# Metaheuristic algorithms for parameter estimation of DC servo motors with quantized sensor measurements

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**ABSTRACT**

Manufacturing, aviation, and robotics have increased servo motor use due to their precision, reliability, and adaptability in various applications. This study compares three metaheuristic techniques for servo motor model parameter estimation with sensor measurement quantization, focusing on their accuracy and efficiency. Armature resistance, back electromotive force (EMF) constant, torque constant, coil inductance, friction coefficient, and rotor-load inertia are crucial to servo motor behavior prediction, significantly impacting overall system performance. Each approach was rigorously tested and analyzed to evaluate its effectiveness in predicting servo motor characteristics. The results revealed that particle swarm optimization and the firefly algorithm delivered comparable performance, particularly excelling in scenarios where sensor measurement quantization introduced noise or imprecision in the data. These methods demonstrated strong resilience and accuracy under such challenging conditions. In contrast, the genetic algorithm did not perform as well, falling short when compared to the other two techniques in handling noisy or imprecise data, indicating its relative inefficiency in such environments. These findings give servo motor designers and engineers across industries a powerful tool for performance prediction.



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## 1. INTRODUCTION

Robotics, computer numerical control (CNC) machining, printing presses, packing equipment [1], and aircraft thrust vector control systems use servo motors due to their precision. These motors provide precise torque, velocity, and angular position control, making them essential for many applications. Robot joints and limbs move precisely and intricately thanks to servo motors [2]. Their use allows robots to do complex tasks with exceptional accuracy, revolutionizing manufacturing and automation. CNC machines precisely regulate cutting tool movements with servo motors. This accuracy produces precisely machined components, vital in precision-intensive sectors. In printing and packaging, servo motors are crucial. This contribution ensures high-quality, reliable products that meet these industries' strict requirements. Servo motors drive nozzles and surfaces in thrust vector control systems in aerospace. This precise control lets rockets change course, a crucial role in space travel [3].

Modern industrial control systems use servo motors extensively. Peak performance in these systems requires precise parameter estimates. System identification, outlined in [4], requires numerous phases to accurately simulate a system's behavior. This method involves careful experiment planning, execution, and evaluation to create models for research projects [5] or adaptive control loops [6]. In physics and other fields, mathematical models are essential. Theoretical and experimental models are included. According to Isermann and Münchhof [7], experimental model system identification uses non-parametric and parametric models. Graphical representations of non-parametric models with ambiguous structures and unbounded parameters are common [8]. In contrast, parametric models [9] have well-defined structures and finite parameters, usually specified by transfer functions or differential equations. This research analyzes three population-based optimization algorithms to demonstrate how to determine model parameters for a simple DC motor while considering sensor quantization. Traditional gradient-based optimization techniques are vulnerable to local optima. They overcome traditional obstacles with heuristics and random search [10], [11]. Metaheuristics, on the other hand, are stochastic optimization algorithms that search the search space for the best solution without using gradients but rather heuristics and random search [12]. Fakhar *et al.* [13] explained metaheuristics are a good option. They are ideal for non-convex and multimodal optimization problems because stochastic optimization algorithms explore search spaces without gradients.

## 2. PARAMETRIC MODEL IDENTIFICATION

This paper quantizes continuous rotation data using the floor function and emulates the transfer function with an armature-controlled DC servo motor. A DC servo motor's behavior can be quantitatively expressed using differential equations [14]. Figure 1 shows how a DC servo motor works: a current passes through a coil, creating a magnetic field that interacts with a permanent magnet to rotate the shaft [15]. Creating electrical and mechanical equations independently and merging them describes electromechanical relationships [16].

