed Methods

As the motor accelerates, fundamental wave models become viable .

- Back EMF Methods: The most mature technology, identifying position by capturing the "zero-crossing" points of the motor's back EMF.
- Model Reference Adaptive System (MRAS): Uses a reference model and an adjustable model; the difference between the two is used to drive an adaptation mechanism that estimates rotor speed and position.
- State Observers: Complex algorithms like the Extended Kalman Filter (EKF) or Sliding Mode Observer (SMO) treat position as a state variable to be estimated despite system noise or disturbances.

The review highlights Artificial Neural Networks (ANN) as a prominent research hotspot for improving the accuracy of sensorless systems.

As early explained, AI is primarily used to address the non-linearity and parameter variations that traditional mathematical models struggle to handle. Table 4. Mentions common AI Architectures.

- Adaptive Learning: Neural networks can connect voltage, current, and rotor position through self-learning strategies to capture signals accurately.
- Function Approximation: AI models like Back Propagation (BP) and Radial Basis Function (RBF) networks are used to approximate the complex non-linear functions of a motor's state space.
- Robustness: By updating network parameters online (e.g., via gradient descent), AI-based observers can maintain accuracy even as motor resistance or inductance changes during operation.

The author explained that the future of sensorless technology in electric vehicle (EV) traction depends on overcoming several critical technical hurdles, specifically the development of seamless "cohesion" algorithms to eliminate torque ripples during transitions between low and high-speed control methods. Furthermore, researchers must advance real-time parameter identification to prevent accuracy loss from parameter drift and implement AI-enhanced estimation methods to ensure reliability during rapid acceleration and frequent stop-and-go conditions. Addressing these challenges is vital for achieving the robust, high-performance operation required for modern EV power systems.

Table 4. Common AI Architectures

Type	***Application in Sensorless control***
BP-NN (Back Propagation)	Used for speed and position observation, though often improved with adjustable weights to speed up convergence.
RBF-NN (Radial Basis Function)	Preferred for its faster convergence and simpler structure compared to standard BP networks.
Deep Learning (CNN/DNN)	Used for more complex diagnostic tasks, such as estimating the Remaining Useful Life (RUL) of the motor.

The article [9] investigated on the application of machine learning (ML) for the sensorless temperature estimation of Brushless DC (BLDC) motor windings to prevent insulation failure and permanent magnet demagnetization. The study compared two predictive models across various cooling conditions (uncooled vs. fan-cooled) using 160 hours of operational data as follows

- Model 1 (Sensorless): Estimates winding temperature using only electrical and mechanical data already available in the drive system (current, speed, and calculated power losses).
- Model 2 (Casing-Sensor Supported): Enhances the feature set by adding temperature data from a single sensor mounted on the motor casing.

The primary role of ML in this context is to act as a virtual sensor, mapping complex non-linear relationships between easily measurable parameters and the internal temperature without requiring physical access to the motor's interior.

A). Eliminating Physical Constraints

- Cost Reduction: Manufacturers can provide thermal protection without the expense of factory-installed internal sensors.
- Simplification: Eliminates the need for "white box" thermal models that require deep expertise in motor geometry and material properties.

B. Feature Engineering and Data Processing

- Short-term History: ML allows for the creation of "look-back" features (mean and standard deviation of current/speed over the last hour) to account for the slow nature of thermal processes.
- Standardization: Algorithm’s scale disparate units (e.g., RPM vs. Amperes) to ensure no single feature dominates the model's cost function.

C. *Optimization and Generalization*

Hyper parameter Tuning: Through techniques like cross-validation and grid search, ML finds the optimal balance between bias and variance, ensuring the model works on new, unseen data rather than just "memorizing" the training set.

- Regularization: Techniques used in ElasticNet penalize overly complex models to prevent overfitting to noise or outliers.

D) Operational Benefits

- Real-time Protection: The models are computationally light enough for real-time execution, allowing for immediate intervention if overheating is predicted.
- Torque Compensation: The high accuracy of Model 2 (MAPE approx. 1%) is sufficient to compensate for torque pulsations caused by temperature-induced changes in winding resistance.

The research [10] introduced an optimized control strategy for the speed regulation of an electric car using an in-wheel Brushless DC (BLDC) motor. The study focuses on a quarter vehicle model and proposes a hybrid controller that integrates Particle Swarm Optimization (PSO) with a Fuzzy PID system (FPIDPSO) to improve performance under various driving conditions. The objective was to optimize the proportional (K_p), integral (K_i), and derivative (K_d) gains of a PID controller in combination with a fuzzy controller to enhance speed tracking and vehicle stability The study utilized a longitudinal vehicle model that includes an in-wheel BLDC motor and the Pacejka Tire Model to accurately simulate road-tire interaction and adhesion. Optimization was performed using MATLAB/Simulink, comparing the proposed FPIDPSO approach against conventional PID techniques during acceleration and deceleration on dry and wet roads. The hybrid structure of the fuzzy PID control is shown in Fig.7

