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OPTIMAL CONTROL OF BRUSHLESS DC MOTOR USING SOFT COMPUTING TECHNIQUES FOR E- VEHICLE

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ABSTRACT

Brushless Direct Current (BLDC) motors are widely utilized in various applications due to their high efficiency, low maintenance, and robust performance. Achieving optimal control of BLDC motors, however, is a complex task due to their nonlinear dynamics, parameter uncertainties, and operating conditions. Traditional control strategies like PID often fail to deliver the desired performance across all operating conditions. Soft computing optimization techniques, such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Fuzzy Logic (FL), Artificial Neural Networks (ANN), and Ant Colony Optimization (ACO), have been proposed to address these challenges. This paper presents a comprehensive review of the application of soft computing techniques for the optimal control of BLDC motors. We provide a detailed analysis of various optimization methods, their advantages, limitations, and specific applications in BLDC motor control. The review highlights the significant improvements in performance achieved through these methods and offers insight into future research directions.

KEYWORDS: *Brushless DC Motor, Optimal Control, Soft Computing, Genetic Algorithm, Particle Swarm Optimization, Fuzzy Logic, Artificial Neural Networks, Ant Colony Optimization, Motor Control.*

1. INTRODUCTION

Brushless DC (BLDC) motors have become a cornerstone in numerous modern applications such as electric vehicles (EVs), robotics, aerospace, and industrial automation due to their superior characteristics, including high efficiency, compact design, and low maintenance requirements. Unlike traditional brushed DC motors, BLDC motors do not employ mechanical commentators and brushes, which reduces friction and wear, making them more reliable and long-lasting.

However, the complexity of controlling BLDC motors arises from their inherent nonlinear dynamics, variations in parameters due to temperature or load changes, and uncertainties in system models. Traditional control techniques, including Proportional-Integral-Derivative (PID) controllers, struggle to achieve optimal performance in such dynamic and uncertain environments.

The advent of **soft computing** techniques has revolutionized motor control by enabling the optimization of control strategies under challenging conditions. Soft computing encompasses computational techniques like **Genetic Algorithms (GA)**, **Particle Swarm Optimization (PSO)**, **Fuzzy Logic (FL)**, **Artificial Neural Networks (ANN)**, and **Ant Colony Optimization (ACO)**, which have been employed to achieve optimal control of BLDC motors. These techniques can handle nonlinearities, uncertainties, and computational complexities better than traditional methods.

This paper reviews the state-of-the-art optimization techniques based on soft computing approaches for BLDC motor control, exploring the key concepts, implementations, benefits, and limitations of each technique. Additionally, it discusses recent trends and potential future directions in this area.

BRUSHLESS DC MOTOR OVERVIEW

A Brushless DC motor (BLDC) consists of three primary components:

- **Stator**: Contains the windings where the electromagnetic field is generated.
- **Rotor**: A permanent magnet that generates its magnetic field.
- **Controller**: An electronic circuit that manages the switching of currents to the motor's stator Windings based on rotor position feedback.

BLDC motors offer several advantages over conventional DC motors, including:

- **High Efficiency**: Due to the absence of brushes and commentators, there is less energy loss in the system.
- **Reduced Maintenance**: The absence of brushless laminates wear and tear.
- **High Power Density**: They offer higher torque perunitsize compared to brushed motors.

2. OBJECTIVES

The main objectives of this review are:

1. To study the fundamental characteristics and control challenges of BLDC motors.
2. To analyze different of computing optimization techniques applied for BLDC motor control.
3. To evaluate the advantages, limitations, and performance outcomes of each method.
4. To compare these techniques in terms of convergence speed, computational eff iciency, and control accuracy.
5. To identify gaps in existing research and suggest future directions for developing hybrid and real-time control strategies.

3. METHODS-SOFTCOMPUTING TECHNIQUES FOR OPTIMAL CONTROL

A. *Genetic Algorithm (GA)*

The Genetic Algorithm (GA) is an **evolution ary optimization method** that simulates the process of natural selection. It starts with a **population of candidate solutions**, each represented by a chromosome (string of parameters).The performance of each candidate is evaluated using a **fitness function**, which measures how well the parameters achieve the desired objectives such as speed regulation, torque minimization, or energy efficiency.