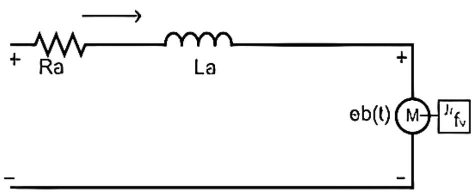



Figure 1. DC motor circuit diagram

The system's input is armature voltage, and its output is the measured shaft angle in degrees. Consider the inputs $e_a(t)$ and $e_b(t)$, and the output $i_a(t)$. Wrap KVL around the armature-mechanical dynamics:

$$e_a(t) = R_a \times i_a(t) + L \times \left(\frac{di_a(t)}{dt}\right) + e_b(t) \tag{1}$$

$$T(t) = J_r \times \left(\frac{d\omega_m(t)}{dt}\right) + f_v \times \omega_m(t) \tag{2}$$

taking Laplace transform on (1) assuming initial conditions to be zero, then:

$$E_a(s) = L_a.I_a(s).s + R_a.I_a(s) + E_b(s) \tag{3}$$

$$i_a(s) = \left[\frac{1}{L_a.s+R_a}\right].[E_a(s) - E_b(s)] \tag{4}$$

taking Laplace transform on mechanical system dynamics on (2), then:

$$T(s) \quad = [J_r \cdot s + f_v] \cdot \Omega_m(s) \ \Rightarrow \Omega_m(s) = \left[\frac{1}{J_r \cdot s + f_v}\right] \cdot T(s) \tag{5}$$

$$\left[\frac{\Omega_m(s)}{E_a(s)}\right] = \left[\frac{K_T}{L_a \cdot J_r \cdot s^2 + (L_a \cdot f_v + R_a \cdot J_r).s + (K_T \cdot K_E + R_a \cdot B_m)}\right] \tag{6}$$

solving for $\Theta_m(s) = \left[\frac{1}{s}\right] \cdot \Omega_m(s)$ can be given as (7).

$$\left[\frac{\Theta_m(s)}{E_a(s)}\right] = \left[\frac{K_T}{L_a \cdot J_m \cdot s^3 + (L_a \cdot f_v + R_a \cdot J_m).s^2 + (K_T \cdot K_E + R_a \cdot B_m) \cdot s}\right] \tag{7}$$

Figure 2 depicts a control system for an actual servo motor. Initially, an input signal undergoes modification through the transfer function of the servo motor, expressed as 1/La.s+Ra. Subsequently, the system traverses several stages, including a torque constant Kt, a mechanical transfer function 1/(J.s+fo), and a floor operation, culminating in the "servo measured output." A feedback loop integrates a back electromotive force constant Kb, contributing to the overall closed-loop control system.

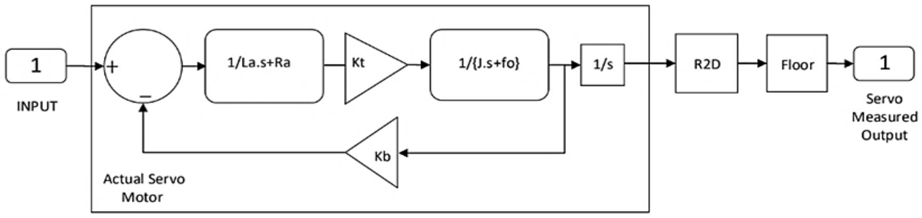



Figure 2. Actual or modeled block diagram of the DC-servo motor along with the rotary encoder

## 3. MODEL VERIFICATION AND RESPONSE

A system with an integrator will increase output over time with a step input. Since the integrator accumulates input, the output grows with time. The system has a pole at the origin, hence step input response is infinitely large [17], as seen in Figure 3. Thus, when given a step input, the system's output rises indefinitely. This unbounded growth is important to consider in integrator system design and analysis because it can affect real-world applications. This uses a 1 V step input. Figure 4 magnifies Figure 3 to show sensor quantization.

The integral absolute error (IAE) cost function was used to evaluate optimization strategies in the paper to reduce computing complexity [18]. Heuristics are used to minimize IAE, the cost function in this study. $L_a$, $R_a$, $K_t$, $K_b$, J, and $F_o$ are the DC-servo motor transfer function predicting parameters. Each set of six variables is a solution.

