Vol. 1, No. 1, 2025, pp. 38-50
DOI:

Ruppell's Fox Optimizer for controlling DC motor

Widi Aribowo
Department Of Electrical Engineering, Faculty of Vocational Studies, Universitas Negeri Surabaya, Indonesia
e-mail address: widiaribowo@unesa.ac.id (corresponding author)

Hewa Majeed Zangana
IT Department, Duhok Technical College, Duhok Polytechnic University, Duhok, Iraq

Received: 18 September 2025 | Revised: 20 October 2025 | Accepted: 30 October 2025

ABSTRACT

This paper presents the implementation and evaluation of the Rüppell's Fox Optimizer (RFO) algorithm for tuning Proportional-Integral-Derivative (PID) controllers in DC motor applications. The RFO algorithm was developed and tested using MATLAB/Simulink on a standard laptop configuration. Initially, RFO's optimization performance was benchmarked against Particle Swarm Optimization (PSO) using CEC2017 benchmark functions across unimodal, multimodal, and fixed multimodal test categories. Results demonstrated RFO's superior convergence accuracy and global optimization capabilities, achieving better best, mean, and worst scores with lower standard deviations and first-rank positioning in all benchmark categories. The RFO algorithm exhibited faster initial convergence but sometimes plateaued compared to PSO's persistent long-term improvement. Subsequently, the RFO optimization technique was applied to tune PID controller parameters for DC motor speed control. Performance comparison with conventional PID and PSO-PID controllers showed that the proposed RFO-PID method delivered exceptional control performance with zero overshoot, fastest settling time (1.72 seconds), and lowest ITSE value (0.0813) over a 0-4 second evaluation period. The RFO-PID controller closely tracked the reference signal, outperforming both conventional PID and PSO-PID methods in terms of stability, accuracy, and response speed, demonstrating its effectiveness for precise DC motor control applications.

Keywords: Rüppell's Fox Optimize; PID Tuning; DC Motor Control; Artificial Intelligence, Metaheuristics

1. INTRODUCTION

The development of electrical technology in 2025 is undergoing a major transformation toward smarter, more efficient, and sustainable systems. Renewable energy sources such as solar and wind power are becoming dominant in electricity generation, supported by advancements in next-generation solar panels like perovskite technology, which offer higher efficiency at lower costs [1][2][3][4][5]. In addition, the implementation of smart grids enables more flexible and responsive power distribution, utilizing the Internet of Things (IoT) and Artificial Intelligence (AI) [6][7][8][9][10][11]. AI plays a key role in energy consumption forecasting, predictive maintenance, and real-time power plant optimization. Electric vehicles (EVs) are also driving the electrical revolution through vehicle-to-grid (V2G) technology, where cars not only consume electricity but can also return excess power to the grid. Charging infrastructure is rapidly evolving, with widespread adoption of fast charging and wireless charging technologies [12][13][14][15][16][17]. On the other hand, energy storage technologies such as lithium-ion and sodium-ion batteries are becoming essential to stabilize the supply from intermittent sources like solar and wind [18][19][20][21].

Decentralization is another emerging trend, marked by the growth of microgrids and nanogrids that allow communities or individuals to manage their own energy generation and consumption. The digitalization of the electrical system is becoming increasingly important, with cloud-based energy management platforms enabling remote monitoring and control, as well as enhancing cybersecurity to protect critical infrastructure from digital threats. Additionally, decarbonization efforts are being advanced through carbon capture technologies applied to fossil-fuel power plants, supporting the global goal of achieving net-zero emissions by 2050. With these innovations, the electrical sector in 2025 is laying the foundation for a clean, reliable, and sustainable energy future [22][23][24][25][26].

The DC motor technology in 2025 has advanced significantly, driven by the growing demand for energy-efficient, compact, and intelligent motion control systems across various industries. Modern DC motors now feature improved efficiency, higher torque-to-weight ratios, and enhanced durability, thanks to advancements in materials such as rare-earth magnets and high-performance composites. The integration of digital control systems, including microcontrollers and embedded processors, allows for more precise speed and torque regulation, adaptive performance, and real-time feedback [27][28][29][30].

Furthermore, the rise of brushless DC motors (BLDC) continues to replace traditional brushed motors in many applications due to their longer lifespan, lower maintenance requirements, and quieter operation. These motors are widely used in electric vehicles, robotics, drones, and industrial automation systems. Smart DC motors equipped with IoT connectivity and AI algorithms are also emerging, enabling predictive maintenance and remote diagnostics, which help reduce downtime and operating costs.In addition, power electronics and motor driver technology have evolved to support more compact, energy-efficient designs, allowing DC motors to be seamlessly integrated into portable and battery-powered devices. Overall, the advancements in DC motor technology are enabling smarter, cleaner, and more reliable motion solutions for both consumer and industrial applications [31][32][29].

The current control of DC motors has become increasingly sophisticated, leveraging advances in electronics, embedded systems, and control algorithms to achieve precise, efficient, and reliable motor operation. Modern DC motor control systems commonly utilize Pulse Width Modulation (PWM) to regulate motor speed by adjusting the average voltage supplied to the motor. This method allows for smooth acceleration, deceleration, and energy-efficient operation. Microcontrollers and digital signal processors (DSPs) are now widely used to implement advanced control techniques such as Proportional-Integral-Derivative (PID) control, which provides accurate speed and position regulation. Additionally, the use of H-bridge driver circuits enables bidirectional control of the motor, allowing it to run forward or in reverse, which is essential in robotics and automation applications. For brushless DC motors (BLDC), sensorless control methods using back-EMF detection or sensor-based systems using Hall-effect sensors are commonly applied to ensure precise rotor positioning and synchronization. Integration with IoT platforms and AI-based systems has further enhanced motor control, enabling features such as remote monitoring, fault detection, and adaptive performance optimization. These developments have made DC motor control more intelligent, responsive, and suitable for a wide range of modern applications, from electric vehicles and drones to industrial automation and smart appliances [33][34][35][36].

Artificial Intelligence (AI) today has reached an advanced stage of development, significantly transforming industries, services, and everyday life[37][38]. Modern AI systems are capable of performing complex tasks such as natural language understanding, image and speech recognition, decision-making, and real-time data analysis with remarkable accuracy. Deep learning and neural network architectures have enabled breakthroughs in areas like autonomous driving, medical diagnostics, financial forecasting, and personalized recommendations. AI is no longer limited to laboratories or large enterprises; it is now integrated into smartphones, smart home devices, and industrial systems, making technology more intuitive and responsive. The combination of AI with the Internet of Things (IoT), robotics, and cloud computing has given rise to intelligent systems that can learn from their environment, adapt to changing conditions, and operate autonomously. Moreover, generative AI models, such as those used for text, image, and code generation, are reshaping creative industries and human-computer interaction. Despite these advancements, ethical considerations, data privacy, and algorithmic transparency remain critical challenges that must be addressed to ensure the responsible and equitable use of AI in society[39][40][41][42].