Algorithmic Steps

1. **Initialization:** Generate an initial population of random solutions.
2. **Fitness Evaluation:** Evaluate each solution using a pride fined objective function (e.g minimizing speed error or torque ripple).
3. **Selection:** Select the best-performing individuals based on fitness value.
4. **Crossover:** Combine selected parents to produce off spring.
5. **Mutation:** Randomly alter some genes to introduce diversity.
6. **Replacement:** Form an repopulation and repeat until convergence criteria are met.

Mathematical Representation

If f(x) represents the fitness function an dx=[x1,x2,...,xn] denotes control parameters, GA seks to Find: $x^* = \arg\max f(x)$ Through it creative genetic operations.

Application in BLDC Motors:

GA has been successfully applied for:

- **PID parameter optimization** for speed and torque control.
- **Torque ripple minimization** by tuning current control loops.
- **Efficiency optimization** by adjusting commutation angles.

By exploring a larges each space, GA finds optimal or near-optimal control parameters that enhance motor dynamic response and stability.

B. *Particle Swarm Optimization (PSO)*

PSO is inspired by the social behavior of birds flocking or fish schooling. Each potential solution is modeled as a “particle” that moves through the search space. The particles communicate with each other to find the best possible solution based on their own experience and the group’s best-known position.

Mathematical Formulation:

Each particle up dates its velocity and position using:

$v_i^{t+1}=\omega v_i^t+c_1r_1(p_i^t-x_i^t)+c_2r_2(g-x_i^t)$ Where:

- ω:inertia weight,
- c_1,c_2:cognitive and social coefficients,
- r_1,r_2:randomnumbersbetween0and1,
- p_i: personal best position,
- g: global best position.

Application in BLDC Motors:

PSO has been applied to optimize the tuning of PID controllers and other motor control parameters. It helps achieve faster response times, reduced overshoot, and improved stability in BLDC motor systems.

C. *Fuzzy Logic (FL)*

Fuzzy Logic controllers use linguistic variables instead of precise numerical ones, making them ideal for systems with uncertainty and imprecision. They rely on if–then rules derived from human reasoning rather than explicit mathematical models.

Structure of a Fuzzy Logic Controller

1. Fuzzification: Converts crisp input values(e.g., error, rate of change of error) in to fuzzy

sets.

2. Rule Base: Contains expert-defined rules (e.g., *If error is small and change of error is negative, then decrease control signal*).
3. In ferenceEngine: Applies fuzzy reasoning to compute control actions.
4. Defuzzification: Converts the fuzzy output back into a crisp control signal.

Mathematical Expression:

The output yyy can be expressed as:

$y=(\Sigma\mu_i(x)\cdot y_i)/(\Sigma\ \mu_i(x))$

where$\mu_i(x)$isthemembershipfunction$y_i$istheoutputassociatedwithrulei.

Application in BLDC Motors

- **Speed and position control** without the need frantic curate motor model.
- **Adaptive torque regulation** in dynamic and noisy environments.
- **Improved robustness** a gain spare meter variations.

Fuzzy control is often combined with GA or PSO to automatically optimize the fuzzyrulesor membership functions, creating hybrid fuzzy systems.

D. ***Artificial Neural Networks (ANN)***

ANN sare power full earning-based systems that approximate online ear relationships through inter connected layers of artificial neurons. Each neuron applies a weighted sum and an activation function to model complex dynamics.

Mathematical Model

For an euron **j :**

$\mathbf{y_j=f(\Sigma w_{ij}x_i +b_j)}$

where $\mathbf{x_i}$ are inputs, $\mathbf{w_{ij}}$are connection weights, $\mathbf{b_j}$ is bias, and fist he activation function (e.g., sigmoid, Re LU).

Training Process:

1. **Data Collection**: Gather motor input-output data (e.g., speed, voltage, current).
2. **Training**: Adjust weights using algorithms like back propagation to minimize error.
3. **Validation**: Test performance under runs even operating conditions.

Application in BLDC Motors:

- **Modeling and prediction** of no nlin ear motor dynamics.
- **Adaptive and self-tuning controllers** that adjust to load variations.
- **Fault detection and diagnosis** using patter nre cognition.

ANNs can be integrated with GA or PSO for hybrid control, where optimization algorithms fine-tune the network's parameters for improved accuracy and faster convergence.

Ant Colony Optimization (ACO)

ACO mimics the foraging behavior of ants in finding optimal paths between their colony and food sources. The artificial ants communicate using pheromone trails, which guide subsequent ants toward better solutions.