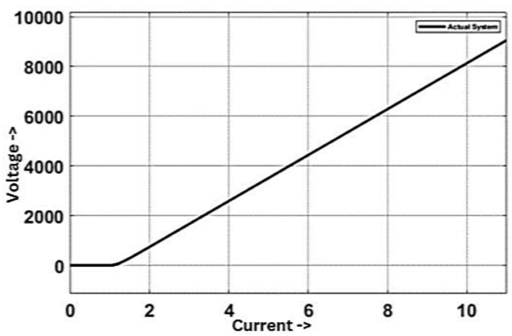



Figure 3. Step response of the motor to 1 V armature voltage

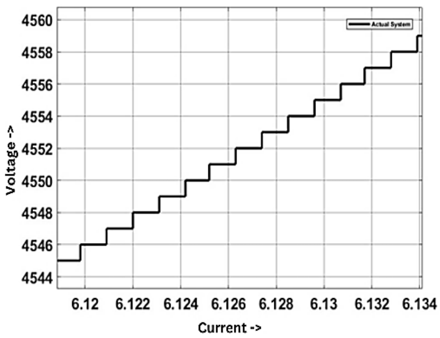



Figure 4. Magnified portion of Figure 3

## 4. DETERMINATION AND IMPLEMENTATION OF THE ALGORITHMS

### 4.1. Genetic algorithm (GA)

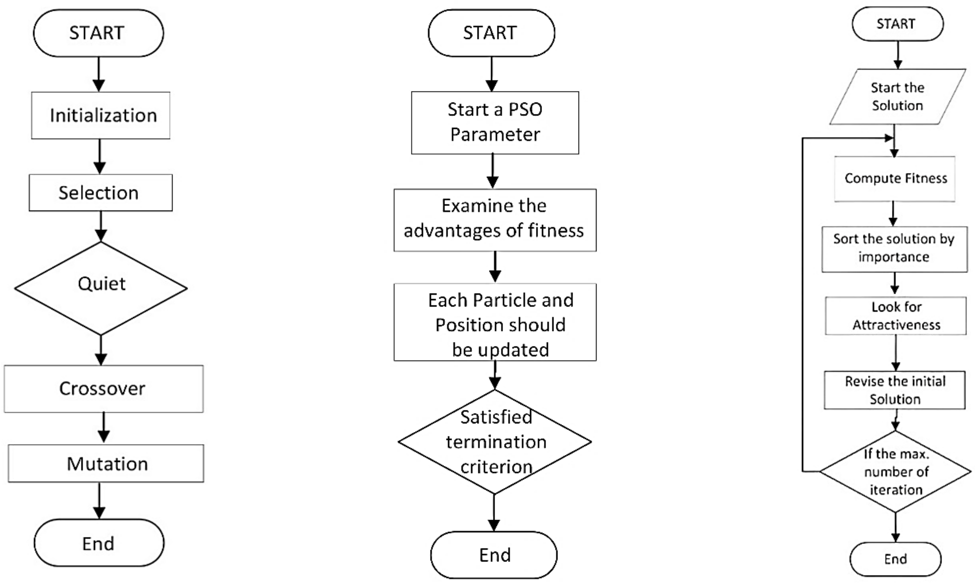
The genetic algorithm (GA) is an optimization technique based on natural selection and genetic evolution. In 1975, John Holland introduced genetic algorithms. They use genetic operations including selects, crossover, and mutation to iteratively evolve a population of candidate solutions to discover the best answer [19]. Figure 5(a) shows the basic steps of a genetic algorithm [20]. The algorithm generates a population of potential solutions. A set of random people representing different problem solutions is usually used. The population depends on the problem and computational resources. Fitness is used to assess each person's problem-solving ability. The fitness function, adapted to the individual situation, establishes the parameters for evaluating the solution's quality [21], [22]. Applying the fitness function to each person gives a fitness score. Each population member's fitness score is calculated during evaluation. The genetic algorithm is extensively used in optimization problems such as finding the optimal solution to a mathematical equation, designing optimal engineering structures, and optimizing financial portfolios.