The control of DC motors using Artificial Intelligence (AI) has become an emerging and powerful approach in modern automation and robotics. AI-based control systems offer enhanced adaptability, precision, and efficiency compared to traditional control methods. By utilizing machine learning algorithms, such systems can learn optimal motor behaviors from data, automatically adjusting control parameters such as speed, torque, and direction in real time based on operating conditions. This results in improved performance, energy savings, and longer motor lifespan. Neural networks and fuzzy logic controllers are among the most widely used AI techniques in DC motor control. These methods allow systems to handle nonlinearities and uncertainties that are difficult to manage with conventional PID control. In addition, AI is increasingly being combined with sensor data and IoT connectivity to enable predictive maintenance, fault detection, and autonomous decision-making. For instance, AI can detect early signs of wear or overload in the motor and adjust operation or trigger alerts before a failure occurs. As a result, AI-driven DC motor control is becoming essential in advanced applications such as robotics, smart manufacturing, electric vehicles, and precision mechatronic systems [43][44][45][46][47][48].

Conventional Proportional Integral Derivative (PID) control is a widely used method due to its simplicity, ease of implementation, and effectiveness in many linear control systems. It uses fixed proportional, integral, and derivative gains that are manually tuned to maintain system stability and performance. While effective for systems with stable and predictable dynamics, conventional PID controllers often struggle with nonlinearity, time-varying behaviors, or disturbances that were not considered during initial tuning. Once set, the parameters remain static, making it less flexible in adapting to changes in the system or environment. In contrast, modern PID control integrates advanced features such as adaptive tuning, gain scheduling, and artificial intelligence. These enhancements allow the controller to automatically adjust its parameters in real-time based on the system's behavior, external conditions, or desired performance. For instance, adaptive PID controllers can retune themselves during operation, while AI-assisted PID systems use machine learning or fuzzy logic to improve responsiveness and handle complex, nonlinear systems. Moreover, modern PID controllers often run on digital platforms, allowing seamless integration with IoT, data logging, remote monitoring, and predictive maintenance. As a result, modern PID control offers greater flexibility, robustness, and efficiency in dynamic or uncertain environments compared to traditional PID methods [49][50][51][52]. Rüppell's Fox Optimizer (RFO) is a metaheuristic algorithm inspired by the behavior of Rüppell's foxes in foraging for food in desert environments. This algorithm mimics the fox's exploration and exploitation strategies to find optimal solutions in a search space. The agent in RFO adapts to the best solution found, thus avoiding local traps and accelerating convergence. With its simple yet effective structure, RFO is suitable for solving various complex optimization problems in engineering, artificial intelligence, and energy systems [53].

To establish PID tuning for DC motors, this paper proposes a control approach based on the Rüppell's Fox Optimizer (RFO) algorithm. Two performance evaluations of RFO are conducted in this study. The first performance measurement utilizes the CEC2017 benchmark function tests compared with other optimization algorithms through a comparative approach to determine the first performance metric. Meanwhile, RFO is tested for PID-based DC motor control in the second evaluation. In the second test, traditional PID tuning serves as the comparative technique. The implementation of PID control on DC motors using RFO represents the main contribution of this paper. The article structure is as follows: RFO algorithm, DC motor, and PID principles are explained in Section 2. Section 3 presents the proposed RFO approach for tuning PID parameters in DC motors. Section 4 contains discussion and simulation results. The conclusion is presented in the final section.

2. METHOD

2.1. DC Motor

The DC motor (Direct Current motor) is an electromechanical device that converts direct electrical energy into mechanical rotational motion. It operates based on Lorentz force, where a current-carrying conductor placed in a magnetic field experiences a force that causes motion. The basic components of a DC motor include the stator (the stationary part that provides the magnetic field), the rotor or armature (the rotating part), the commutator, and brushes. When direct current flows through the armature winding, the interaction between the magnetic field and the electric current generates torque, which causes the rotor to spin. There are two main types of DC motors: brushed and brushless (BLDC). In a brushed DC motor, mechanical brushes and a commutator are used to switch the current direction in the rotor windings as it rotates. This design is simple and cost-effective, but it has disadvantages such as brush wear, electrical noise, and regular maintenance needs. On the other hand, brushless DC motors eliminate brushes and the commutator by using an electronic controller and sensors (or sensorless algorithms) to manage the timing of current flow. BLDC motors are more efficient, produce less noise, and have a longer lifespan because they don't suffer from mechanical wear of brushes. The advantages of DC motors include excellent speed control over a wide range, high starting torque, fast response to load changes, and ease of use in battery-powered systems. These characteristics make DC motors ideal for applications such as robotics, drones, electric vehicles, fans, conveyor systems, and portable tools. Despite the differences in design and control methods, all DC motors share the same core principle: the conversion of direct current electrical energy into mechanical motion through electromagnetic interaction. The similarity lies in the fundamental working mechanism — using current through windings in a magnetic field to produce motion. However, they differ in terms of efficiency, maintenance, and control complexity. Brushed motors are simpler to control and cheaper, making them suitable for low-cost or small-scale systems. In contrast, brushless motors offer better performance, are quieter, and require less maintenance, which is essential for applications that demand reliability and long operational life [54][55][56][57].

The DC motor remains a crucial component in many modern electromechanical systems due to its simplicity, reliability, and versatility. The choice between brushed and brushless types depends on the application's specific needs, such as cost, efficiency, control complexity, and maintenance requirements. a linear model of a DC motor is created using the mechanical and electrical equations in conjunction. There is an explanation of mathematical models and model concepts. The model's correctness is the main factor in control design. Efficiency is increased, and time and money are saved. The idea of creating the ideal model is a crucial first step [58][59][35]. The image in Figure 1 illustrates the widely recognized principle of DC motor modeling: the integration of electrical and mechanical equations.

A linear model of a DC motor is created using the mechanical and electrical equations in conjunction. There is an explanation of mathematical models and model concepts. The model's correctness is the main factor in control design. Efficiency is increased, and time and money are saved. The idea of creating the ideal model is a crucial first step. The image in Figure 1 illustrates the widely recognized principle of DC motor modeling: the integration of electrical and mechanical equations.

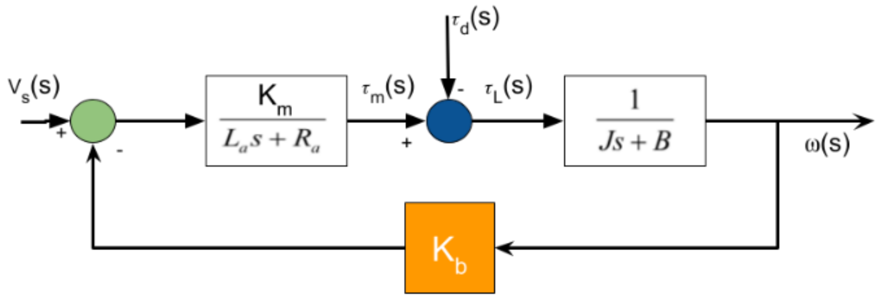

Figure. 1. The DC Motor schematic

2.2. Proportional Integral Derivative (PID)

Proportional-Integral-Derivative (PID) control is one of the most widely used control algorithms in industrial and engineering systems due to its simplicity, effectiveness, and adaptability to various types of processes. A PID controller continuously calculates an error value as the difference between a desired setpoint and a measured process variable (actual value). It then applies a correction based on three terms: Proportional (P), Integral (I), and Derivative (D), each of which addresses different aspects of the system's performance.