Mathematical Frame work

The probability of an antk moving from no deit on odej is given by:

$$P_{ij}^{k}=([\tau_{ij}]^\alpha[\eta_{ij}]^\beta)/(\Sigma_{l\in N_i^k}[\tau_{il}]^\alpha[\eta_{il}]^\beta)$$

Where:

τ_{ij}: pheromone level,

η_{ij}: heuristic in formation (e.g., inverse of cost), α, β : influence parameters.

Application in BLDC Motors:

- **Optimal commutation sequence selection** to minimize torque ripple.
- **Path optimization** in multi-objective control tasks.
- **Parameter tuning** form online ar controllers.

Although ACO is computationally intensive, it provides **robust and accurate solutions** in systems with dynamic and uncertain environments.

RESULTS

The following table provides a comparison of the soft computing techniques based on the reapplication in BLDC motor control:

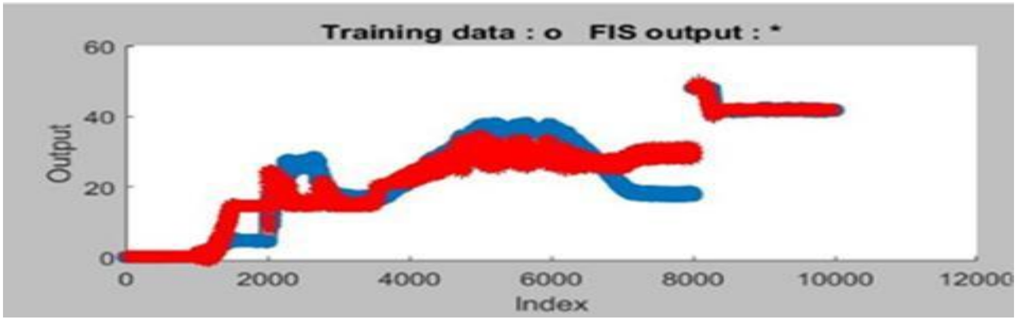


Figure 1: Training fit:targetvs.ANFIS-1 output.

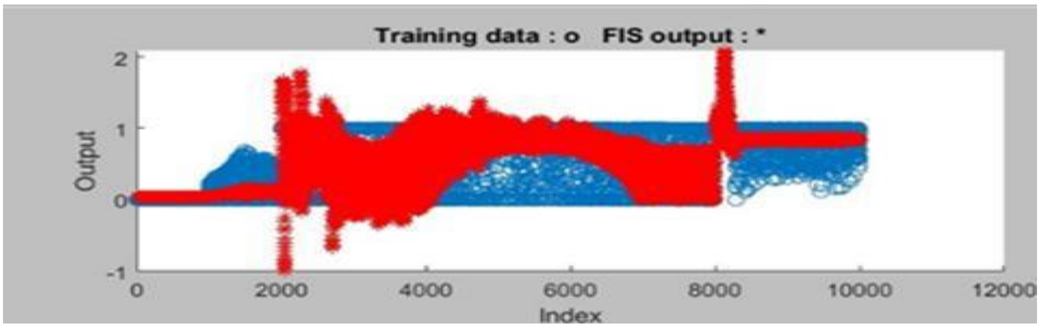


Figure 2: Training fit: target vs.ANFIS-2 output.

The ANFIS-1 results begin with the schematic representation of its topology and logical operations (Figure 7), depicting the multi-layered structure responsible for mapping the input error signals and their derivatives into appropriate control outputs through fuzzification, rule evaluation, and defuzzification stages [37]. This is followed by the learned input–output surface plot (Figure 8), which visually captures the nonlinear mapping realized by ANFIS-1 after training, showing smooth gradient transitions and appropriate curvature that reflect the system's adaptive learning capability [38].The training fit plot (Figure 9) shows that the level of correlation existing between the target outputs and the ANFIS-1 predictions is high making the deviation negligible reflecting on high generalization and accurate error reduction in the process of learning [39] .

Likewise, the ANFIS-2 results start with its topology and logical operation diagram (Figure 10), which displays a parallel structure that is optimized to the DC-link voltage control loop, in which membership functions and fuzzy rules are adjusted to respond to any voltage change promptly [40] . The corresponding learned input output surface (Figure11) indicates a developed nonlinear control surface which indicates that the model was effective in capturing the underlying dynamics of the voltage regulation task [41] . Lastly, the training fit plot (Figure 12) indicates that there is a close overlap between the desired and actual output, which proves successful convergence of the learning algorithm and support that the model can be used to control the cascaded BLDC drive right-hand-rule drive architecture in real-time [42].

