An Effective Controller Design for BLDC Motor Drive with Nature Inspired Heuristic Algorithm

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Abstract. In this paper, an effective controller design for the BLDC motor drive is proposed using nature inspired Whale Optimization Algorithm (WOA). The PI controller is developed for the speed control of BLDC motor using Whale Optimization Algorithm. The gain settings of a PI controller are improved using WOA, with Integral square Error (ISE) as the objective function. The dynamic characteristics of the BLDC motor are observed by the developed model using MATLAB/simulink environment. The suggested controller's performance is evaluated under a variety of load and set speed settings, and it is compared to other known optimization approaches such as PSO and DE. Based on the simulation results, it is clear that the suggested controller performs better under all of the drive's operating conditions.

Keywords: BLDC motor · PI Controller · Speed Deviation · Whale Optimization Algorithm

1 Introduction

DC motors are extremely efficient, and their properties make them ideal for variable-speed drives. The sole disadvantage is that a commutator and brushes are required, both of which wear out and must be replaced. Solid state switches perform the roles of the commutator and brushes, resulting in maintenance-free, efficient motors. These motors are known as Brushless Direct Current (BLDC) Motors [1].

A BLDC motor features three phase concentric windings on the stator and permanent magnets on the rotor, and commutation is accomplished electronically using a three phase static inverter with semiconductor switches and is powered by a continuous dc source. The Hall element is the most common position sensor, and it is mounted on the stator [2–5].

BLDC motors are rapidly gaining popularity in many industrial applications since they have high dynamic response, efficiency, rigidness noiseless operation, high torque and low volume. Furthermore, the torque provided per unit of motor size is greater, making it helpful in situations where space and weight are important considerations.

The present work proposes a control strategy for the speed control of BLDC motor. PI controllers are simple and commonly used for many industrial applications. However in practice, BLDC motors have a high degree of nonlinearity and the mathematical model

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of the system is unclear, tuning PI controller parameters is challenging, and so getting the best performance with conventionally tuned PI controllers is difficult. Hence the tuning of PI controller parameters is of interest now.

The most well-known thumb rule tuning approach is the Ziegler-Nichols tuning method. Manual tuning, on the other hand, will take longer and may result in hardware damage throughout the control process. In addition, rule-based approaches may or may not be capable of handling some higher-order plants. Many optimization-based techniques for a number of applications have recently been developed, with an integral square error (ISE) as the PI tuning objective function. [6] offers a new Bat metaheuristic optimization technique for a PID controller-based Power System Stabilizer. [7] employs a Bacterial Foraging Optimization (BFO) approach for the PI controller of a Permanent Magnet Synchronous Generator (PMSG) to harvest the most power from the wind. For the Switched Reluctance Generator, [8] employs a traditional Hill Climb Searching technique with ANN. The Genetic Algorithm Method is utilised to optimise PID controllers in different applications in [9, 10]. In [11, 12], Particle Swarm Optimization (PSO) is used. [13] offers self-tuning of a fuzzy PID controller for a BLDC motor using model reference adaptive control (MRAC). PSO and Bacterial foraging algorithms were also created for BLDC motors in [14]. [15] uses the Flower Pollination Algorithm to tune a PID controller with Hysteresis control for a BLDC motor.

Many engineering challenges are tackled using nature-inspired algorithms, such as the Genetic Algorithm, which is based on biological evolution, the Particle Swarm Optimization (PSO) approach, which employs the swarm behaviour of birds and fish, the bat-inspired algorithm, which mimics the behaviour of tiny bats, and the fire-fly algorithm, which uses the flashing light patterns of fireflies.

All standard optimization methods, on the other hand, fail to handle the complicated engineering problems that come with increasing nonlinearity. In this work Whale Optimization Algorithm (WOA) a newly suggested meta heuristic optimization algorithm is used to optimize PID gains for the non-linear BLDC motor in this study.

2 Mathematical Modelling of BLDC Motor

BLDC motors [19], in general, will have rotor with permanent magnets and trapezoidal electromotive force (EMF). A three-phase inverter is usually used to drive BLDC motors, which necessitates the use of a rotor position sensor element for beginning and a correct commutation sequence for the supply to run the inverter module. A six-step commutation mechanism is used by the three-phase inverter to drive the BLDC motor.

Positional sensors must be used for appropriate commutation sequence and commencing hall-effect. In each phase, there will be a 120° second break between conducting. In accordance with Fig. 1, the conducting sequence will be 5–6, 1–6, 1–2, 3–2, 3–4, and 5–4.