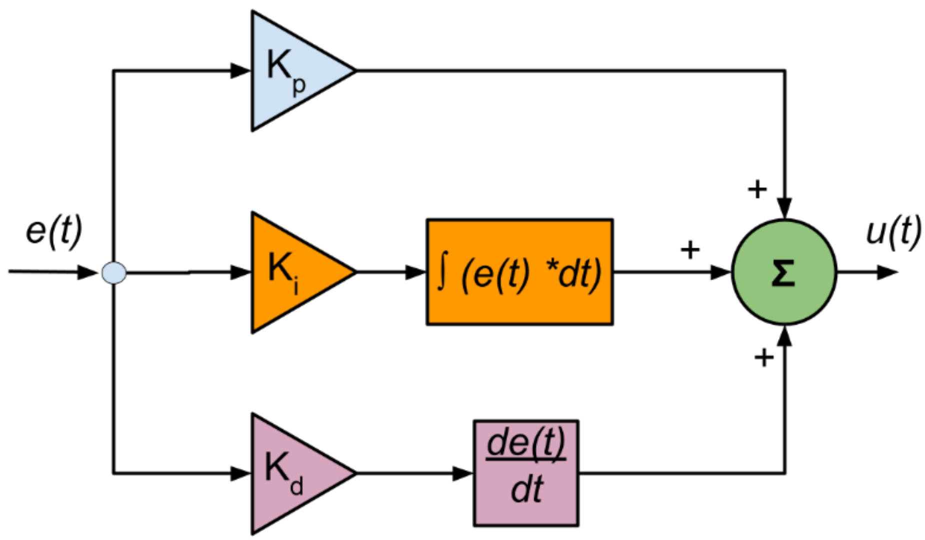

Figure. 2. The PID schematic

Figure 2 is a block representation of a PID (Proportional-Integral-Derivative) controller, which is one of the most common controllers in automatic control systems. A PID controller is used to generate a control signal based on the difference between a setpoint (goal) and an actual value (system output). The following is an explanation of its components:

- The Proportional (P) term responds to the current error. It produces an output that is directly proportional to the error value. The larger the error, the stronger the control response. However, using proportional control alone often results in a steady-state error, where the system settles close to the setpoint but never fully reaches it.
- The Integral (I) term addresses this issue by considering the accumulation of past errors over time. It integrates the error signal and applies a correction based on the total accumulated error. This allows the controller to eliminate the steady-state error and bring the process variable exactly to the setpoint. However, too much integral action can cause the system to oscillate or become unstable.
- The Derivative (D) term predicts future error based on the rate of change of the error. It introduces a damping effect that helps reduce overshoot and improves the stability of the system, especially in systems with fast dynamics. Derivative control is particularly useful in processes where quick response and precision are required, though it is sensitive to noise in the error signal.

When combined, these three terms allow a PID controller to respond to present, past, and anticipated future behavior of a system. The performance of a PID controller heavily depends on the proper tuning of its three parameters: the proportional gain (Kp), integral gain (Ki), and derivative gain (Kd). Tuning can be done manually, through trial and error, or using methods such as Ziegler–Nichols, Cohen–Coon, or modern optimization techniques like genetic algorithms and machine learning. PID controllers are widely applied in fields such as temperature control, motor speed regulation, robotics, flight systems, and process industries like chemical and manufacturing plants. Despite the rise of advanced control strategies, PID remains a popular choice due to its balance of simplicity, reliability, and robustness [60][61][49][50][62][63][64]. The PID controller is a powerful tool for automatic control systems. By combining proportional, integral, and derivative actions, it can effectively manage a wide variety of dynamic systems, maintaining stability, minimizing error, and improving response time. Proper tuning and implementation ensure that the PID controller performs optimally in real-world applications.

2.3. Rüppell's foxoptimizer (RFO)

The Rüppell's Fox Optimizer (RFO) is a nature-inspired meta-heuristic algorithm based on the intelligent hunting behavior of Rüppell's foxes. These foxes live in harsh environments like deserts and grasslands and are known for their adaptability, flexibility, and efficient foraging strategies. Their ability to survive by adjusting their diet and behavior according to seasonal changes inspired the RFO's design. Rüppell's foxes use a combination of sight, hearing, and smell to locate and hunt prey. Their vision allows activity both day and night, with vertically slit pupils and binocular vision for precise movement detection. Their hearing is extremely sensitive, capable of detecting low-frequency sounds like the rustling of rodents. They can move each ear independently to locate the direction of sounds. Their sense of smell helps them detect hidden food and mark territory. These traits form the core of the RFO algorithm, which mimics the foxes' ability to efficiently explore and exploit the search space, making it effective for solving complex optimization problems. The pseudo code of RFO can be seen in Algorithm 1.

Algorithm 1: A pseudo code Rüppell's foxoptimizer

```
Set control parameters of RFO
Initialize the population of RFO
Evaluate the fitness of the population
// Main loop
while (stop condition is not met) do
// Evaluate the best solution so far
best_solution = FindBestSolution(population)
for each fox in population do
// Generate random values
rand1 = Random(0, 1)
rand2 = Random(0, 1)
rand3 = Random(0, 1)
rand4 = Random(0, 1)
rand5 = Random(0, 1)

 // Update positions based on conditions
if rand1 >= 0.25 then
if s >= h then
            if (beta - 0.5) * rand2 >= 0 then
               UpdatePositionUsingEquation(fox, Equation_19)
            else
               UpdatePositionUsingEquation(fox, Equation_20)
         else
            if rand3 >= 0.75 then
               UpdatePositionUsingEquation(fox, Equation_19)
            else
               UpdatePositionUsingEquation(fox, Equation_20)
      else
         if rand3 >= 0.75 then
            UpdatePositionUsingEquation(fox, Equation_3)
         else
            UpdatePositionUsingEquation(fox, Equation_26)
      // Night update
      if rand4 >= 0.25 then
```

```
        if h > s then
            UpdatePositionUsingEquation(fox, Equation_28)
        else
            UpdatePositionUsingEquation(fox, Equation_27)
    else
        if rand5 >= 0.75 then
            UpdatePositionUsingEquation(fox, Equation_28)
        else
            UpdatePositionUsingEquation(fox, Equation_27)

    // Smell-based update
    if rand >= smell then
        UpdatePositionUsingEquation(fox, First Part Of Equation_29)
    else
        UpdatePositionUsingEquation(fox, Second Part Of Equation_29)

    // Flag-based update
    if flag == t then
        UpdatePositionUsingEquation(fox, Equation_37)
    else
        UpdatePositionUsingEquation(fox, FirstPart Of Equation_34)

    // Additional updates
    if rand >= 0.1 then
        UpdatePositionUsingEquation(fox, Second Part Of Equation_34)

  // Evaluate the new population
  EvaluateFitness(population)
// Check stop condition
  if StopConditionMet() then
    break
  end while
Return the best solution found
Return best_solution
```

3. PROPOSED METHOD

The proposed method is a population-based RFO approach, which uses a migration mechanism to update the population. This algorithm is designed to find the optimal PID control parameters for a DC motor. The main steps include population initialization, fitness calculation, population sorting, updating the best agent, migration, and storing the best solution. The process continues until the maximum iteration limit is reached. Figure 2 shows that this method is optimized to obtain the PID control parameters (Kp, Ki, Kd) for a DC motor. The RFO method is used to find the optimal combination of PID parameters to control a DC motor.