### 4.2. Particle swarm optimization (PSO)

PSO is a population-based optimization method inspired by bird and fish behavior. Kenndy and Eberhart introduced PSO in 1995. PSO mimics the social behavior of a swarm of particles searching a multi-dimensional space to solve optimization problems. The particles update their positions and velocities based on their best position, the nest position found by any particle in the swarm, and their current position as they search the space. Figure 5(b) shows the PSO stages [22].

### 4.3. Firefly algorithm (FA)

The flashing patterns and attraction behavior seen in fireflies served as the inspiration for the FA, which Xin-She Yang first published in 2008 [23], [24]. The basic objective of this method is to identify the best solution by mimicking the flashing and attracting behavior of each firefly, which symbolizes a potential solution. It shows efficiency in dealing with issues where there are numerous local optima. The following steps are a part of the FA, which is depicted in Figure 5(c) [25], [26]. FA is a powerful optimization method used to solve complicated problems. FA is highly effective in solving a wide range of challenges that require optimization, such as optimizing engineering designs [27], [28]. One of the strengths of the FA is its capability to discover the global optimum solution in a search space with multi-modes [29].




(a) (b) (c)

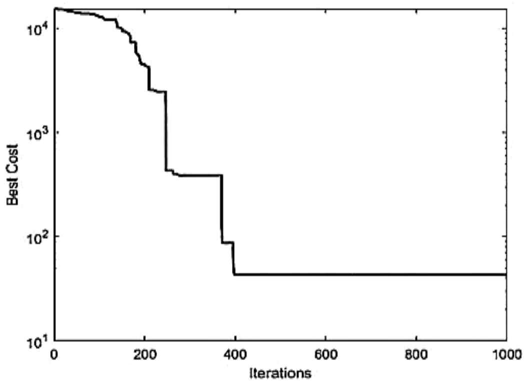
Figure 5. Flowchart for pseudo code to program (a) GA, (b) PSO, and (c) FA

## 5. RESULTS AND ANALYSIS

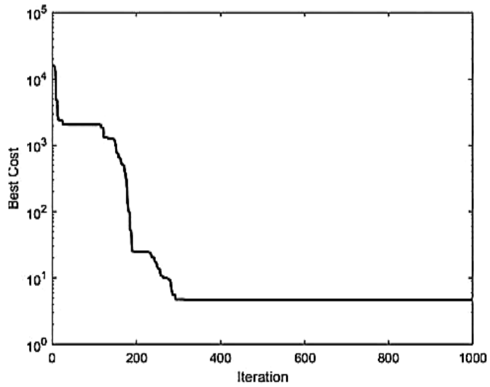
This research initialized all three optimization methods with 5 sets of solutions randomly distributed over the search space with lower and higher bounds of [0.0001 0.0001 0.0001 0.0001 0.0001] and [1.5 1.5 1.5 1.5 1.5 1.5] for La, Ra, Kt, J, fo, and $K_b$. Three algorithms must minimize the IAE cost function. Simulink models are similar in all three techniques. After defining algorithm parameters, simulations began. Best-cost advancement across each cycle for the three optimization calculations was plotted.

Figure 6 shows the cost-value evolution for genetic, PSO, and firefly algorithms. Figure 6(a) shows the cost-value evolution for GA and it has the worst best-cost and time performance. Figures 6(b) and 6(c) show that PSO and firefly algorithms converge to similar solutions. GA has the worst best-cost and time performance. PSO exceeds others in best-cost evolution speed. As shown above, PSO reaches its lowest cost around the $270^{th}$ iteration, whereas FA and GA lag behind. PSO is known for its fast convergence due to its efficient search space exploration and ability to approach the best solution. The FA may need more rounds to converge, especially for complex tasks. Genetic operators make the GA computationally complex and slow [30], [31]. The table compares techniques based on global best cost [32], DC-motor parameter values, and gain and phase margin from the three anticipated models' frequency response estimation.