The applied current defines the functioning of a BLDC motor, and it must be synced with the back electromotive force voltage signal. The resulting currents are rectangular in shape, and the motor's switching consists of six distinct steps controlled by a switching block with six steps control mechanism. The converters switch the current depending on the rotor position, which may be determined with position sensors or without them.

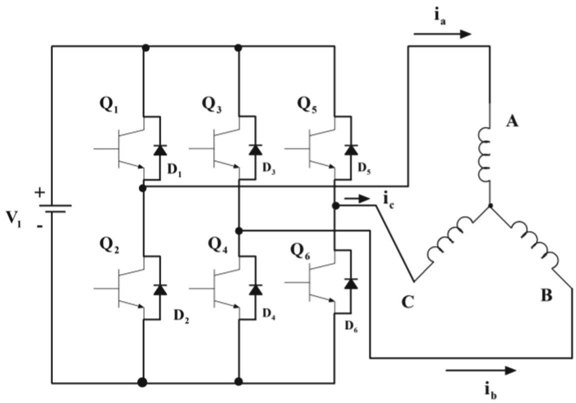

Fig. 1. Simplified BLDC Drive Scheme

The current passes through two phase windings in star connected BLDC motors, and the uncontrolled phase is used to calculate the voltage with regard to the back EMF [16–18].

The equations given below describe a star connected BLDC motor.

$$v_a = Ri_a + L\frac{di_a}{dt} + e_a \tag{1}$$

$$v_b = Ri_b + L\frac{di_b}{dt} + e_b \tag{2}$$

$$v_c = Ri_c + L\frac{di_c}{dt} + e_c \tag{3}$$

$$T_e = k_f\omega_m + J\frac{d\omega_m}{dt} + T_L \tag{4}$$

where the per phase stator voltages are v_a, v_b, v_c the phase currents are i_a, i_b, i_c and the stator phase back emf's are e_a, e_b, e_c. R is the stator per phase resistance, and L is the stator winding per phase self inductance. T_e is the developed electromagnetic.

The block diagram of BLDC motor drive scheme is shown in Fig. 2. The motor's actual speed is measured and compared to the reference speed. The PI controller receives the speed error and generates the desired input voltage for the inverter.

The hall sensors determine the rotor position, which is used to generate the inverter's switching pulses. The efficiency of speed control is mostly determined by the controller's PI improvements. In this work, the PI gains of the controller are modified using WOA with Integral Square Error (ISE) as the objective function.

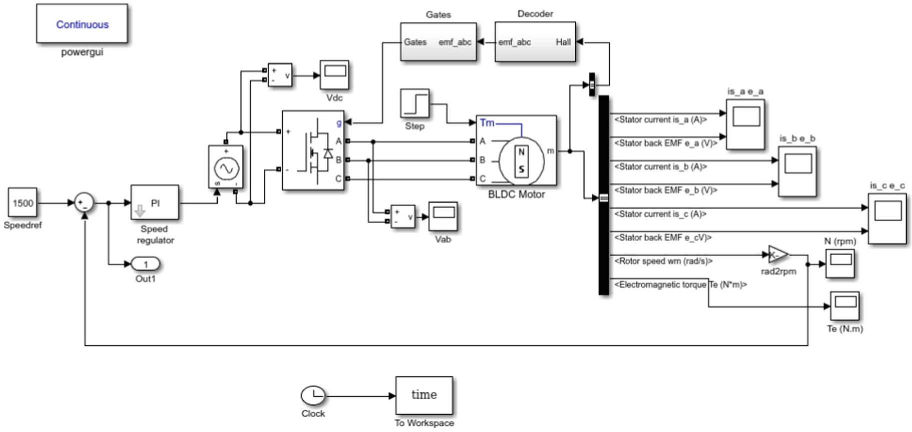

Fig. 2. Simulink model for speed control of BLDC motor

Table 1. BLDC motor specifications

Motor Specifications	Parametric Values
Voltage	470 V
Power	52 W
Nominal Speed	1500 rpm
Current	50 A
No. of poles	4
Stator resistance/phase R	3 Ω
Stator inductance/phase L	0.001 H
Flux linkages λ	0.175 wb.turn
Moment of inertia J	0.0008 kg-m^2/rad
Viscous coefficient k_f	0.001 N-m/(rad/s)
Torque constant	1.4 N-m/A
Voltage constant	0.1466 V/rpm