Figure 3 illustrates a control system architecture designed to optimize the performance of a DC motor using an error-based feedback loop, with a focus on minimizing the Integral Time Absolute Error (ITAE) through the application of a PID controller and an RFO (Ruppell's Fox Optimization) algorithm. Here is a detailed explanation of the process:
Explanation of the Diagram

- DC Motor: The DC Motor is the primary controlled system in this setup. It represents the physical plant or actuator that needs to be controlled to achieve a desired output.
- PID Controller: The PID (Proportional-Integral-Derivative) Controller is a widely used control strategy for regulating dynamic systems. It calculates the control signal based on three components:
  Proportional (P): Reacts to the current error.
  Integral (I): Accumulates past errors to eliminate steady-state offset.
  Derivative (D): Predicts future errors based on the rate of change of the error.
  The PID controller receives the error signal as input and generates a control signal to adjust the behavior of the DC motor.
- RFO (Ruppell's Fox Optimization): The RFO Algorithm is an optimization technique used to tune the parameters of the PID controller. This metaheuristic algorithm searches for optimal values of the PID gains to minimize the ITAE. By

optimizing these parameters, the RFO ensures that the PID controller performs effectively in controlling the DC motor under varying conditions.

- Error Calculation: The Error Calculation block computes the difference between the reference input (desired output) and the actual output of the DC motor. This error signal is fed back into the PID controller to adjust the control action dynamically. The error is continuously monitored to ensure that the system converges to the desired performance.
- ITAE (Integral Time Absolute Error):
The ITAE is a performance index used to evaluate the quality of the control system. It integrates the absolute value of the error over time, weighted by time, to penalize both large errors and slow response times[63][65]. Mathematically, ITAE is defined as:

$$ITAE = \int_0^{\infty} t.e(t).dt \qquad (1)$$

where $e(t)$ is the error at time t. Minimizing ITAE ensures that the system not only reduces steady-state error but also responds quickly to disturbances or changes in the setpoint.
- Summing Junction (Σ): The summing junction combines the reference input signal with the negative feedback from the error calculation. This creates the error signal that drives the PID controller. The summing junction ensures that the system continuously compares the actual output with the desired output, enabling closed-loop control.
- Overall Process Flow: The reference input is compared with the actual output of the DC motor in the summing junction to compute the error. The error is then passed to the PID controller, which generates a control signal based on the proportional, integral, and derivative terms. The control signal is applied to the DC motor, adjusting its behavior to reduce the error. The RFO algorithm tunes the PID parameters in real-time to minimize the ITAE, ensuring optimal performance. The ITAE serves as a metric to evaluate the effectiveness of the control system, guiding the RFO algorithm in refining the PID parameters.

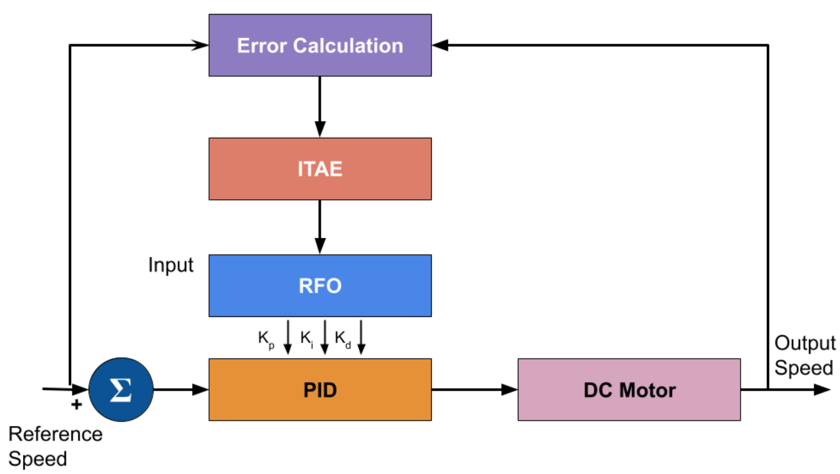

Figure. 3. The RFO-PID for DC Motor

4. RESULT AND DISCUSSION

The RFO algorithm code has been implemented and tested on a laptop equipped with an AMD A9-9425 processor with a clock speed of 3.1 GHz and 4 GB of RAM. The software used is MATLAB/Simulink. Table 1 provides a comprehensive overview of the RFO parameters. The performance of the proposed PID-RFO method is evaluated using global optima and comparative analysis methods. Figure 4 displays the results of this comparison in Benchmark Function.

The Figure 4(a) compares the performance of two optimization algorithms, RFO and PSO , over 50 iterations. Both algorithms start with similar high scores around 5×10^4, but their performance diverges significantly after iteration 10. RFO (blue line) converges rapidly within the first 10 iterations, stabilizing at approximately 1×10^4, but shows limited improvement thereafter. In contrast, PSO (orange line) demonstrates superior long-term performance, continuously improving its score and approaching zero by iteration 50. This indicates that while RFO offers faster initial convergence, it becomes trapped in a local optimum, whereas PSO exhibits better global search capability and achieves a more optimal solution over time

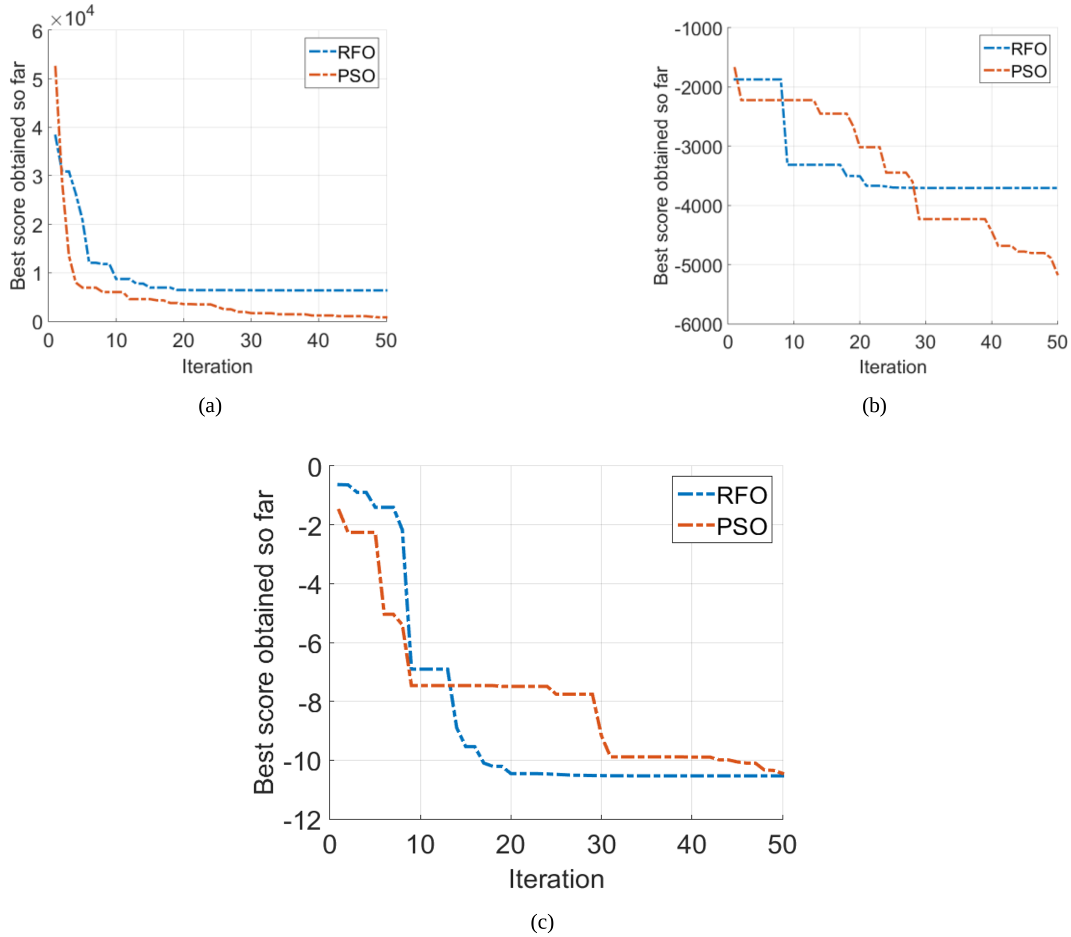

Figure. 4. Benchmark Function Comparison (a) Unimodal (b) Multimodal (c) Multimodal Fixed

