Vokasi Unesa Bulletin of Engineering, Technology and Applied Science (VUBETA)
https://journal.unesa.ac.id/index.php/vubeta
Vol. 1, No. 1, September 2024, pp. 15~21 DOI:
ISSN: xxxx-xxxx

Frilled Lizard Optimization to optimize parameters Proportional Integral Derivative of DC Motor

Widi Aribowo[1], Laith Abualigah[2,3,4,5,6,7,8], Diego Oliva[9], Toufik Mzili[10], Aliyu Sabo[11], Hisham A. Shehadeh[12]

[1]Department of Electrical Engineering, Faculty of Vocational, Universitas Negeri Surabaya, Surabaya, Indonesia
[2]Computer Science Department, Al al-Bayt University, Mafraq 25113, Jordan.
[3]Hourani Center for Applied Scientific Research, Al-Ahliyya Amman University, Amman 19328, Jordan.
[4]MEU Research Unit, Middle East University, Amman, Jordan
[5]Department of Electrical and Computer Engineering, Lebanese American University, Byblos 13-5053, Lebanon.
[6]School of Computer Sciences, Universiti Sains Malaysia, Pulau Pinang 11800, Malaysia.
[7]School of Engineering and Technology, Sunway University Malaysia, Petaling Jaya 27500, Malaysia.
[8]Applied science research center, Applied science private university, Amman 11931, Jordan
[9]Depto. de Ingeniería Electro-Fotónica, Universidad de Guadalajara, CUCEI, Guadalajara, México
[10]Department of computer science, Université Chouaib Eddoukali, Morocco
[11]Department of Electrical and Electronic Engineering, Nigerian Defence Academy, Kaduna, Nigeria
[12]Department of Information Technology, Al-Huson University College, Al-Balqa Applied University, Al-Huson, Jordan

Article Info

Article history:

Received Jul 28, 2024
Revised Aug 9, 2024
Accepted Aug 18, 2024

Keywords:

Frilled Lizard Optimization
DC Motor
Innovation
Metaheuristic
Proportional-Integral-Derivative

ABSTRACT

This paper presents a Proportional-Integral-Derivative (PID) parameter optimization method for direct current (dc) motors. The method utilizes a metaheuristic technique known as Frilled Lizard Optimization (FLO), which is inspired by natural processes. FLO draws inspiration from the lizard's hunting method of employing a sit-and-wait approach with great patience. The method is divided into two distinct phases: the exploration phase, which simulates a swift predator attack by a lizard, and the exploitation phase, which imitates the lizard's return to the treetop after feeding. This study confirms the effectiveness of FLO by conducting performance tests on the CEC2017 benchmark function and a DC motor. Through the simulations conducted on the CEC2017 benchmark function, it has been determined that FLO has superior exploration and exploitation capabilities. When testing a DC motor, it was discovered that the PID-FLO approach is effective in reducing overshoot and achieving optimal performance.

1. INTRODUCTION

Direct current (DC) motors are extensively utilized in a diverse range of industrial and home equipment, including servo control and other operational capacities[1]–[5]. DC motors exhibit high efficiency, long-lasting performance, and facilitate the implementation of suitable feedback control systems, particularly those based on proportional-integral (PI) and proportional integral derivative (PID) configurations. The controller is a component that works to reduce erroneous signals[6]–[8]. The PID controller is the most often used type of controller. The proportional (P), integral (I), and derivative (D) controller elements all strive to enhance the response time of a system, eliminate any deviations from the desired value, and generate significant initial adjustments[9]–[11]. The PID controller has demonstrated its ability to deliver excellent control performance, despite its straightforward and easily comprehensible algorithm. The key aspect in the design of a PID controller is the adjustment of the P, I, and D parameters in order to get the desired response of the system[12]–[14].

Optimization is a systematic approach to achieve a reduced or improved value or cost relative to alternative techniques. Optimization has permeated multiple disciplines, including engineering, science,

*Corresponding Author
Email: widiaribowo@unesa.ac.id

business, and economics. Various approaches have been proposed to address difficulties with distinct attributes. Alternative approaches offer an alternative approach to problem-solving compared to conventional methods[15], [16].