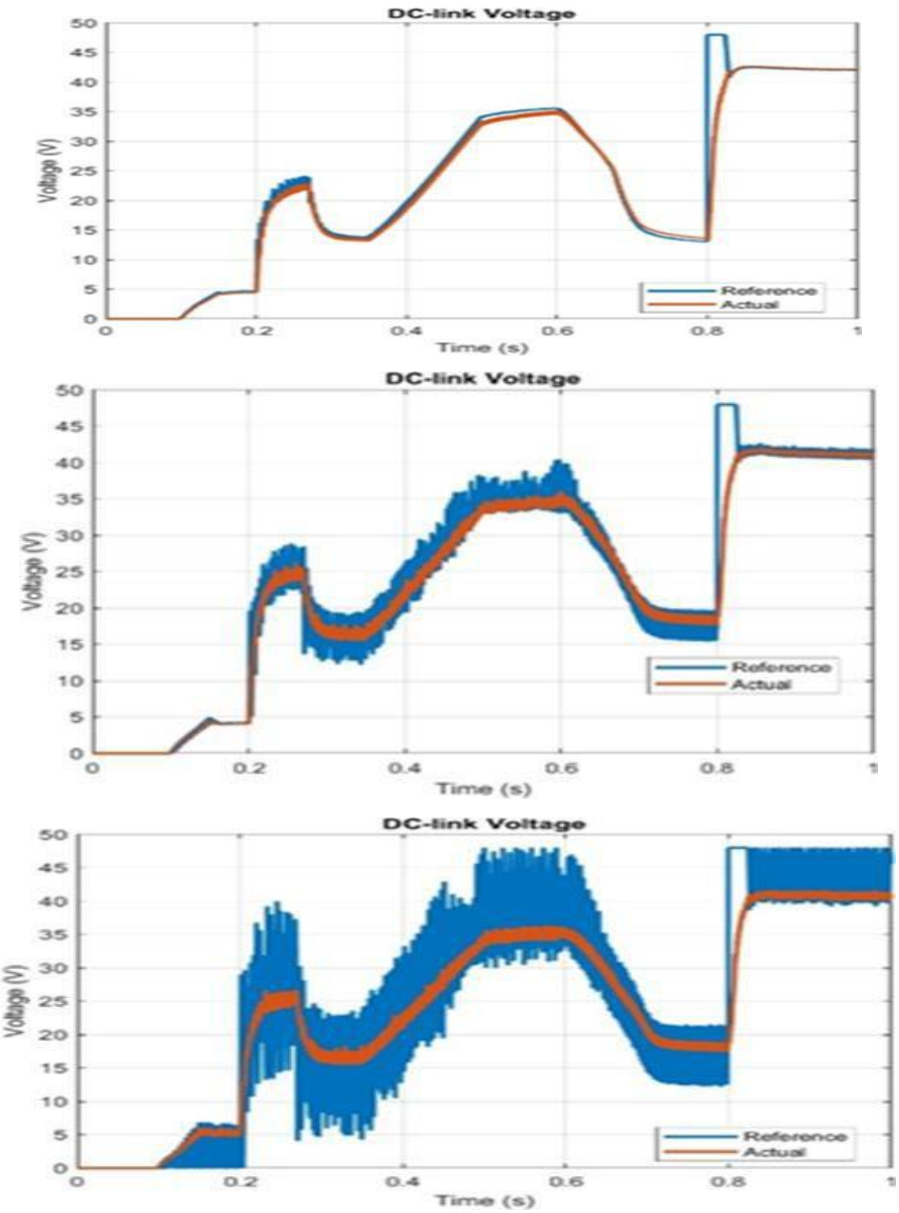


Figure 3: System response using theoptimized ANFIS controller, showing improved accuracy and faster convergence compared to conventional approaches.