3 Proposed Whale Optimization Algorithm

In 2016, Seyedali Mirjalili proposed WOA in 2016 by imitating the actions of humpback whales. They have a unique hunting strategy known as bubble-net feeding. This algorithm was created using this foraging strategy. Figure 3 depicts the humpback whales' Bubble–net feeding method. The reason for employing the WOA approach to optimize the PI controller gains is that it has several advantages, including the following: WOA takes less time to evolve than DE and PSO since it has fewer control parameters (two). Exploitation (integration) and exploration (diversification) are critical stages in any optimization

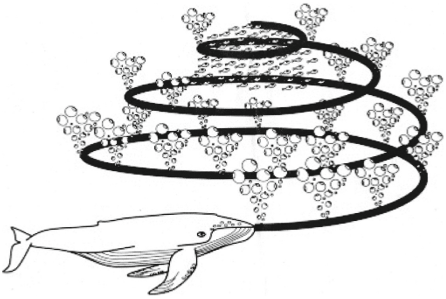

Fig. 3. Bubble net feeding of Humpback Whales

method, and making a fine equilibrium between these two causes increased performance ceases to have global solutions. This can be happened in WOA [20] and it was tested and succeeded in many research areas. The transit between these two important phases can be achieved by only one parameter. Furthermore, the research suggests that current techniques may constantly be improved in order to achieve better results [20–25]. As a result of this motivation, WOA has been used to optimize the PI controller settings.

WOA was created to improve the PI controller gains for BLDC motor speed control. The steps to be followed in applying WOA for effective PI controller tuning are shown below:

Step 1: Initialization
To begin, the algorithm's population size is set at 40, and the total number of generations is set at 100. Gain settings of PI controller are taken as control variables. Using the expression given below, the initial populations are produced at random.

$$M_{ji}^{0} = M_{j}^{min} + rand \cdot \left(M_{j}^{min} - M_{j}^{max}\right) \tag{5}$$

where M is the control variable and M_{j}^{min}, M_{j}^{max} are the lowermost and uppermost boundary values design parameters. $j = 1, 2\ldots, Z$. Here Z is considered as the total number of design parameters that are to be optimized, $i = 1, 2, 3\ldots, Y$, *where Y is selected as the total number of populations*, rand ϵ [0, 1] is the arbitrary number that alters between 0 to 1.

Step 2: Objective function evaluation
In the present work, the gain settings of the PI controller are tuned using WOA by considering Integral Square Error (ISE) as the objective function. The main objective is to minimize the ISE, by minimising the error between the reference speed and the actual speed. The objective function is given by the following equation

$$ISE = \int_{0}^{T} [e(t)]^{2}\, dt \tag{6}$$

where T is the time for the system to reach steady state and e(t) is the error between reference speed and actual speed.

Step 3: Shrinking encircle mechanism for updation of search agents (exploration phase) In this work, the PI controller gains are taken as the search agents. The WOA is utilized to find the optimum solutions found till now. Because the ideal position is unknown when the fitness function is determined on a random basis, the current best answer is deemed target prey or close to the optimum in the search place. After the best search agent is selected using the equation below, the positions of the additional search agents will be updated.

$$\overrightarrow{M_{ji}}(t+1) = \overrightarrow{M_{ji}}^{*}(t) - \overrightarrow{Y} \cdot \overrightarrow{V} \tag{7}$$

$$\overrightarrow{V} = \left| \overrightarrow{F} \cdot \overrightarrow{M_{ji}}^{*}(t) - \overrightarrow{M_{ji}}(t) \right| \tag{8}$$

where t is the present iteration, $\overrightarrow{Y}$, $\overrightarrow{V}$ are the coefficients vectors, $\overrightarrow{M_{ji}}^{*}$ is finest solution attained until now, $\overrightarrow{M_{ji}}$ is the position vector, || is absolute value and '.' shows multiplication between elements.

Here, $\overrightarrow{Y}$, $\overrightarrow{V}$ are given by

$$\overrightarrow{Y} = 2\vec{y} \cdot \vec{r} - \vec{y} \tag{9}$$

$$\overrightarrow{F} = 2 \cdot \vec{r} \tag{10}$$

here the range of $\overrightarrow{Y}$ is between –*y* and *y*, where y alters between 2 and 0 throughout process of optimization. The values of *y*, *Y*, *F* are updated for each search agent and updates its position by Eq. 7, if the value of $\overrightarrow{Y}$ is less than 1.