An essential factor in the design of the PID controller is the process of determining the parameters of the controller in order to ensure that the closed-loop system satisfies the specified performance criteria. This process is commonly referred to as controller tuning. Various traditional approaches of PID control have been described in multiple works, including Ziegler-Nichols[17]–[19] and Cohen-Coon[20], [21]. The conventional technique is known for its time-consuming process of optimizing PID parameters and occasionally resulting in severe overshoot levels. Various alternative approaches have been proposed to address the limitations of PID tuning. The metaheuristic method is widely recognized as one of the most popular approaches. Multiple papers have demonstrated the utilization of various versions of metaheuristic techniques, including the JAYA algorithm[22], Harris Hawks optimization[23], [24], Snake Optimizer[25], Ant Colony Optimization[26]–[28], Particle Swarm Optimized[29]–[31], Grasshopper Optimization Algorithm[32], [33], and Firefly Algorithm[34]–[36].

This article introduces the tuning approach for power system stabilizers utilizing the modified Frilled Lizard Optimization (FLO) method[37]. The FLO method being offered is an algorithm that is based on the frilled lizard. The design of FLO is derived from two distinct behavioral patterns observed in frilled lizards. The initial behavior pertains to the intelligent tactic employed by frilled lizards while hunting, known as the sit-and-wait hunting method. The second activity pertains to the frilled lizards' approach of climbing trees after dining. The objective is to enhance the proficiency of RTH. The research has made the following contributions:

1. Use the 23 CEC2017 Benchmark function, the performance of FLO in solving optimization problems is assessed and compared with Aquila Optimizer (AO)[38] and Marine Predator Algorithm (MPA)[39]. The benchmark function is designed to provide an objective evaluation standard for optimization algorithms, such as genetic algorithms, swarm algorithms, and other evolutionary algorithms
2. Apply the Frilled Lizard Optimization (FLO) approach to PID for DC Motor.

The essay is organized as follows: Section 2 provides a description of the Frilled Lizard Optimization and DC Motor. Section 3 includes both discussions and simulations. The conclusion is provided in the final section.

2. METHOD

2.1. DC Motor

The DC motor possesses the attribute of a single control system that is capable of operating in two control modes. The initial mode is the armature control mode, in which the field current remains constant. Alternatively, it is referred to as a field control mode with a constant armature current. The features of a DC motor consist of resistance, inductance, and return electromotive-force voltage, as seen in Figure 1.

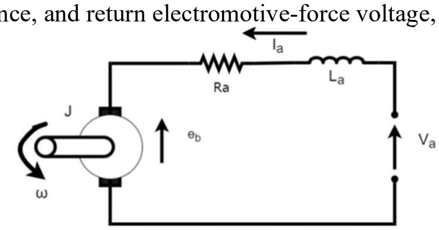


Figure 1. Illustration DC motor circuit[40]

$$V_a(s) = (R_a + L_a.s).I_a(s) + e_b(s) \quad (1)$$

$$e_b(s) = K_b\omega(s) \quad (2)$$

Where R_a and L_a are Armature resistance and Armature inductance. e_b is back electromotive force.

2.2. Frilled Lizard Optimization

During each iteration of Algorithm FLO, the position of the frilled lizard in the problem-solving space is updated in two independent phases. The exploration phase initially replicates the frilled lizard's motion towards its prey while hunting, with the goal of expanding the range of possible solutions and investigating new potential options. This stage enables the algorithm to explore various regions of the issue space, making it easier to find new locations that may hold the best possible answers. Additionally, the exploitation phase replicates the frilled lizard's motion when it ascends a tree following a meal. During this phase, the algorithm utilizes the knowledge acquired during exploration to take advantage of interesting regions that have been recognized as potential optimal solutions. The exploitation phase strives to enhance the quality of solutions and converge towards the global optimum by focusing on improving these regions.

Phase 1: Hunting Strategy (Exploration)
The frilled lizard exhibits a distinctive hunting approach, which is one of its most notable natural behaviors. The frilled lizard is an ambush predator that pounces on its target once it has visually detected it. The frilled lizard's movement simulation towards the prey causes significant shifts in the positions of the population members in the problem-solving space, hence enhancing the algorithm's ability to explore globally in search of solutions. During the initial phase of FLO, the positions of the individuals in the population are updated in the solution space of the issue, using the hunting strategy of the frilled lizard. In the design of FLO, the prey position for each frilled lizard is determined by considering the location of other population members who have a superior objective function value. Based on this information, the positions of potential prey for each frilled lizard are determined using Equation (3).

$$CFL_i = \{X_i | F_k < F_i \; and \; k \neq i \} where \; i = 1,2, \dots . N \; and \; k \in \{1,2, \dots, N\} \tag{3}$$

$$X_{i,j}^{PI} = x_{i,j} + r_{i,j} \cdot (SP_{i,j} - I_{i,j} \cdot x_{i,j}) \tag{4}$$

$$X_i = \begin{cases} X_i^{PI}, \; F_i^{PI} < F_i \\ \quad X_i, else \end{cases} \tag{5}$$

Where CFL_i represents the placements of prey, while X_best refers to the optimal candidate solution, which is the best osprey. The new position of the prey, denoted as$X_{i,j}^{PI}$, is determined by the first phase. Here, i th represents the prey's index, $SP_{i,j}$ represents its i-th dimension, $r_{i,j}$is a randomly generated and $I_{i,j}$ is another randomly generated number.