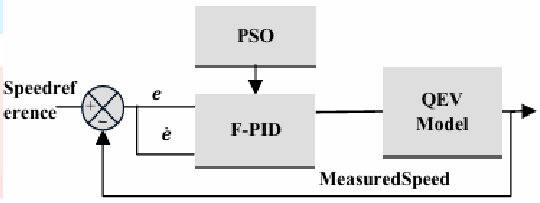

Fig. 7. The hybrid structure of the fuzzy PID control (adapted Fig. from ref.10)

The FPIDPSO controller demonstrated superior efficacy in minimizing error and following setpoints smoothly compared to standard PID controllers. While the PID controller failed to reach set points, the FPIDPSO followed input commands accurately with an acceptable longitudinal slip ratio (3.5% during acceleration). The hybrid approach improved driving comfort and vehicle stability. In this research, AI specifically in the form of Fuzzy Logic and Heuristic Optimization (PSO)

which is used to address the nonlinear characteristics of BLDC motors that traditional controllers struggle to manage.

A) Heuristic Parameter Optimization (PSO):

- Collective Intelligence: PSO mimics the behavior of animal groups (like birds or fish) to navigate complex search spaces.
- Automated Tuning: It is used to systematically find the optimal K_p, K_i, and K_d gains by minimizing a fitness function, specifically the Integral Time Absolute Error (ITAE).
- Iterative Learning: Each "particle" in the swarm updates its position and velocity based on its own experience and the group's best-discovered solution, ensuring rapid convergence toward an optimal control state.

B) Intelligent Control (Fuzzy Logic):

- Data Transformation: The fuzzy system converts ordinary input data (tracking error and its derivative) into interpretable outcomes through fuzzification and defuzzification.
- Knowledge-Based Rules: It utilizes a set of "IF-THEN" rules and membership functions to define required control actions, enhancing the dynamic reaction of the motor.

- Steady-State Error Mitigation: The role of the fuzzy inference system is to minimize or completely eradicate steady-state errors that occur during complex driving maneuvers.

Virtual Performance Enhancement:

Driving Experience: AI serves as a critical component in orchestrating vehicle operations to optimize speed, acceleration, and battery efficiency.

Stability: By synergizing AI techniques, the system achieves a better linear speed response and wheel speed stability than classical architectures

III.CONCLUSION

This review paper highlights the significant advancements in Artificial Intelligence (AI)-based control strategies for Brushless DC (BLDC) motors used in Electric Vehicles Learning (DTL), and optimization algorithms like PSO and SOA provide superior dynamic performance, improved speed regulation, reduced torque ripple, minimized overshoot, and enhanced energy efficiency.

The study also emphasizes the growing importance of sensorless control and predictive maintenance techniques in reducing hardware complexity and improving system reliability. AI-enabled virtual sensing and Remaining Useful Life (RUL) prediction methods contribute to enhanced operational safety and longer motor lifespan. Overall, the integration of AI into BLDC motor control systems represents a major step toward intelligent, adaptive, and energy-efficient EV powertrains capable of meeting future transportation demands.

(EVs) and Fuel Cell Electric Vehicles (FCEVs). Conventional PI/PID controllers, although simple and widely adopted, are unable to effectively handle the nonlinear behavior, parameter uncertainties, and varying load conditions associated with modern EV propulsion systems. The reviewed literature demonstrates that AI-driven approaches such as ANFIS, Artificial Neural Networks (ANN), Deep Reinforcement Learning (DRL), Deep Transfer Learning (DTL), and optimization algorithms like PSO and SOA provide superior dynamic performance, improved speed regulation, reduced torque ripple, minimized overshoot, and enhanced energy efficiency.

The study also emphasizes the growing importance of sensorless control and predictive maintenance techniques in reducing hardware complexity and improving system reliability. AI-enabled virtual sensing and Remaining Useful Life (RUL) prediction methods contribute to enhanced operational safety and longer motor lifespan. Overall, the integration of AI into BLDC motor control systems represents a major step toward intelligent, adaptive, and energy-efficient EV powertrains capable of meeting future transportation demands.

IV.FUTURE SCOPE

✓ Developing lightweight and computationally efficient AI algorithms suitable for real-time implementation on embedded automotive hardware remains a major challenge

✓ Combining AI-controlled BLDC systems with IoT platforms and edge computing can enable remote diagnostics, cloud-based monitoring, and intelligent fleet management.

✓ Further exploration of advanced deep learning techniques such as Transformer models, federated learning, and explainable AI (XAI) can improve prediction accuracy and controller transparency.

✓ As EV systems become increasingly connected, ensuring cybersecurity and robustness of AI controllers against malicious attacks and sensor failures will be essential.

✓ The use of digital twins for BLDC motor systems can support predictive maintenance, fault simulation, and performance optimization under different operating conditions.

✓ Future EV architectures may integrate solar, fuel cells, and battery systems simultaneously, requiring intelligent AI-based energy management strategies.

✓ Reinforcement learning-based autonomous controllers capable of self-learning under varying road and environmental conditions can further enhance EV efficiency and driving performance.

✓ Future studies may focus on reducing overall power consumption and improving battery utilization through intelligent torque and speed optimization techniques.

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