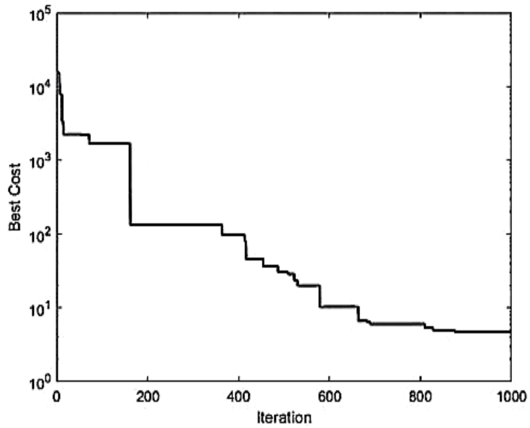
Figure 7 depicts bode plots of the actual system, PSO, GA, and FA. From Figure 7, it can be concluded that in spite of the fact that all four DC-servo motor models produced the same time domain response, they don’t appear to have the same frequency response. By comparing the gain margins and phase margins of the models, it is seen that they are stable in a closed loop in all the models. Table 1 gives a comparison of different calculations based on the best cost fetched, values of DC-motor parameters, and the frequency response gain margins of the three models along with the actual system.




(a)




(b)




(c)

Figure 6. The cost-value evolution for (a) genetic, (b) PSO, and (c) firefly algorithms