Phase 2: Ascending the Hierarchy (Exploitation)

Following its meal, the frilled lizard seeks refuge at the highest point of a nearby tree. By simulating the frilled lizard's movement to the top of the tree, slight adjustments are made to the positions of the individuals in the population within the problem's solution space. Consequently, this enhances the algorithm's ability to utilize local search. During the second phase of FLO, the individuals in the population are repositioned in the solution space using the technique of a frilled lizard retiring to the top of a tree after feeding. By employing a mathematical model to simulate the locomotion of the frilled lizard towards the uppermost part of the adjacent tree, a revised position is determined for each member of the population using Equation (6). Subsequently, if the new position enhances the value of the objective function, it will supplant the prior position of the relevant individual according to Equation (7):

$$X_{i,j}^{P2} = x_{i,j} + (1 - 2r) \frac{\cdot (ub_j - lb_j)}{t} \; ; \; i = 1,2, \dots, N; j = 1,2, \dots, m; \; t = 1,2, ..T \tag{6}$$

$$X_i = \begin{cases} X_i^{P2}, \; F_i^{P2} < F_i \\ \quad X_i, else \end{cases} \tag{7}$$

Where $X_{i,j}^{P2}$ represents the updated position of the prey during the second phase. The symbol $x_{i,j}$^ represents a variable or element in a mathematical equation or expression. F_i represents the j th dimension, denoted as, F_i^{P2} represents the numerical value of the goal function.

The first iteration of the Frilled Lizard Optimization (FLO) algorithm ends after updating the positions of all frilled lizards in the problem-solving space, following the execution of the first and second phases. After obtaining the updated values, the algorithm starts the next iteration to continue updating the positions of the frilled lizards. This procedure continues until the algorithm reaches completion, following equations (3) to (7). During each iteration, the algorithm continuously updates and keeps track of the best candidate solution by comparing the resulting objective function values. After the algorithm has completed all of its iterations, the best candidate solution obtained is presented as the final FLO solution for the given problem.

3. RESULTS AND DISCUSSION

3.1. Convergence Curve

The FLO algorithm code has been implemented and tested on a laptop equipped with an AMD A9-9425 processor running at a clock speed of 3.1 GHz, and 4 GB of RAM. The software utilized is MATLAB/Simulink. Table 1 provides a comprehensive overview of the FLO parameters. Evaluation of the proposed method's performance PID-FLO utilizes the global optima function and employs the RTH and AO methods for comparison. Figure 3 displays the outcomes of this comparison.