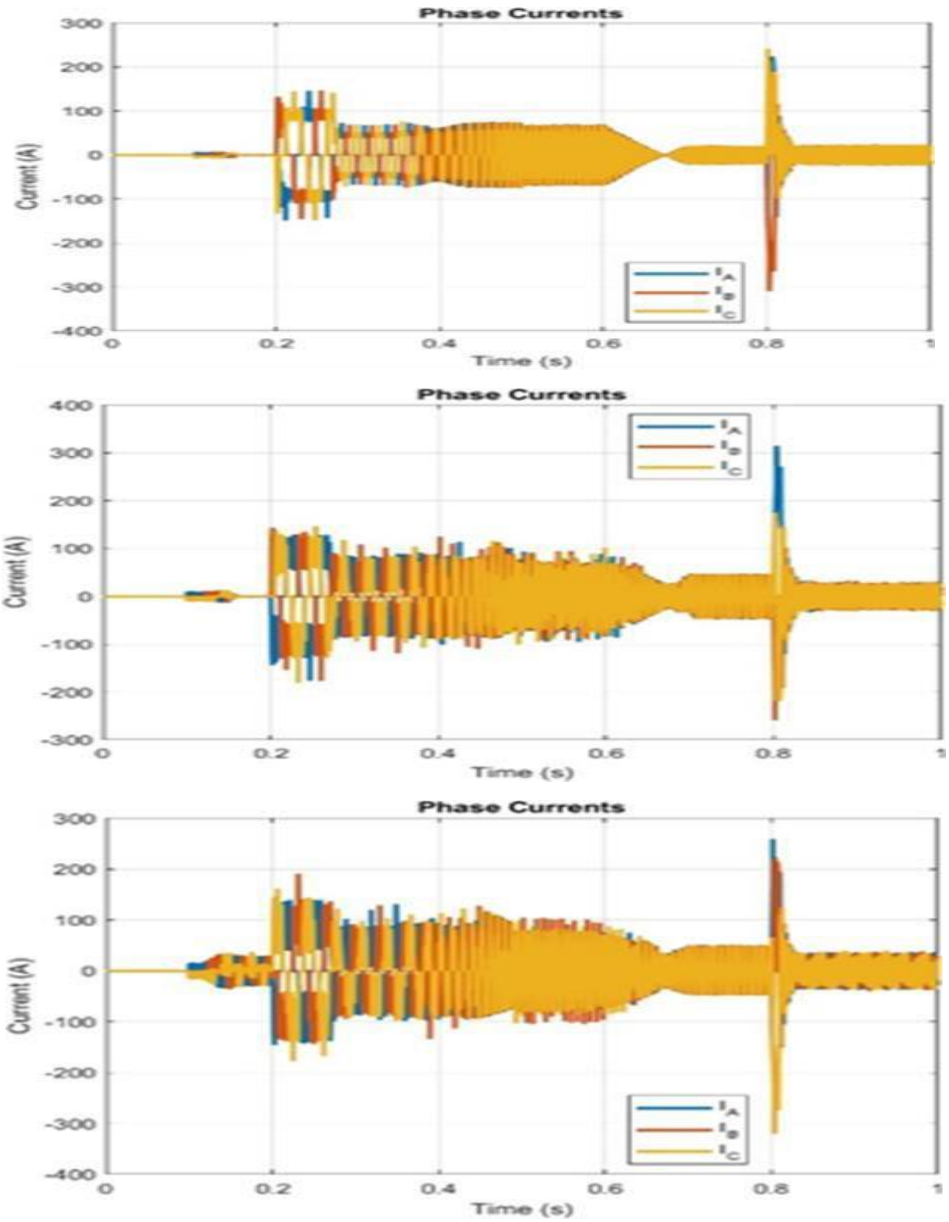
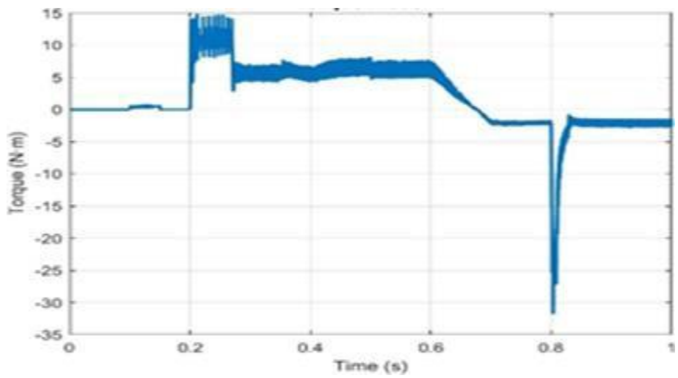


Figure 4: System response under the standard ANFIS controller, highlighting it is nonlinear modeling capability without parameter optimization.