Step 4: Updating particles via a spiral mechanism
Humpback whales swim in a decreasing circle and spiral-shaped path around their prey, producing a curved equation between the target and position of the whale's to impersonate the humpback whale's twisted-shaped movement. The equation below is followed by all of the search agents.

$$\overrightarrow{M_{ji}}(t+1) = \overrightarrow{V'} e^{bl} \cdot \cos(2\pi l) + \overrightarrow{M_{ji}}^{*}(t) - \overrightarrow{Y} \cdot \overrightarrow{V} \tag{11}$$

where

$$\overrightarrow{V'} = \left| \overrightarrow{M_{ji}}^{*}(t) - \overrightarrow{M_{ji}}(t) \right| \tag{12}$$

where $\overrightarrow{V'}$ is the distance between the i^{th} whale and the prey, *l* is a random value from the interval [−1, 1], and *b* is a constant number that defines the spiral's structure. In the simulation employed in this work, it is assumed that the two techniques have a 50% chance of being chosen and at the end the search agent follows the below equations:

$$\overrightarrow{M_{ji}}(t+1) = \overrightarrow{M_{ji}}^{*}(t) - \overrightarrow{Y} \cdot \overrightarrow{V} \quad if\ \delta \leq 0.5 \tag{13}$$

$$\overrightarrow{M_{ji}}(t+1) = \overrightarrow{V'}e^{bl} \cdot \cos(2\pi l) + \overrightarrow{M_{ji}}^{*}(t) - \overrightarrow{Y} \cdot \overrightarrow{V} \quad if\ \delta \geq 0.5 \tag{14}$$

where, δ is a random number in [0, 1]

Step 5: Search for prey (exploitation phase)
If $\overrightarrow{Y}$ is larger than 1, the search agent's exploitation phase location is updated using a randomly picked search agent rather than the best search agent. The following equation is followed by the search agent.

$$\overrightarrow{M_{ji}}(t+1) = \overrightarrow{M_{ji}}\,rand - \overrightarrow{Y} \cdot \overrightarrow{V} \tag{15}$$

$$\overrightarrow{V} = \left| \overrightarrow{F} \cdot \overrightarrow{M_{ji}}\,rand - \overrightarrow{M_{ji}}(t) \right| \tag{16}$$

where $\overrightarrow{M_{ji}}\,rand$ is the arbitrary number changes while iterations are going on.

4 Performance Analysis of the Proposed WOA Based PI Controller for BLDC Motor

Initially, the BLDC motor along with control signals is developed in MATLAB/Simulink 2017 environment. The BLDC motor specifications that are used for simulation are given in Table 1. The performance of the closed loop speed control of BLDC motor is tested for different varying load conditions. The effectiveness of the proposed WOA based PI controller is contrasted with some bio-inspired optimization algorithms such as PSO and DE by taking integral square error as the objective function. The design parameters for the nature inspired algorithms used in this work are given in Table 2. Here, to have the more uniformity number of population, iterations have considered as same values, while designing the optimum values. All the algorithms have run till best results derived. The developed parameters gain settings of the PI controller with PSO, DE and WOA are displayed in Table 3.

Here to investigate the worth of the proposed control method to tune the PI controller gains three different cases have been considered and are mentioned in Table 2:

Case 1: Full load condition
The reference speed for the BLDC motor is set at 1500 rpm and full load torque of 25 Nm is applied at 0.2 s. The comparisons of the BLDC motor speed response with the suggested approach and other existing methods are shown in Fig. 4. The speed response with a PSO-based controller is shown in brown, the speed response with a DE-based controller is shown in red, and the speed response with the suggested WOA-based controller is shown in pink. It is evident from the figure that the speed drop after the application of load is less with the proposed controller when compared with PSO and DE based controllers.

Table 2. Parameters selected for various algorithms

Algorithm	Parametric Values
PSO	Size of the Populations = 50 Number of iterations = 100 $C_1 = 2$, $C_2 = 2$ Weighing factor, w = (0.9–0.4)
DE	Size of the Populations = 50 Mutation constant, F = 0.5 Cross over constant, C.R = 0.8
WOA	Size of the Populations = 50 Number of iterations = 100 Constant, y = varies between 2 & 0