TABLE 1. Comparison of HLAO and HLO

Function		AO	MPA	FLO
F1	Best	7.47E-21	1.47E+01	9.52E-44
	Mean	2.55E-12	5.50E+01	1.69E-33
	Worst	1.27E-10	1.08E+02	4.32E-32
	Std	1.79E-11	19.5982	7.00E-33
	Rank	2	3	1
F2	Best	7.88E-12	1.49E+00	1.14E-22
	Mean	1.65E-07	2.94E+00	7.14E-18
	Worst	2.69E-06	5.48E+00	1.40E-16
	Std	5.33E-07	0.75899	2.11E-17
	Rank	2	3	1
F3	Best	7.84E-19	5.90E+02	7.14E-36
	Mean	4.39E-11	2.05E+03	1.67E-21
	Worst	1.39E-09	3.36E+03	8.25E-20
	Std	2.16E-10	587.9437	1.17E-20
	Rank	2	3	1
F4	Best	4.46E-12	2.56E+00	1.43E-22
	Mean	3.83E-08	5.65E+00	1.12E-18
	Worst	9.30E-07	9.40E+00	1.99E-17
	Std	1.44E-07	1.3201	3.44E-18
	Rank	2	3	1
F5	Best	0.001187	227.2413	0
	Mean	0.5736	1079.057	0
	Worst	4.3004	4015.648	0
	Std	0.812	735.8228	0
	Rank	2	3	1
F6	Best	1.61E-06	16.9108	9.13E-19
	Mean	0.02093	56.0154	3.71E-05
	Worst	0.42304	114.4697	0.000515
	Std	0.06143	23.4712	0.000104
	Rank	2	3	1
F7	Best	2.78E-05	0.007981	7.66E-05
	Mean	0.001058	0.028045	0.000872
	Worst	0.005411	0.053379	0.003383
	Std	0.001054	0.012176	0.000706
	Rank	2	3	1
F8	Best	-4890.34	-7511.68	-12569.5
	Mean	-3562.16	-6018.06	-9926.96
	Worst	-2569.97	-5047.56	-8787.52
	Std	555.0943	535.2971	1568.465
	Rank	3	2	1
F9	Best	0	13.8898	0
	Mean	2.11E-12	77.896	0
	Worst	7.11E-11	129.1826	0
	Std	1.07E-11	28.5761	0
	Rank	2	3	1
F10	Best	9.99E-13	1.93E+00	8.88E-16
	Mean	9.44E-07	3.05E+00	8.88E-16
	Worst	4.38E-05	4.18E+00	8.88E-16
	Std	6.20E-06	0.47033	0
	Rank	2	3	1
F11	Best	0	1.1539	0
	Mean	1.29E-11	1.4544	0
	Worst	3.60E-10	2.0579	0
	Std	5.89E-11	0.19577	0
	Rank	2	3	1
F12	Best	1.06E-07	0.33299	1.11E-20
	Mean	0.00039	1.084	3.75E-07
	Worst	0.005224	2.462	9.52E-06
	Std	0.00091	0.49735	1.61E-06
	Rank	2	3	1
F13	Best	2.58E-06	2.0104	9.89E-20
	Mean	0.001997	5.537	2.85E-05
	Worst	0.013171	9.0103	0.001341
	Std	0.003007	1.8026	0.00019
	Rank	2	3	1

TABLE 1. Comparison of HLAO and HLO *(Continued)*

Function		AO	MPA	FLO
F14	Best	0.998	0.998	0.998
	Mean	4.5758	1.1966	0.998
	Worst	12.6705	2.9821	0.998
	Std	3.7922	0.53052	3.04E-12
	Rank	3	2	1
F15	Best	0.000341	0.00031	0.000312
	Mean	0.001048	0.00069	0.000802
	Worst	0.001885	0.001362	0.001675
	Std	0.000476	0.000223	0.000393
	Rank	3	1	2
F16	Best	-1.0316	-1.0316	-1.0316
	Mean	-1.0243	-1.0316	-1.0272
	Worst	-1.001	-1.0316	-0.9969
	Std	0.00769	1.08E-10	0.008682
	Rank	3	1	2
F17	Best	0.39797	0.39789	0.39789
	Mean	0.40281	0.39789	0.43729
	Worst	0.43284	0.39789	0.94495
	Std	0.006949	1.56E-09	0.10434
	Rank	2	1	3
F18	Best	3.0063	3	3
	Mean	4.3032	3	10.9987
	Worst	30.1117	3.0005	30.8746
	Std	3.8089	7.78E-05	10.6578
	Rank	2	1	3
F19	Best	-3.8607	-3.8628	-3.8626
	Mean	-3.7662	-3.8628	-3.7504
	Worst	-3.4808	-3.8624	-3.336
	Std	0.098385	6.95E-05	0.11655
	Rank	2	1	3
F20	Best	-3.1828	-3.322	-3.1283
	Mean	-2.6376	-3.2996	-2.4404
	Worst	-1.6816	-3.187	-1.581
	Std	0.34201	0.042411	0.41276
	Rank	2	1	3
F21	Best	-10.1526	-10.1532	-10.1532
	Mean	-9.8613	-9.5414	-9.5187
	Worst	-8.4401	-5.0551	-5.0552
	Std	0.39528	1.6735	1.5389
	Rank	3	1	2
F22	Best	-10.4023	-10.4029	-10.4029
	Mean	-10.1216	-9.2289	-10.0026
	Worst	-8.9104	-5.0103	-5.0877
	Std	0.30735	2.2277	1.283
	Rank	2	3	1
F23	Best	-10.5361	-10.5364	-10.5364
	Mean	-10.2377	-9.2307	-10.2437
	Worst	-9.2924	-4.9298	-5.1285
	Std	0.33418	2.3474	1.1063
	Rank	1	3	2
SUM Rank		50	53	35
MEAN Rank		2.173913	2.304348	1.521739

TABLE 2. Rank comparison of unimodal functions between algorithms (F1-F7)