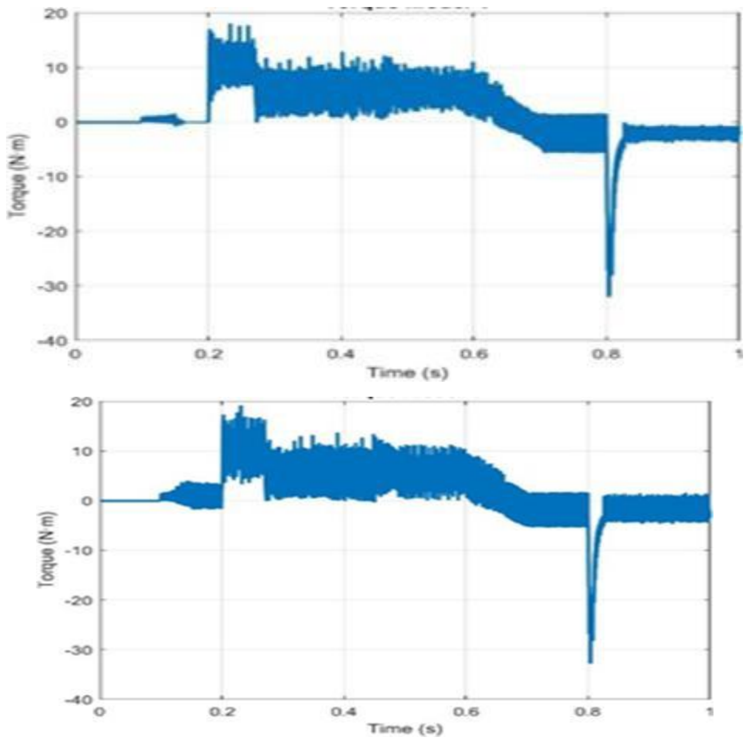
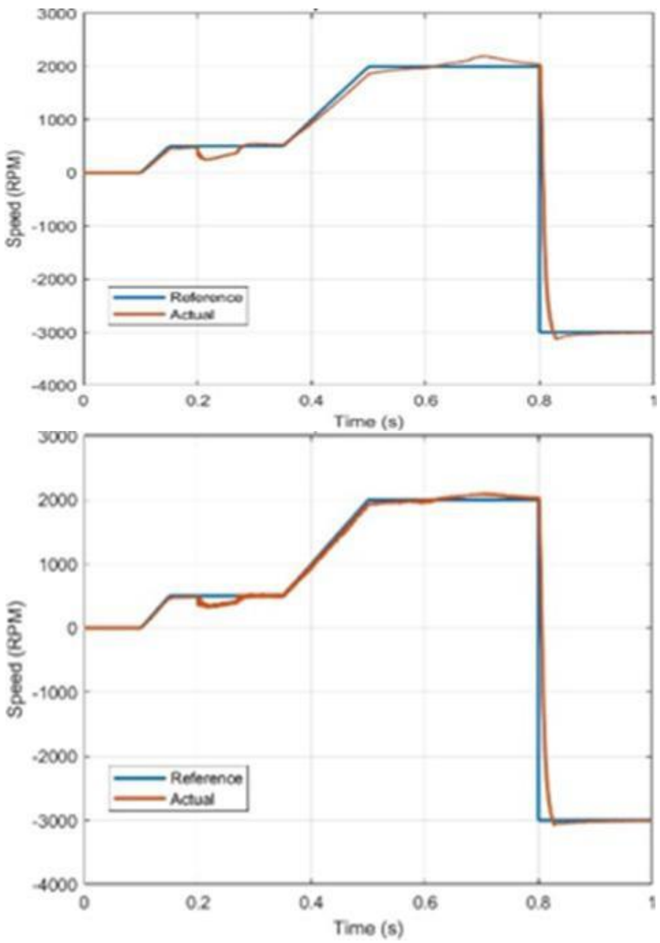


Figure 5: System response with the conventional PI controller, serving as a baseline for comparison with ANFIS and optimized ANFIS methods



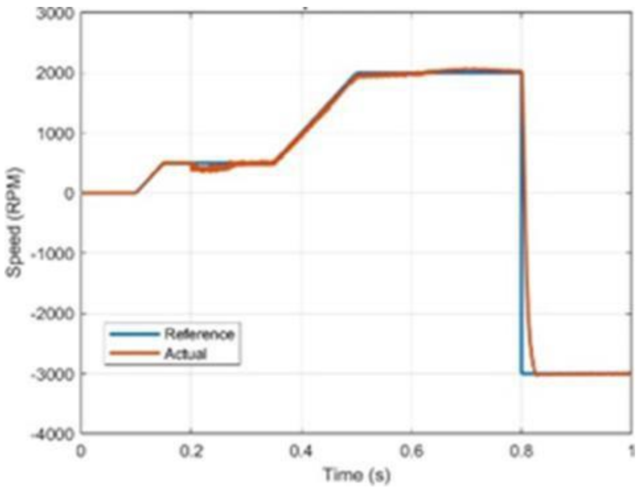


Figure 6: Comparative system responses under PI, standard ANFIS, and optimized ANFIS controllers, demonstrating the superior accuracy, stability, and faster converge nce of the optimized ANFIS compared to the conventional PI and standard ANFIS approaches.