TABLE 1. COMPARISON RFO AND PSO

	PSO	RFO	
Best	2596.115	269.6608	Unimodal
Mean	8485.665	814.7669	
Worst	14304.07	1358.857	
Std	2820.991	201.4568	
Rank	2	1	
Best	-4336.02	-7096.04	Multimodal
Mean	-2877.78	-5171.1	
Worst	-1689.47	-3085.78	
Std	619.1436	876.3209	
Rank	2	1	
Best	-10.5364	-10.5365	Multimodal Fixed
Mean	-6.7392	-5.5787	
Worst	-1.8382	-1.8584	
Std	3.8266	3.6259	
Rank	2	1	

The Figure 4(b) compares the performance of RFO and PSO algorithms over 50 iterations. Both start with high scores near -1,000 but show different convergence patterns. RFO (blue line) rapidly improves its score within the first 10 iterations, stabilizing around -4,000 after iteration 20. In contrast, PSO (orange line) initially converges slower but continues to improve, reaching a significantly lower score of approximately -5,000 by iteration 50. This suggests that while RFO converges quickly, it may get stuck in a local optimum, whereas PSO demonstrates better global exploration capabilities, achieving a more optimal solution over time. The graph highlights the trade-off between fast initial convergence and long-term optimization effectiveness.

The Figure 4(c) compares the performance of RFO and PSO algorithms over 50 iterations. Both algorithms start with similar high scores near -2 but exhibit distinct convergence behaviors. RFO (blue line) rapidly improves its score, reaching a stable value around -10 by iteration 10 and maintaining it thereafter. In contrast, PSO (orange line) shows slower initial convergence but continues to improve gradually, achieving a slightly better score than RFO by iteration 50. This suggests that while RFO converges quickly, it may settle into a local optimum, whereas PSO demonstrates persistent optimization capabilities, potentially finding a more optimal solution over time. The graph highlights the balance between fast convergence and long-term refinement in these algorithms.

The comparative analysis in Table 1 shows that RFO consistently outperforms PSO across all benchmark functions. In unimodal tests, RFO achieves significantly better results with a best score of 269.66 compared to PSO's 2596.11, demonstrating superior convergence accuracy. For multimodal functions, RFO again excels with a best score of -7096.04 versus PSO's -4336.02, indicating better global optimization capabilities. Even in fixed multimodal scenarios, RFO maintains its advantage with a best score of -10.5365 against PSO's -10.5364. The lower standard deviations for RFO suggest more consistent performance, while its first-rank positioning across all test categories confirms its overall superiority in optimization accuracy and reliability compared to the PSO algorithm. The next experiment is the application of the RFO method to tune PID parameters for the purpose of controlling a DC motor.

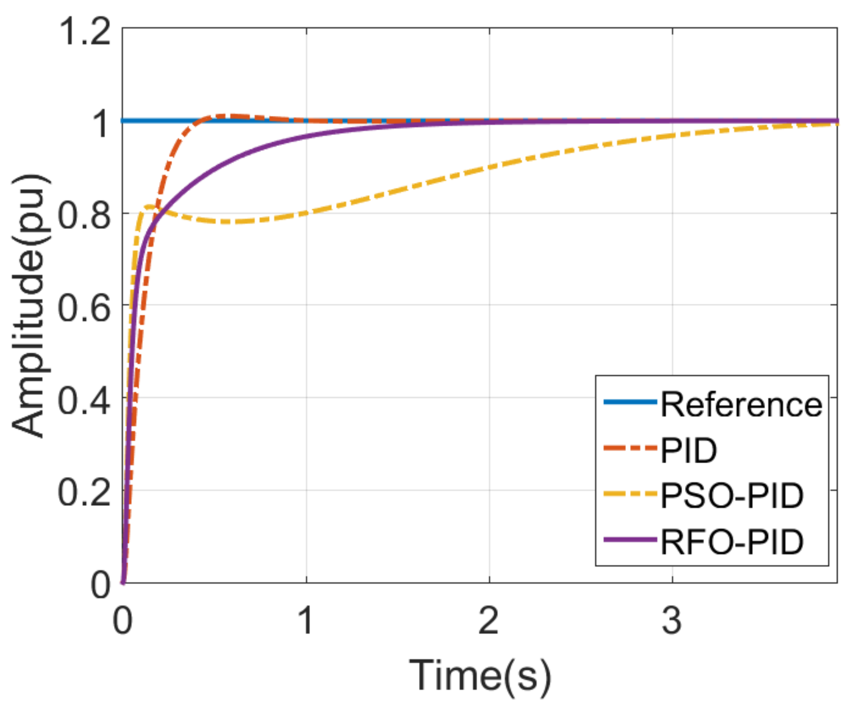

Figure. 5. The Response Of DC Motor

The Figure 5 compares the performance of four control strategies: Reference, PID, PSO-PID, and RFO-PID. The x-axis represents time (in seconds), while the y-axis shows amplitude in per unit (pu). The Reference line (blue) represents the desired output, which all controllers aim to track. PID (dashed orange line) closely follows the reference but exhibits a slight overshoot initially. PSO-PID (dotted yellow line) tracks the reference more smoothly than PID, with minimal overshoot and faster settling time. RFO-PID (solid purple line) demonstrates the best performance, closely matching the reference with no overshoot and achieving steady-state tracking almost immediately. Overall, RFO-PID outperforms both PID and PSO-PID in terms of accuracy and speed, making it the most effective control strategy among the tested methods.

TABLE 2. THE OUTPUT DC MOTOR WITH PID IN 0-4 SECOND

Controller	Overshoo	Rise Time	Settling Time	ITSE
PID	1.01	0.4058	2.24	0.7944
PSO-PID	No Overshoot	0.4027	3.54	0.8634
RFO-PID	No Overshoot	0.4033	1.72	0.0813

Table 2 presents the performance comparison of three PID controller variants for DC motor control over 0-4 seconds. The RFO-PID controller demonstrates superior performance with no overshoot, fastest settling time (1.72 seconds), and lowest ITSE value (0.0813), indicating excellent stability and accuracy. While PSO-PID also eliminates overshoot, it has slower settling time (3.54 seconds) and higher ITSE (0.8634). Conventional PID shows minimal overshoot (1.01) with moderate settling time (2.24 seconds) but higher ITSE (0.7944). Rise times are comparable across all controllers, ranging from 0.4027 to 0.4058 seconds. Overall, RFO-PID achieves the best balance of fast response, stability, and minimal error integration.