Function	AO	MPA	FLO
Sum Rank	12	18	6
Mean Rank	1.71	2.57	0.86
Total Rank	2	3	1

TABLE 3. Rank comparison of multimodal functions between algorithms (F8-F13)

Function	AO	MPA	FLO
sum rank	13	17	6
mean rank	2.167	2.833	1
Total rank	2	3	1

TABLE 4. Rank comparison of fixed-multimodal functions between algorithms (F14-F23)

Function	AO	MPA	FLO
sum rank	23	15	22
mean rank	2.3	1.5	2.2
Total rank	3	1	2

The statistical analysis compares the performance of FLO with that of competing algorithms to determine if FLO has a statistically significant advantage over the other algorithms. The average rank value of any algorithm can be determined by knowing the rank of each function. The statistical analysis for each function is presented in Table 1. A rating is a numerical representation of the highest average value. The value of FLO is 1, as demonstrated by the cumulative rank value for each algorithm. The average rank value is 1.52173913. Table 2 displays a comparison of the rankings of unimodal algorithm functions. FLO holds the top rank in the field of multimodal. Table 3 displays a comparative analysis of the various multimodal functions utilized, focusing on their ranks. Table 4 displays a comparison of fixed-multimodal ranks.

3.2. Application to DC Motor

PID-based DC motor control requires precise and accurate parameter tuning. In order to achieve the best PID settings, it is necessary to verify the performance of the implementation of FLO. Figure 4 displays the results of the Proportional-Integral-Derivative (PID) control applied to DC motors utilizing Fuzzy Logic Optimization (FLO). The performance of a control can be assessed using many theoretical frameworks. Two well-known theories in the field are the Integral of Time-weighted Absolute Error (ITAE) and the Integrated of Time-weighted Squared Error (ITSE). In this work, ITSE and ITAE are employed as measures to validate performance.

$$ITSE = \int_0^{\infty} t.e^2(t).dt \qquad (8)$$

$$ITAE = \int_0^{\infty} t.e(t).dt \qquad (9)$$

By doing FLO-based PID testing on a DC motor with a reference speed of 1 per unit (pu), the ITSE value of PID-FLO is 0.0062 and the ITAE value of PID-FLO is 0.0813. The Overshoot value of FLO-PID is superior. Table 5 provides a comprehensive breakdown of the performance testing findings for each algorithm.

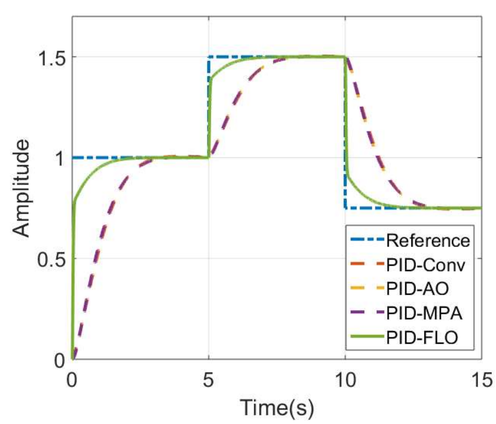


Figure 4. The Response Of DC Motor

TABLE 5. Response DC Motor With PID

Controller	Overshoot	Rise Time	Settling Time	ITSE	ITAE
PID	1.007	1.18	2.78	0.3069	0.7944
PID-AO	1.0032	1.777	2.82	0.2924	0.7644
PID-MPA	1.0027	1.784	2.854	0.2905	0.7634
PID-FLO	1.0002	0. 573	1.462	0.0062	0.0813

4. CONCLUSION AND LIMITATION

This study introduces the optimization of Proportional-Integral-Derivative (PID) parameters for a direct current (dc) motor using a novel metaheuristic technique called Frilled Lizard Optimization (FLO), which is inspired by natural processes. FLO draws inspiration from the lizard's hunting strategy of patiently sitting and waiting. The algorithm's fundamental concepts are meticulously outlined and organized into two separate phases: (i) the exploration phase, which emulates a rapid predatory attack by a lizard, and (ii) the exploitation phase, which replicates a lizard's return to the treetop after feasting. This study validates the performance of FLO using performance tests on the CEC2017 benchmark function and DC motors. From the simulation on the CEC2017 benchmark function, it was found that the performance of FLO has more promising exploration and exploitation capabilities. Testing on a DC motor, it was found that the PID-FLO method can reduce overshoot. In addition, PID-FLO has the best ITSE Score. The ITSE value of FLO is 97.98% better than conventional PID and the ITAE value is 89.77% better than conventional PID. This research can be further developed using various other methods and using more complex objects. This research can be developed with FLO modifications such as combining it with other methods and applying it to more complex systems.