The DC-link voltage regulation in Optimized ANFIS has the best tracking of the reference with the least ripple and lowest settling even in the face of abrupt load and speed fluctuations. ANFIS is also well tracked and at slightly higher rip levelers, especially when tracking transients. Model-3, despite remaining on the reference, has the High value of ripple amplitude, and slow ripple suppression, implying poorer smoothness of voltages than in the other two models.

Regarding the quality of phase currents, Optimized ANFIS can stabilize three-phase currents (IA, IB, IC) and dampen oscillations rapidly after being disturbed. ANFIS has the same balance and higher transient oscillations. PI demonstrates the maximum transient oscillation and more significant amplitude changes in the events of dynamic nature, which implies ineffective damping.

Optimized ANFIS provides the smoothest torque response, low steady-state ripple and controlled responses to sharp acceleration and deceleration command, in terms of torque. ANFIS also generates a slightly higher ripple but is still within acceptable levels whereas PI shows the maximum torque ripple under steady conditions and additional variation under reversals.

Speed tracking performance is also good in all three models and each model has a negligible steady-state error. Optimized ANFIS however reacts a bit quicker to acceleration and braking transitions, ANFIS reacts relatively equally and PI exhibits a little longer lag and small transient over-shoot.

Table 1:Time Domain Performance Metrics.

Controller	Rise Time(s)	Over shoot (%)	Settling Time(s)
Optimized ANFIS	0.335	50	0.905
ANFIS	0.33	50	0.89
PI	0.365	50	0.89

The temporary performance analysis of the three controllers, the Optimized ANFIS, ANFIS, and PI, discloses that Optimized ANFIS controllers have a higher rise time of 0.335 as compared to the PI of 0.365 s and close to the normal ANFIS of 0.330 s, the response to commands to increase velocity is quicker. The overshoot of all three controllers compared to the target speed is 50%, which can be attributed to the nature of the aggressive acceleration of torques of the BLDC drive. The Optimized ANFIS has the lowest settling time with a value of 0.905 s which is slightly better than the standard ANFIS, and the same as the PI controller with a settling time of 0.890 s. On the whole, Optimized ANFIS has enhanced transient behavior, being faster and more stable to settling behavior than the conventional PI controller, and having similar levels of overshoot.

CONCLUSION

In short, ANFIS with SFLA used in cascaded BLDC motor controller is a powerful and successful approach in circumventing the constraints of traditional PI and fixed parameter fuzzy controllers. The two-loop system with an outer speed loop and inner DC-link voltage loop is decoupled, such that the system can perform its tasks both rapidly, precisely and stably over a wide range of conditions. According to the simulation results, the Optimized ANFIS is found to greatly improve the torque smoothness, reduce DC-link ripple, and transient speed response with only a slight steady-state error. The optimized approach has greater damping of the phase current oscillations, quicker recovery of disturbances, and enhanced performance than the PI and the traditional ANFIS controllers. These enhancements presuppose that the ANFIS-SFLA method developed is a perfect choice to be used in the problematic applications such as electric cars, robotics, and renewable energy systems, where the reliability and adaptability to the new conditions are of utmost importance. The future research may be directed at experimental validation and generalization of the methodology to include fault-tolerant conditions of control to increase reliability.