5. CONCLUSION

This study successfully demonstrated the effectiveness of the Rüppell's Fox Optimizer (RFO) algorithm for tuning Proportional-Integral-Derivative (PID) controllers in DC motor applications. Through comprehensive benchmark testing using CEC2017 functions, RFO consistently outperformed Particle Swarm Optimization (PSO) across unimodal, multimodal, and fixed multimodal categories, achieving superior convergence accuracy with lower standard deviations and first-rank positioning in all tests. While RFO exhibited rapid initial convergence, it sometimes plateaued compared to PSO's persistent long-term improvement. The implementation of RFO-based PID tuning for DC motor control yielded exceptional results, with the RFO-PID controller demonstrating zero overshoot, the fastest settling time (1.72 seconds), and the lowest ITSE value (0.0813) compared to conventional PID and PSO-PID methods. The RFO-PID system closely tracked the reference signal, showcasing superior stability, accuracy, and response speed. These findings confirm that the RFO algorithm is a highly effective optimization tool for PID parameter tuning, offering significant advantages in terms of control performance and system reliability for DC motor applications. The research validates RFO as a promising metaheuristic approach for engineering optimization problems, particularly in motor control systems where precision and stability are paramount.

REFERENCES

[1] A. K. ALAhmad, R. Verayiah, S. Ba-swaimi, H. Shareef, and A. Abu-Rayash, "Optimal allocation and configuration of renewable energy sources, electric vehicle parking lots, and fixed and mobile batteries under uncertainty and demand response program," *Energy Convers. Manag. X*, p. 101041, 2025. https://doi.org/10.1016/j.ecmx.2025.101041

[2] G. Ramkumar, S. Kannan, V. Mohanavel, S. Karthikeyan, and A. Titus, "The Future of Green Mobility: A Review Exploring Renewable Energy Systems Integration in Electric Vehicles," *Results Eng.*, p. 105647, 2025. https://doi.org/10.1016/j.rineng.2025.105647

[3] A. M. Abed, M. A. Nazari, M. H. Ahmadi, A. Mukhtar, R. Kumar, and N. Gharib, "Power generation by utilization of different renewable energy sources in five Middle Eastern countries: Present status, opportunities and challenges," *Sustain. Energy Technol. Assessments*, vol. 73, p. 104101, 2025. https://doi.org/10.1016/j.seta.2024.104101

[4] R. Aridi, M. Aridi, M.-L. Pannier, and T. Lemenand, "Eco-environmental, and social impacts of producing electricity with various renewable energy sources," *Energy*, vol. 320, p. 135139, 2025.

[5] Y. F. Nassar, H. J. El-Khozondar, and M. A. Fakher, "The role of hybrid renewable energy systems in covering power shortages in public electricity grid: An economic, environmental and technical optimization analysis," *J. Energy Storage*, vol. 108, p. 115224, 2025. https://doi.org/10.1016/j.energy.2025.135139

[6] S. Kanagamalliga, T. S. Aarthi Radha, S. Vengadakrishnan, R. Sridhar, K. Adinkrah-Appiah, and S. Rajalingam, "Harnessing IoT-powered fire detection systems for enhanced security," in *International Conference on Advances in Distributed Computing and Machine Learning*, Springer, 2024, pp. 347–356. https://doi.org/10.1016/j.est.2024.115224

[7] P. Campana, R. Censi, R. Ruggieri, and C. Amendola, "Smart Grids and Sustainability: The Impact of Digital Technologies on the Energy Transition," *Energies*, vol. 18, no. 9, p. 2149, 2025. https://doi.org/10.3390/en18092149

[8] S. Mahadik, M. Gedam, and D. Shah, "Environment sustainability with smart grid sensor," *Front. Artif. Intell.*, vol. 7, p. 1510410, 2025. https://doi.org/10.3389/frai.2024.1510410

[9] R. R. Ramya and J. Banumathi, "An optimized approach with 128-bit key management for IoT-enabled smart grid: enhancing efficiency, security, and sustainability," *Electr. Eng.*, vol. 107, no. 2, pp. 2207–2225, 2025.

[10] T. Mazhar, T. Shahzad, A. U. Rehman, and H. Hamam, "Integration of smart grid with industry 5.0: applications, challenges and solutions," *Meas. Energy*, vol. 5, p. 100031, 2025. https://doi.org/10.1016/j.meaene.2024.100031

[11] Z. Buksh, N. A. Sharma, R. Chand, J. Kumar, and A. B. M. Shawkat Ali, "Cybersecurity Challenges in Smart Grid IoT," *IoT Smart Grid Revolutionizing Electr. Eng.*, pp. 175–206, 2025. https://doi.org/10.1002/9781394279401.ch8

[12] A. Zentani, A. M. Almaktoof, and M. T. E. Kahn, "Exploring Review of Advancements in Fast-Charging Techniques and

Infrastructure for Electric Vehicles Revolution," *Energy Sci. Eng.*, vol. 13, no. 6, pp. 3437–3447, 2025. https://doi.org/10.1002/ese3.70051

[13] M. Cavus, H. Ayan, M. Bell, O. K. Oyebamiji, and D. Dissanayake, "Deep charge-fusion model: Advanced hybrid modelling for predicting electric vehicle charging patterns with socio-demographic considerations," *Int. J. Transp. Sci. Technol.*, 2025. https://doi.org/10.1016/j.ijtst.2025.03.002

[14] F. Makhmudov, D. Kilichev, U. Giyosov, and F. Akhmedov, "Online machine learning for intrusion detection in electric vehicle charging systems," *Mathematics*, vol. 13, no. 5, p. 712, 2025. https://doi.org/10.3390/math13050712

[15] W. Zhang *et al.*, "Long-lifespan and sterilizable face masks leveraging the power of light and electricity," *Sep. Purif. Technol.*, vol. 354, p. 128697, 2025. https://doi.org/10.1016/j.seppur.2024.128697

[16] B. Zhang, J. Kang, and T. Feng, "A novel approach to evaluating the accessibility of electric vehicle charging infrastructure via dynamic thresholding in machine learning," *Environ. Plan. B Urban Anal. City Sci.*, vol. 52, no. 1, pp. 26–43, 2025. https://doi.org/10.1177/23998083241249322

[17] P. Prakhar, S. Gupta, and R. Jaiswal, "Battery technology and charging infrastructure for EVs: a resource-based and dynamic capability view of entrepreneurial opportunities," *Inf. Discov. Deliv.*, 2025. https://doi.org/10.1108/IDD-09-2024-0143

[18] J. Schöberl *et al.*, "Thermal runaway characterization of cylindrical lithium-ion and sodium-ion batteries with various sizes and energy contents," *J. Power Sources*, vol. 648, p. 237240, 2025. https://doi.org/10.1016/j.jpowsour.2025.237240

[19] K. Xiong, T. Qi, and X. Zhang, "Advancements in Graphite Anodes for Lithium-Ion and Sodium-Ion Batteries: A Review," *Electroanalysis*, vol. 37, no. 1, p. e202400318, 2025. https://doi.org/10.1002/elan.202400318

[20] K. Nikgoftar, A. K. Madikere Raghunatha Reddy, M. V. Reddy, and K. Zaghib, "Carbonaceous Materials as Anodes for Lithium-Ion and Sodium-Ion Batteries," *Batteries*, vol. 11, no. 4, p. 123, 2025. https://doi.org/10.3390/batteries11040123

[21] A. Prapanca, Nasreddine Belhaouas, and Imed Mahmoud, "Modified FATA Morgana Algorithm Based on Levy Flight," *Vokasi Unesa Bull. Eng. Technol. Appl. Sci.*, vol. 2, no. 1 SE-Article, pp. 1–11, Mar. 2025, doi: 10.26740/vubeta.v2i1.37066.