REFERENCES

[1] A. G. Rojas-López, M. G. Villarreal-Cervantes, and A. Rodríguez-Molina, "Surrogate indirect adaptive controller tuning based on polynomial response surface method and bioinspired optimization: Application to the brushless direct current motor controller," *Expert Syst. Appl.*, vol. 245, p. 123070, 2024.

[2] N. Popov, "Non-linear model in region of very low speeds for a permanent magnet direct current motor," in *ENVIRONMENT. TECHNOLOGIES. RESOURCES. Proceedings of the International Scientific and Practical Conference*, 2024, vol. 3, pp. 225–231.

[3] W. Qin, H. Li, M. Luo, and S. Cong, "Design of ACO variable structure controller for brushless direct current motor," in *2024 IEEE 7th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)*, 2024, vol. 7, pp. 1267–1271.

[4] D. Cordes *et al.*, "Efficacy and safety of transcranial direct current stimulation to the ipsilesional motor cortex in subacute stroke (NETS): a multicenter, randomized, double-blind, placebo-controlled trial," *Lancet Reg. Heal.*, vol. 38, 2024.

[5] W. Aribowo, H. Suryoatmojo, and F. A. Pamuji, "Optimalization Droop Control Based on Aquila Optimizer Algorithm For DC Microgrid," in *2022 International Seminar on Intelligent Technology and Its Applications (ISITIA)*, 2022, pp. 460–465.

[6] C. Luo, J. Wang, E. Zio, and Q. Miao, "Subdomain adaptation order network for fault diagnosis of brushless DC motors," *IEEE Trans. Instrum. Meas.*, 2024.

[7] J. B. S. Freitas, L. Marquezan, P. J. D. de Oliveira Evald, E. A. G. Peñaloza, and M. M. H. Cely, "A fuzzy-based Predictive PID for DC motor speed control," *Int. J. Dyn. Control*, pp. 1–11, 2024.

[8] P. Zhang, Z. Shi, B. Yu, and H. Qi, "Research on the Control Method of a Brushless DC Motor Based on Second-Order Active Disturbance Rejection Control," *Machines*, vol. 12, no. 4, p. 244, 2024.

[9] A. Kanungo, P. Kumar, V. Gupta, and N. K. Saxena, "A design an optimized fuzzy adaptive proportional-integral-derivative controller for anti-lock braking systems," *Eng. Appl. Artif. Intell.*, vol. 133, p. 108556, 2024.

[10] X. Zhang *et al.*, "System Identification and Fractional-Order Proportional–Integral–Derivative Control of a Distributed Piping System," *Fractal Fract.*, vol. 8, no. 2, p. 122, 2024.

[11] R. Pazmiño, W. Pavon, M. Armstrong, and S. Simani, "Performance Evaluation of Fractional Proportional–Integral–Derivative Controllers Tuned by Heuristic Algorithms for Nonlinear Interconnected Tanks," *Algorithms*, vol. 17, no. 7, p. 306, 2024.

[12] M. Ghasemi, A. Rahimnejad, M. Gil, E. Akbari, and S. A. Gadsden, "A self-competitive mutation strategy for Differential Evolution algorithms with applications to Proportional–Integral–Derivative controllers and Automatic Voltage Regulator systems," *Decis. Anal. J.*, vol. 7, p. 100205, 2023.

[13] X. Zhou, J. Zhang, X. Jia, and D. Wu, "Linear programming-based proportional-integral-derivative control of positive systems," *IET Control Theory Appl.*, vol. 17, no. 10, pp. 1342–1353, 2023.

[14] M. I. Abdelwanis, F. F. M. El-Sousy, and M. M. Ali, "A Fuzzy-Based Proportional–Integral–Derivative with Space-Vector Control and Direct Thrust Control for a Linear Induction Motor," *Electronics*, vol. 12, no. 24, p. 4955, 2023.

[15] M. Emmerich and A. Deutz, "Multicriteria optimization and decision making: principles, algorithms and case studies," *arXiv Prepr. arXiv2407.00359*, 2024.

[16] C. Carissimo and M. Korecki, "Limits of optimization," *Minds Mach.*, vol. 34, no. Suppl 1, pp. 117–137, 2024.

[17] M. Huba, P. Bistak, J. Brieznik, and D. Vrancic, "Constrained Series PI, PID and PIDA Controller Design Inspired by Ziegler–Nichols," *Power Electron. Drives*, vol. 9, no. 1, pp. 331–346.