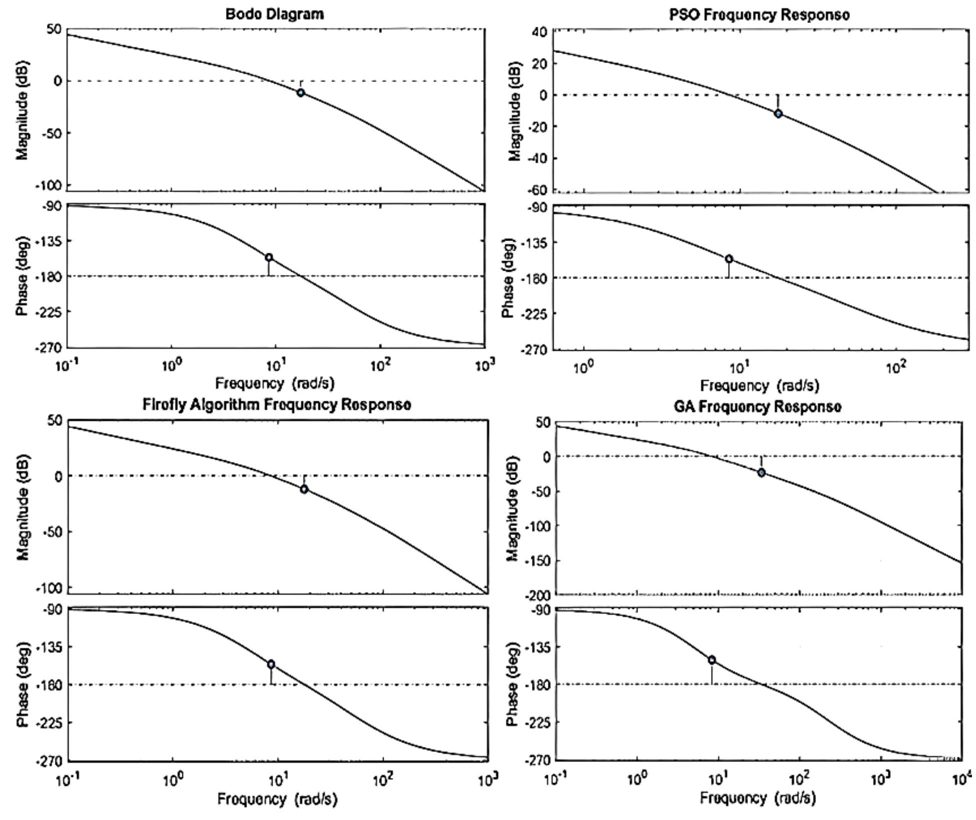



Figure 7. Bode plots of the actual system, PSO, GA, and FA

Table 1. Simulation results

| Algorithm | PSO | GA | Firefly algorithm | Actual system |
|---|---|---|---|---|
| Best-cost | 4.7092 deg | 42.8792 deg | 4.7148 deg | - |
| La(H) | 0.0001 | 0.0011 | 0.87116 | 0.02 |
| Ra(Ω) | 0.0001 | 0.2554 | 1.4494 | 1.2 |
| $K_t$((N-m)/A) | 0.0111 | 1.5 | 1.182 | 0.06 |
| J(N.m.$s^2$/rad) | 0.0221 | 0.0727 | 0.00026979 | 6.2 x 10-4 |
| $f_o$(N.m.s/rad) | 1.3621 | 0.1949 | 0.016418 | 0.0001 |
| $K_b$(V.s/rad) | 0.0498 | 0.0289 | 0.041856 | 0.06 |
| Gain margin | 11.8 dB | 23.3 dB | 11.8 dB | 11.4 dB |
| Phase margin | 24 deg | 29.2 deg | 24 deg | 23.7 deg |

## 6. CONCLUSION

Effective optimization method firefly algorithm solves complex issues. A well-planned process with initialization: a swarm of fireflies represents search space solutions in the algorithm. Fireflies are randomly placed in this space and given fitness values reflecting optimization efficiency. This fitness value begins with the firefly position. Firefly fitness testing is essential. Dedicated fitness functions evaluate firefly solutions. How well the firefly's location fits problem goals is assessed by this function. A numerical score shows firefly's fitness and performance. Firefly beauty depends on luminosity and fitness. Shiny fireflies naturally pull their swarm mates harder. Fireflies attract each other via distance and brightness. Fireflies' brightness attracts people. The most gorgeous firefly attracts fireflies. Attraction rating, which considers brightness and inter-firefly distance, influences this movement. Fireflies naturally approach the most appealing ones. Fireflies can also brighten to attract swarms. Repeat fitness evaluation, attraction, and movement till halting. This iteration helps the algorithm find optimal solutions. The firefly algorithm optimizes complex problems utilizing these mimicked fireflies' collective intelligence.