[22] Y. Zhang and H. Chen, "Research on the realization path of China multi-agent value co-creation in new energy microgrids-based on fsQCA method," *Sci. Rep.*, vol. 15, no. 1, p. 23486, 2025. https://doi.org/10.1038/s41598-025-08966-4

[23] S. Yadav, P. Kumar, and A. Kumar, "Excess energy management and techno-economic analysis of optimal designed isolated microgrid with reliability and environmental aspects," *Energy Convers. Manag.*, vol. 333, p. 119772, 2025. https://doi.org/10.1016/j.enconman.2025.119772

[24] S. Kashyap, C. Schaffer, W. Schwinger, G. Hartner, M. Kurz, and O. Hödl, "A Framework for Overcoming Data Accessibility Challenges in Urban Microgrids for Smart Cities," in *2025 2nd International Conference on Advanced Innovations in Smart Cities (ICAISC)*, IEEE, 2025, pp. 1–6.https://doi.org/10.1109/ICAISC64594.2025.10959532

[25] M. Mohanty, S. K. Bhuyan, and N. Nayak, "Real-Time Validation of Load Frequency Control in Renewable-Powered Microgrids: Opal-Rt Hil Testing," in *2025 International Conference in Advances in Power, Signal, and Information Technology (APSIT)*, IEEE, 2025, pp. 1–7.https://doi.org/10.1109/APSIT63993.2025.11086228

[26] A. Norasing and N. Abe, "Scenario Analysis of Electricity Demand Growth with Rural Electrification for the Evaluation of the Reliability and Sustainability of an off-Grid Microgrid System: A Case Study in Lao PDR," *IEEJ Trans. Electr. Electron. Eng.*, 2025.https://doi.org/10.1002/tee.70047

[27] Q. S. Kadhim *et al.*, "Optimum design of bearingless brushless DC motor modeling with dual loop controller using dragonfly optimizers," *e-Prime-Advances Electr. Eng. Electron. Energy*, vol. 11, p. 100942, 2025.https://doi.org/10.1016/j.prime.2025.100942

[28] W. Bu, Z. Fan, J. Zhang, and W. Tao, "Research on the Bearingless Brushless DC Motor Structure with Like-Tangential Parallel-Magnetization Interpolar Magnetic Poles and Its Air-Gap Magnetic Field Analytical Calculation," in *Actuators*, MDPI, 2025, p. 198. https://doi.org/10.3390/act14040198

[29] K. Usha, T. D. Saraswathy, V. S. Harini Sree, R. Sai Kanna, and K. Pritha, "IoT-Based DC Motor Monitoring System," in *2025 International Conference on Computing and Communication Technologies (ICCCT)*, IEEE, 2025, pp. 1–5. https://doi.org/10.1109/ICCCT63501.2025.11020053

[30] X. Zheng, H. Wen, X. Yang, X. Yu, and J. J. Rodriguez-Andina, "Adaptive neural zeta-backstepping with predefined damping ratio. Application to DC motors," *IEEE Trans. Cybern.*, 2025. https://doi.org/10.1109/TCYB.2025.3539544

[31] D. Makararpong, M. Ketcham, T. Ganokratanaa, N. Chumuang, W. Yimyam, and P. Pramkeaw, "Development of a System for Measuring pH and Oxygen Levels in Water Using Internet of Things (IoT) Technology," in *2025 IEEE International Conference on Cybernetics and Innovations (ICCI)*, IEEE, 2025, pp. 1–7. https://doi.org/10.1109/ICCI64209.2025.10987306

[32] M. M. Raikar, S. Kulkarni, O. S. P. Patil, K. Halingali, and A. Darshan, "Remote motor condition monitoring using IoT and Machine Learning: A predictive approach," *Procedia Comput. Sci.*, vol. 259, pp. 1096–1105, 2025. https://doi.org/10.1016/j.procs.2025.04.063

[33] A. Sen, B. Singh, K. Mahtani, A. Moradzadeh, and S. M. Muyeen, "Optimized design of a permanent magnet brushless DC motor for solar water-pumping applications," *Results Eng.*, vol. 26, 2025, doi: 10.1016/j.rineng.2025.104633. https://doi.org/10.1016/j.rineng.2025.104633

[34] M. Kchaou *et al.*, "Event-Triggered control strategy for discrete-time fuzzy systems with infinite delay under DoS attacks: Application to DC motor-gear train system," *Expert Syst. Appl.*, vol. 277, p. 127138, 2025. https://doi.org/10.1016/j.eswa.2025.127138

[35] E. Molina-Santana, L. A. Iturralde Carrera, J. M. Álvarez-Alvarado, M. Aviles, and J. Rodríguez-Resendiz, "Modeling and Control of a Permanent Magnet DC Motor: A Case Study for a Bidirectional Conveyor Belt's Application," *Eng*, vol. 6, no. 3, p. 42, 2025. https://doi.org/10.3390/eng6030042

[36] L. R. Devi, S. Sreekumar, R. Bhakar, and S. Padmanaban, "Electric motor modeling, analysis, and design for E-mobility applications: A state of the art," *e-Prime-Advances Electr. Eng. Electron. Energy*, p. 100985, 2025. https://doi.org/10.1016/j.prime.2025.100985

[37] R. Jawad and R. Jawad, "Comparison Feed Forward Back Propagation Networks (FFBPNs) with Support Vector Machine (SVM) for

Diagnosis Skin Cancer Based on Images," *Vokasi Unesa Bull. Eng. Technol. Appl. Sci.*, vol. 2, no. 2, pp. 28–36, 2025. https://doi.org/10.26740/vubeta.v2i2.36117

[38] D. S. Aondonenge *et al.*, "Early Heart Disease Prediction Using Data Mining Techniques," *Vokasi Unesa Bull. Eng. Technol. Appl. Sci.*, vol. 2, no. 2, pp. 112–127, 2025. https://doi.org/10.26740/vubeta.v2i2.36735

[39] J. Kokina, S. Blanchette, T. H. Davenport, and D. Pachamanova, "Challenges and opportunities for artificial intelligence in auditing: Evidence from the field," *Int. J. Account. Inf. Syst.*, vol. 56, p. 100734, 2025. https://doi.org/10.1016/j.accinf.2025.100734

[40] M. Al-Raeei, "The future of oral oncology: How artificial intelligence is redefining surgical procedures and patient management," *Int. Dent. J.*, vol. 75, no. 1, pp. 109–116, 2025. https://doi.org/10.1016/j.identj.2024.09.032

[41] D. Harisanty, N. E. V. Anna, T. E. Putri, A. A. Firdaus, and N. A. Noor Azizi, "Is adopting artificial intelligence in libraries urgency or a buzzword? A systematic literature review," *J. Inf. Sci.*, vol. 51, no. 2, pp. 511–522, 2025. https://doi.org/10.1177/01655515221141034

[42] R. Sieber, A. Brandusescu, S. Sangiambut, and A. Adu-Daako, "What is civic participation in artificial intelligence?," *Environ. Plan. B Urban Anal. City Sci.*, vol. 52, no. 6, pp. 1388–1406, 2025. https://doi.org/10.1177/23998083241296200