[18] C. Lu, R. Tang, C. Li, J. Nwoke, J. Viola, and Y. Chen, "A fast relay feedback auto-tuning tilt-integral-derivative (TID) controller method with the fractional-order Ziegler–Nichols approach," *ISA Trans.*, 2024.

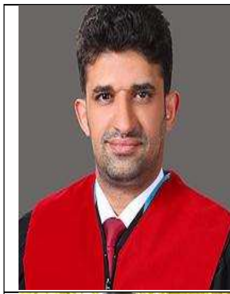
[19] R. Nutenki and B. V. Varma, "PID Controller Design for DC Motor Speed Control," in *2024 Fourth International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT)*, 2024, pp. 1–6.

[20] S. R. Pradhan, "FINE-TUNING INDUSTRIAL PROCESSES: EXPLORING EFFECTIVE PID CONTROLLER TECHNIQUES FOR OPTIMAL LEVEL CONTROL," *Am. J. Eng. Technol.*, vol. 6, no. 07, pp. 8–12, 2024.

[21] I. A. Abbas and M. K. Mustafa, “A review of adaptive tuning of PID-controller: Optimization techniques and applications,” *Int. J. Nonlinear Anal. Appl.*, vol. 15, no. 2, pp. 29–37, 2024.
[22] Y. Cheng, X. Lyu, and S. Mao, “Optimization design of brushless DC motor based on improved JAYA algorithm,” *Sci. Rep.*, vol. 14, no. 1, p. 5427, 2024.
[23] S. Ekinci, D. Izci, and B. Hekimoğlu, “PID Speed Control of DC Motor Using Harris Hawks Optimization Algorithm,” in *International Conference on Electrical, Communication, and Computer Engineering (ICECCE)*, 2020, pp. 1–6.
[24] S. L. Ayinla *et al.*, “Optimal control of DC motor using leader-based Harris Hawks optimization algorithm,” *Franklin open*, vol. 6, p. 100058, 2024.
[25] E. Çelik and M. Karayel, “Effective speed control of brushless DC motor using cascade 1PDf-PI controller tuned by snake optimizer,” *Neural Comput. Appl.*, vol. 36, no. 13, pp. 7439–7454, 2024.
[26] N. Gupta, M. Kaur, and R. Gupta, “Ant colony optimization based optimal tuning of Fractional Order (FO) PID controller for controlling the speed of a DC motor,” *J. Eng. Res.*, vol. 11, no. 3, 2023.
[27] Y. K. Poudel and P. Bhandari, “Control of the BLDC Motor Using Ant Colony Optimization Algorithm for Tuning PID Parameters,” *Arch. Adv. Eng. Sci.*, vol. 2, no. 2, pp. 108–113, 2024.
[28] S. Mahfoud, A. Derouich, N. El Ouanjli, N. V. Quynh, and M. A. Mossa, “A New Hybrid Ant Colony Optimization Based PID of the Direct Torque Control for a Doubly Fed Induction Motor,” *World Electr. Veh. J.*, vol. 13, no. 5, p. 78, 2022.
[29] T. Tao and L. Hua, “Decoupling control of bearingless brushless DC motor using particle swarm optimized neural network inverse system,” *Meas. Sensors*, vol. 31, p. 100952, 2024.
[30] N. Hemalatha, 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,” *Meas. Sensors*, vol. 31, p. 100960, 2024.
[31] F. Pangerang, S. Sulaeman, and B. Prasetiyo, “Particle swarm optimization based PID controller tuning for speed control BLDC system,” in *AIP Conference Proceedings*, 2024, vol. 3140, no. 1.
[32] C. Caraveo, L. Cervantes, J. Soto, and O. Castillo, “Optimal Fuzzy Logic Controller for DC Motor Using Grasshopper Optimization Algorithm,” in *New Directions on Hybrid Intelligent Systems Based on Neural Networks, Fuzzy Logic, and Optimization Algorithms*, Springer, 2024, pp. 169–181.
[33] S. V. Egoigwe and J. Eke, “Optimization and control of the brushless DC motor speed for a Battery Electric Vehicle (BEV) using Fuzzy-grasshopper optimization regenerative braking system,” *Glob. J. Eng. Technol. Adv.*, vol. 18, no. 02, pp. 165–171, 2024.
[34] B. N. Kommula and V. R. Kota, “An effective sustainable control of brushless DC motor using firefly algorithm–artificial neural network based FOPID controller,” *Sustain. Energy Technol. Assessments*, vol. 52, p. 102097, 2022.
[35] J. Jallad and O. Badran, “Firefly algorithm tuning of PID position control of DC motor using parameter estimator toolbox,” *Bull. Electr. Eng. Informatics*, vol. 13, no. 2, pp. 916–929, 2024.
[36] S. Pandey, “Optimization of PID controller parameters for speed control of DC motor using firefly and fminsearch algorithms,” *Available SSRN 4378784*, 2023.
[37] I. A. Falahah *et al.*, “Frilled Lizard Optimization: A Novel Bio-Inspired Optimizer for Solving Engineering Applications.,” *Comput. Mater. Contin.*, vol. 79, no. 3, 2024.
[38] L. Abualigah, D. Yousri, M. Abd Elaziz, A. A. Ewees, M. A. A. Al-Qaness, and A. H. Gandomi, “Aquila optimizer: a novel meta-heuristic optimization algorithm,” *Comput. Ind. Eng.*, vol. 157, p. 107250, 2021.
[39] A. Faramarzi, M. Heidarinejad, S. Mirjalili, and A. H. Gandomi, “Marine Predators Algorithm: A nature-inspired metaheuristic,” *Expert Syst. Appl.*, vol. 152, p. 113377, 2020, doi: https://doi.org/10.1016/j.eswa.2020.113377.
[40] W. Aribowo, B. Suprianto, U. T. Kartini, and A. L. Wardani, “Optimal tuning proportional integral derivative controller on direct current motor using reptile search algorithm,” *Int. J. Electr. Comput. Eng.*, vol. 13, no. 5, pp. 4901–4908, 2023.