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## REFERENCES

[1] M. Karamuk and O. B. Alankus, "Development and Experimental Implementation of Active Tilt Control System Using a Servo Motor Actuator for Narrow Tilting Electric Vehicle," *Energies*, vol. 15, no. 6, p. 1996, 2022, doi: 10.3390/en15061996.
[2] D. Nataliana, R. Syafruddin, G. Devira Ramady, Y. Liklikwatil, and A. Ghea Mahardika, "Servo Control for Missile System," *Journal of Physics: Conference Series*, vol. 1424, no. 1, 2019, doi: 10.1088/1742-6596/1424/1/012040.
[3] X. Mu, F. Cai, R. Zheng, D. Zhang, and D. Gu, "A Predictive Current Control for Aerospace Servo Motor," in *Proceedings - 2021 3rd International Conference on Applied Machine Learning, ICAML 2021*, 2021, pp. 366–369, doi: 10.1109/ICAML54311.2021.00084.
[4] L. Ljung, "System Identification," in *Signal analysis and prediction*, Boston, MA, USA: Birkhäuser Boston, 1998, pp. 163–173, doi: 10.1007/978-1-4612-1768-8_11.
[5] M. Jirgl, L. Obsilova, J. Boril, and R. Jalovecky, "Parameter identification for pilot behaviour model using the MATLAB system identification toolbox," in *ICMT 2017 - 6th International Conference on Military Technologies*, 2017, pp. 582–587, doi: 10.1109/MILTECHS.2017.7988824.
[6] S. R. Salkuti, "Emerging and Advanced Green Energy Technologies for Sustainable and Resilient Future Grid," *Energies*, vol. 15, no. 18, p. 6667, 2022, doi: 10.3390/en15186667.
[7] R. Isermann and M. Münchhof, *Identification of dynamic systems: An introduction with applications*, Germany: Springer Berlin, Heidelberg, 2011, pp. 379–408, doi: 10.1007/978-3-540-78879-9.
[8] J. Wang and A. Boukerche, "Non-parametric models with optimized training strategy for vehicles traffic flow prediction," *Computer Networks*, vol. 187, 2021, doi: 10.1016/j.comnet.2020.107791.
[9] A. M. Humada *et al.*, "Modeling of PV system and parameter extraction based on experimental data: Review and investigation," *Solar Energy*, vol. 199, pp. 742–760, 2020, doi: 10.1016/j.solener.2020.02.068.
[10] S. M. A. Altbawi *et al.*, "An Improved Gradient-Based Optimization Algorithm for Solving Complex Optimization Problems," *Processes*, vol. 11, no. 2, 2023, doi: 10.3390/pr11020498.
[11] Z. Gu, G. Xiong, and X. Fu, "Parameter Extraction of Solar Photovoltaic Cell and Module Models with Metaheuristic Algorithms: A Review," *Sustainability*, vol. 15, no. 4, 2023, doi: 10.3390/su15043312.
[12] A. Kumar, G. Wu, M. Z. Ali, R. Mallipeddi, P. N. Suganthan, and S. Das, "A test-suite of non-convex constrained optimization problems from the real-world and some baseline results," *Swarm and Evolutionary Computation*, vol. 56, 2020, doi: 10.1016/j.swevo.2020.100693.
[13] M. S. Fakhar *et al.*, "Conventional and Metaheuristic Optimization Algorithms for Solving Short Term Hydrothermal Scheduling Problem: A Review," *IEEE Access*, vol. 9, pp. 25993–26025, 2021, doi: 10.1109/ACCESS.2021.3055292.
[14] S. S. Sami, Z. A. Obaid, M. T. Muhssin, and A. N. Hussain, "Detailed modelling and simulation of different dc motor types for research and educational purposes," *International Journal of Power Electronics and Drive Systems*, vol. 12, no. 2, pp. 703–714, 2021, doi: 10.11591/IJPEDS.V12.I2.PP703-714.
[15] M. Atif Siddiqui, S. H. Laskar, M. N. Anwar, and A. Yadav, "Cascade Controller Design Based on Pole Placement and Model Matching Technique," *Emerging Electronics and Automation*, 2022, pp. 55–65, doi: 10.1007/978-981-19-4300-3_5.