[43] D. Barri, F. Soresini, M. Gobbi, A. di Gerlando, and G. Mastinu, "Optimal design of traction electric motors by a new adaptive pareto algorithm," *IEEE Trans. Veh. Technol.*, 2025. https://doi.org/10.1109/TVT.2025.3532752

[44] M. Habyarimana and A. A. Adebiyi, "A Review of Artificial Intelligence Applications in Predicting Faults in Electrical Machines," *Energies*, vol. 18, no. 7, p. 1616, 2025. https://doi.org/10.3390/en18071616

[45] S. Abood, A. Annamalai, M. Chouikha, and T. Nejress, "Fault diagnostics of synchronous motor based on artificial intelligence," *Machines*, vol. 13, no. 2, p. 73, 2025. https://doi.org/10.3390/machines13020073

[46] B. R. Rao, G. S. J. Gautam, and S. He, "High-Fidelity NVH Model Development for Electric Motors Using Deep Learning and Machine Learning Algorithms," SAE Technical Paper, 2025. https://doi.org/10.4271/2025-01-0123

[47] A. Mohammad-Alikhani, E. Jamshidpour, S. Dhale, M. Akrami, S. Pardhan, and B. Nahid-Mobarakeh, "Fault diagnosis of electric motors by a channel-wise regulated CNN and differential of STFT," *IEEE Trans. Ind. Appl.*, 2025.

[48] A. Sabo, S. Buba, O. Ogunleye, K. Mohammed, S. E. Kalau, and D. P. Olaniyi, "The Use of Genetic Algorithm Optimization Approach In Comparison With Lambda Iteration Technique to Solve Economic Load Dispatch Problem.," *Vokasi Unesa Bull. Eng. Technol. Appl. Sci.*, vol. 2, no. 2, pp. 309–321, 2025. https://doi.org/10.1109/TIA.2025.3532556

[49] G. Tang, J. Lei, H. Du, B. Yao, W. Zhu, and X. Hu, "Proportional-integral-derivative controller optimization by particle swarm optimization and back propagation neural network for a parallel stabilized platform in marine operations," *J. Ocean Eng. Sci.*, 2022.

[50] J.-Y. Lee, G.-G. Jin, and G.-B. So, "Adaptive Nonlinear Proportional–Integral–Derivative Control of a Continuous Stirred Tank Reactor Process Using a Radial Basis Function Neural Network," *Algorithms*, vol. 18, no. 7, p. 442, 2025.

[51] C.-P. Wu, N.-K. Hsieh, L.-R. Chen, and V. E. Balas, "Enhancing Longitudinal Flight Stability of Electric-powered Micro Unmanned Aerial Vehicles Using Fuzzy Proportional-integral-derivative Control," *Int. J. Control. Autom. Syst.*, vol. 23, no. 7, pp. 2132–2141, 2025. https://doi.org/10.1007/s12555-024-0930-0

[52] M. I. A. Shithil *et al.*, "Performance enhancement of a vented quarter-circular solar thermal collector using proportional, proportional-integral, and proportional-integral-derivative controllers," *Appl. Therm. Eng.*, vol. 269, p. 126127, 2025. https://doi.org/10.1016/j.applthermaleng.2025.126127

[53] M. Braik and H. Al-Hiary, "Rüppell's fox optimizer: A novel meta-heuristic approach for solving global optimization problems," *Cluster Comput.*, vol. 28, no. 5, pp. 1–77, 2025. https://doi.org/10.1007/s10586-024-04950-1

[54] A. Kumar *et al.*, "Comparative analysis of brushless DC and switched reluctance motors for optimizing off-grid water pumping," *Sci. Rep.*, vol. 15, no. 1, 2025, doi: 10.1038/s41598-025-88045-w. https://doi.org/10.1038/s41598-025-88045-w

[55] X. Li, Y. Zhang, and J. Wu, "Optimization of tangential interior brushless DC motor rotor for hybrid vehicles," *Sci. Rep.*, vol. 15, no. 1, 2025, doi: 10.1038/s41598-025-98799-y. https://doi.org/10.1038/s41598-025-98799-y

[56] M. A. Bhayo *et al.*, "High precision experimentally validated adaptive neuro fuzzy inference system controller for DC motor drive system," *Sci. Rep.*, vol. 15, no. 1, 2025, doi: 10.1038/s41598-025-97549-4. https://doi.org/10.1038/s41598-025-97549-4

[57] R. Asnawi *et al.*, "Fuzzy Logic Controller-Proportional-Integral for Motor Velocity Control of Electric Rail Train Using DC-DC Converter," *J. Adv. Res. Appl. Sci. Eng. Technol.*, vol. 54, no. 1, pp. 62–79, 2025, doi: 10.37934/araset.54.1.6279.

[58] E. Arévalo, R. Herrera Hernández, D. Katselis, C. Reusser, and R. Carvajal, "On Modelling and State Estimation of DC Motors," in *Actuators*, MDPI, 2025, p. 160. https://doi.org/10.3390/act14040160

[59] N. Dasanayake and S. Perera, "Motor state prediction and friction compensation for brushless DC motor drives using data-driven techniques," *Nonlinear Dyn.*, vol. 113, no. 5, pp. 4147–4162, 2025. https://doi.org/10.1007/s11071-024-09980-3

[60] M. Farman *et al.*, "Chaos and Proportional Integral Derivative (PID) Control on Cancer Dynamics with Fractal fractional Operator," *Results Eng.*, p. 105052, 2025. https://doi.org/10.1016/j.rineng.2025.105052

[61] A. Kuzmin, V. Pinchuk, S. Khudoliy, D. A. G. Arango, C. A. E. Gutiérrez, and M. S. E. Gutiérrez, "Feasibility of proportional–integral–derivative control for high-inertia heating systems: Energy use and dynamic response," *Appl. Therm. Eng.*, p. 126784, 2025. https://doi.org/10.1016/j.applthermaleng.2025.126784

[62] P. Wang, S. Chen, J. Liu, S. Cai, and C. Xu, "PIDNODEs: Neural ordinary differential equations inspired by a proportional–integral–derivative controller," *Neurocomputing*, vol. 614, p. 128769, 2025. https://doi.org/10.1016/j.neucom.2024.128769

[63] X. Zhou, Y. Hao, Y. Liu, L. Dang, B. Qiao, and X. Zuo, "Short-term prediction of dissolved oxygen and water temperature using deep learning with dual proportional-integral-derivative error corrector in pond culture," *Eng. Appl. Artif. Intell.*, vol. 142, p. 109964, 2025. https://doi.org/10.1016/j.engappai.2024.109964

[64] S. Audomsi, S. Wattana, N. Uthathip, and W. Sa-ngiamvibool, "Development and Design of an Optimal Fuzzy Logic Two Degrees of Freedom-Proportional Integral Derivative Controller for a Two-Area Power System Using the Bee Algorithm," *Energies*, vol. 18,

no. 4, p. 915, 2025. https://doi.org/10.3390/en18040915

[65] A. M. El-Rifaie, “A novel lyrebird optimization algorithm for enhanced generation rate-constrained load frequency control in multi-area power systems with proportional integral derivative controllers,” *Processes*, vol. 13, no. 4, p. 949, 2025. https://doi.org/10.3390/pr13040949