BIOGRAPHIES OF AUTHORS

Widi Aribowo is a lecturer in the Department of Electrical Engineering, Universitas Negeri Surabaya, Indonesia. He is received the BSc from the Sepuluh Nopember Institute of Technology (ITS) in Power Engineering, Surabaya in 2005. He is received the M.Eng from the Sepuluh Nopember Institute of Technology (ITS) in Power Engineering, Surabaya in 2009. He is mainly research in the power system and control. He can be contacted at email: widiaribowo@unesa.ac.id.

	**Laith Abualigah** is an Associate Professor at the Department of Computer Science, Al Al-Bayt University, Jordan. He received the Ph.D. degree from the School of Computer Science in Universiti Sains Malaysia (USM), Malaysia in 2018. His main research interests focus on bio-inspired computing, artificial intelligence, metaheuristic modeling, and optimization algorithms, evolutionary computations, information retrieval, feature selection, combinatorial problems, optimization, and NLP. He can be contacted at email: Aligah.2020@gmail.com.
	**Diego Oliva** is an Associate Professor at the University of Guadalajara in Mexico. He has the distinction of National Researcher Rank 2 by the Mexican Council of Science and Technology. Currently, he is a Senior member of the IEEE. His research interests include evolutionary and swarm algorithms, hybridization of evolutionary and swarm algorithms, computational intelligence, and image processing. He can be contacted at email: diego.oliva@cucei.udg.mx.
	**Toufik Mzili** is an Assistant Professor in the Department of Computer Science at the prestigious Faculty of Science at Chouaib Doukkali University. His extensive expertise and notable achievements in the areas of metaheuristics, optimization, and scheduling problems underscore his standing as a distinguished researcher. Dr. Toufik's scholarly impact is evident in his prolific contributions to prestigious Q1 journals. He can be contacted at email: mzili.t@ucd.ac.ma.
	**Aliyu Sabo** is currently a senior lecturer at the Department of Electrical and Electronic Engineering, Nigerian Defence Academy, Kaduna, Nigeria. His current project is 'Rotor Angle Stability Assessment of Power Systems. He can be contacted at email: saboaliyu98@gmail.com.
	**Hisham A. Shehadeh** received the B.S. degree in computer science from Al-Balqa` Applied University, Jordan, in 2012, the M.S. degree in computer science from the Jordan University of Science and Technology, Irbid, Jordan, in 2014, and the Ph.D. degree from the Department of Computer System and Technology, Universiti Malaya (UM), Kuala Lumpur, Malaysia, in 2018. He was a research assistant at UM from 2017 to2018. He was a Teaching Assistant and a lecturer with CS Department, College of Computer and Information Technology, Jordan University of Science and Technology from 2013 to 2014 and from 2014 to 2016 respectively. Currently, He is an Assistant Professor of Computer Science at the Department of Information Technology, Al-Huson University College, Al-Balqa Applied University, Al-Huson, Jordan. His current research interests are, intelligent computing, metaheuristic algorithms and algorithmic engineering applications of wireless networks. He can be contacted at email: sh7adeh1990@hotmail.com