[16] V. Veerasamy *et al.*, "A Hankel Matrix Based Reduced Order Model for Stability Analysis of Hybrid Power System Using PSO-GSA Optimized Cascade PI-PD Controller for Automatic Load Frequency Control," *IEEE Access*, vol. 8, pp. 71422–71446, 2020, doi: 10.1109/ACCESS.2020.2987387.
[17] C. Sankar Rao, S. Santosh, and V. Dhanya Ram, "Tuning optimal PID controllers for open loop unstable first order plus time delay systems by minimizing ITAE criterion," *IFAC-PapersOnLine*, vol. 53, no. 1, pp. 123–128, 2020, doi: 10.1016/j.ifacol.2020.06.021.
[18] M. A. Alawan and O. J. M. Al-Furaiji, "Numerous speeds-loads controller for DC-shunt motor based on PID controller with on-line parameters tuning supported by genetic algorithm," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 21, no. 1, pp. 64–73, 2021, doi: 10.11591/ijeecs.v21.i1.pp64-73.
[19] S. R. Behera, D. P. Mishra, S. Parida, and A. R. Patro, "Proposal of User-Friendly Design of NFT Marketplace," *2023 4th International Conference on Computing and Communication Systems (I3CS)*, 2023, pp. 1–6, doi: 10.1109/I3CS58314.2023.10127468.
[20] J. Wu, Y. G. Wang, K. Burrage, Y. C. Tian, B. Lawson, and Z. Ding, "An improved firefly algorithm for global continuous optimization problems," *Expert Systems with Applications*, vol. 149, 2020, doi: 10.1016/j.eswa.2020.113340.
[21] N. Bacanin and M. Tuba, "Firefly algorithm for cardinality constrained mean-variance portfolio optimization problem with entropy diversity constraint," *The Scientific World Journal*, vol. 2014, no. 1, 2014, doi: 10.1155/2014/721521.
[22] N. Bacanin, R. Stoean, M. Zivkovic, A. Petrovic, T. A. Rashid, and T. Bezdan, "Performance of a novel chaotic firefly algorithm with enhanced exploration for tackling global optimization problems: Application for dropout regularization," *Mathematics*, vol. 9, no. 21, 2021, doi: 10.3390/math9212705.
[23] S. Katoch, S. S. Chauhan, and V. Kumar, "A review on genetic algorithm: past, present, and future," *Multimedia Tools and Applications*, vol. 80, pp. 8091–8126, 2021, doi: 10.1007/s11042-020-10139-6.
[24] M. A. Fkirin and M. A. E. Khira, "Enhanced Antenna Positioning Control System Using Adapted DC Servo Motor and Fuzzy-PI Controller," *IEEE Access*, vol. 11, pp. 102661–102668, 2023, doi: 10.1109/ACCESS.2023.3313976.
[25] T. Yang, K. T. Chau, Z. Hua, and H. Pang, "Toroidal Field Excitation for Axial-Field Double-Rotor Flux-Reversal DC Motors with Magnetic Differential," *IEEE Transactions on Magnetics*, vol. 59, no. 11, 2023, doi: 10.1109/TMAG.2023.3277700.
[26] H. Liu *et al.*, "Compact and Efficient Wireless Motor Drive With Bidirectional Motion Capability," *IEEE Transactions on Power Electronics*, vol. 38, no. 12, pp. 15097–15101, 2023, doi: 10.1109/TPEL.2023.3308389.
[27] M. Abdelbar *et al.*, "Optimization of PI-Cascaded Controller's Parameters for Linear Servo Mechanism: A Comparative Study of Multiple Algorithms," *IEEE Access*, vol. 11, pp. 86377–86396, 2023, doi: 10.1109/ACCESS.2023.3304333.
[28] S. K. Kim, S. Lim, and C. K. Ahn, "Current Sensor-Free Output-Feedback Voltage Control for DC/DC Converters via Critical Damping Injection Technique for Converter-Fed Servo System Applications," *IEEE Transactions on Industrial Electronics*, vol. 71, no. 2, pp. 1906–1916, 2024, doi: 10.1109/TIE.2023.3260361.
[29] H. Chen *et al.*, "Design and Analysis of a Variable-Speed Constant-Amplitude Wind Generator for Stand-Alone DC Power Applications," *IEEE Transactions on Industrial Electronics*, vol. 70, no. 8, pp. 7731–7742, 2023, doi: 10.1109/TIE.2023.3234149.
[30] S. R. Salkuti, "Solving optimal generation scheduling problem of Microgrid using teaching learning based optimization algorithm," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 17, no. 3, pp. 1632–1638, 2020, doi: 10.11591/ijeecs.v17.i3.pp1632-1638.
[31] S. C. Kim and S. R. Salkuti, "Optimal power flow based congestion management using enhanced genetic algorithms," *International Journal of Electrical and Computer Engineering*, vol. 9, no. 2, pp. 875–883, 2019, doi: 10.11591/ijece.v9i2.pp875-883.
[32] S. K. Kim and K. B. Lee, "Active Second-Order Pole-Zero Cancellation Control for Speed Servo Systems With Current Sensor Fault Tolerance," *IEEE Transactions on Circuits and Systems II: Express Briefs*, vol. 70, no. 6, pp. 2196–2200, 2023, doi: 10.1109/TCSII.2023.3236347.

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