REFERENCES

1. Malla, Siva Ganesh, Priyanka Malla, Jagan Mohana Rao Malla, Ruchira Singla, Pallavi Choudekar, Rajesh Koilada, andManoj Kumar Sahu. "Whale optimization algorithm for PV basedwater pumping system driven by BLDC motor using sliding mode controller." IEEE Journal of Emerging and Selected Topics in Power Electronics 10, no. 4 (2022): 4832-4844.
2. Zhang, Yang, Radomir Gono, and Michał Jasiński. "An improvement in dynamic behavior of single phasePM brushless DC motor using deep neural network and mixture of experts." IEEE Access 11 (2023): 64260-64271.
3. Unlersen, Muhammed Fahri, Selami Balci, Muhammet Fatih Aslan, and Kadir Sabanci. "The speedestimation via BiLSTM-based network of a BLDC motor drive for fan applications." Arabian Journal for Science and Engineering 47, no. 3 (2022): 2639-2648.
4. Mahmouditabar, Farshid, Abolfazl Vahedi, and Noureddine Takorabet. "Robust design of BLDC motor considering driving cycle." IEEE Transactions on Transportation Electrification 10, no. 1(2023): 1414-1424.
5. Kristiyono, Roedy, and Wiyono Wiyono. "Autotuning fuzzy PID controller for speed control of BLDC motor." Journal of Robotics and Control (JRC) 2, no. 5 (2021): 400-407.
6. Maghfiroh, Hari, Agus Ramelan, and Feri Adriyanto. "Fuzzy-PID in BLDC motor speed control using MATLAB/Simulink." Journal of Robotics and Control (JRC) 3, no. 1 (2021): 8-13.
7. Dutta, Pallav, and Santanu Kumar Nayak. "Grey wolf optimizer based PID controller for speed control of BLDC motor." Journal of Electrical Engineering & Technology 16, no. 2 (2021): 955-961.
8. Agrawal, L. K., B. K. Chauhan, N. K. Saxena, and P. Joshi. "Speed control of BLDC motor with neural controller." Indian Journal of Science and Technology 14, no. 4 (2021): 373-381.
9. Al-Mutayeb, Yousef, and Moayed Almobaied. "Luenberger observer-based speed sensor fault detection of BLDCMotors."In2021 International Conferenceon ElectricPower Engineering–Palestine(ICEPE-P),pp.1-IEEE,2021.
10. Hemalatha, N., S. Venkatesan, R. Kannan, S. Kannan, A. Bhuvanesh, and A. S. Kamaraja. "Sensorless speed and position control of permanent magnet BLDC motor using particle swarm optimization and ANFIS." Measurement: Sensors 31 (2024): 100960.

11. Mahmud,Md,S.M. A.Motakabber,AHMZahirulAlam,AnisNurashikin Nordin,andAKM Ahasan Habib. "Modeling and performance analysis of an adaptive PID speed controller for the BLDC motor." International Journal of Advanced Computer Science and Applications 11, no. 7 (2020).
12. Hammoodi,SalmanJasim, Kareem Sayegh Flayyih,and AhmedRefaatHamad. "Design andimplementation speedcontrolsystemofDCmotorbasedon PIDcontrol andmatlab simulink."InternationalJournalofPower Electronics and Drive Systems 11, no. 1 (2020): 127-134.
13. Genc, Naci, and Zhansaya Seidakhanovna Kalimbetova. "Cuckoo optimization algorithm based fuzzy logic speed controller for BLDC motor." Electric Power Components and Systems 52, no. 11 (2024): 2065-2077.
14. Wang, Tingting, Hongzhi Wang, Chuhang Wang, and Huangshui Hu. "A novel PID controller for BLDCM speed control using dual fuzzy logic systems with HSA optimization." Scientific Reports 12, no. 1 (2022): 11316.
15. Begum, Shaik Ruksana, Loveswara Rao Burthi, and Shobha Rani Depuru. "Regenerative braking in electric vehicles using BLDC motor with modified torque and adaptive-Neuro-Fuzzy-control." Przegląd Elektrotechniczny 100 (2024).
16. Anshory, Izza, Dwi Hadidjaja, and Ribangun Bambang Jakaria. "Bldc Motor: Modeling and Optimization Speed Control Using Firefly Algorithm." Dinamik 25, no. 2 (2020): 51-58.
17. Razmjooy, Navid, Zahra Vahedi, Vania V. Estrela, Reinaldo Padilha, and Ana Carolina Borges Monteiro. "Speed control of a DC motor using PID controller based on improved whale optimization algorithm." In Metaheuristics and Optimization in Computer and Electrical Engineering, pp. 153-167. Cham: Springer International Publishing, 2020.
18. Saleh, Isiyaku, Amir Abdullahi Bature, Salinda Buyamin, and Mohamad Amir Shamsudin. "Speed control of a BLDC motor using artificial neural network with ESP32 microcontroller based implementation." InControl, Instrumentation and Mechatronics: Theory and Practice, pp. 358-368. Singapore: Springer Nature Singapore, 2022.