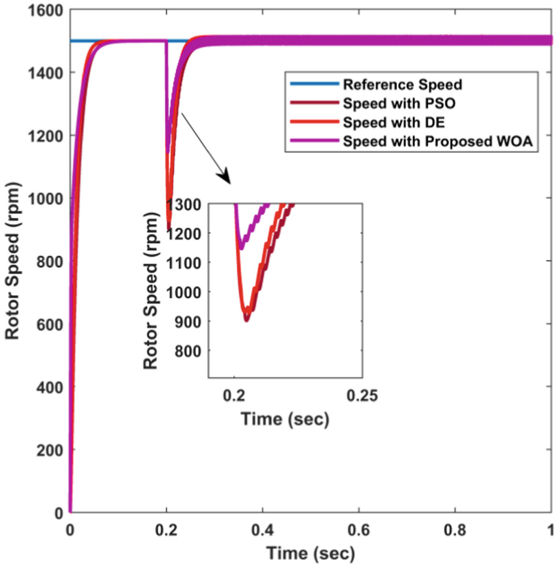

Fig. 4. Speed response of BLDC motor at full load condition

Table 3. Global best values of PI controller gains obtained

Tuning Algorithm	K_p	K_i
PSO	0.012	10.012
DE	0.013	12.123
WOA	0.16	17.036

Case 2: Over load condition (150% of full load)
The reference speed for the BLDC motor is set at 1500 rpm and a load torque of 37.5 Nm is applied at 0.2 s. The comparisons of the BLDC motor speed response with the suggested approach and other existing methods are shown in Fig. 5. The speed response with a PSO-based controller is shown in brown, the speed response with a DE-based controller is shown in red, and the speed response with the suggested WOA-based controller is shown in pink. It is evident from the figure that the speed drop after the application of load is less with the proposed controller when compared with PSO and DE based controllers.

Case 3: Under load condition (50% of full load)
The reference speed for the BLDC motor is set at 1500 rpm and a load torque of 12.5 Nm is applied at 0.2 s. The comparisons of the BLDC motor speed response with the suggested approach and other existing methods are shown in Fig. 6. The speed response with a PSO-based controller is shown in brown, the speed response with a DE-based controller is shown in red, and the speed response with the suggested WOA-based controller is shown in pink. It is evident from the figure that the speed drop after the application of load is less with the proposed controller when compared with PSO and DE based controllers.

The time response specifications of the BLDC drive with the controller is depicted in Table 4. All the transient response specifications for the three loading conditions are displayed. For under loading conditions the rise time with PSO is observed as 0.03 s, where as with DE it is viewed as 0.0253 s and when WOA is used the peak time is observed as 0.0239 s. The undershoot for the same loading condition with PSO algorithm-based controller detected as 0.2 s while DE is used it is around 0.166 s and with WOA is utilized the undershoot is detected as 0.1 s only. Similarly recovery time is obtained as 0.0291 s when PSO is used, while DE is placed in the controller circuit the recovery time comes

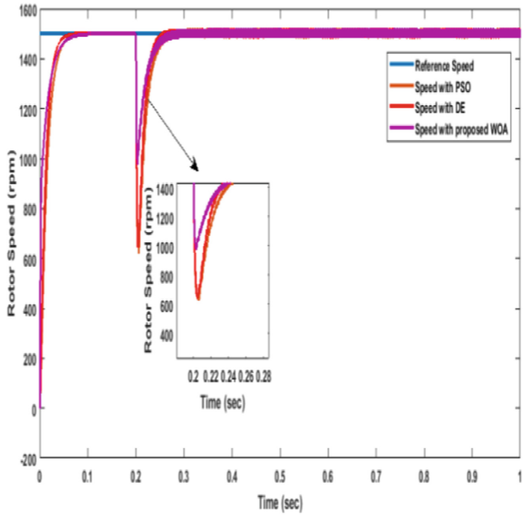

Fig. 5. Speed response of BLDC motor at over load condition

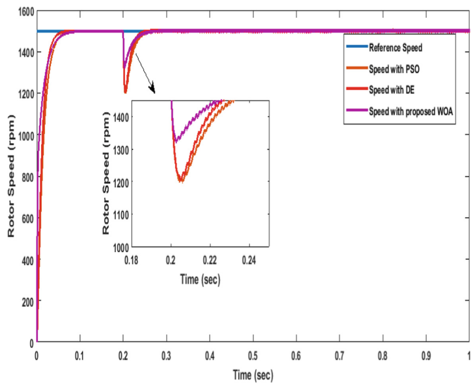

Fig. 6. Speed response of BLDC motor at under load condition

Table 4. Time Response Specifications at different Loading Conditions

Load	Time Domain Specifications	Algorithm		
		PSO	DE	WOA
Under Load	Rise Time (s)	0.03	0.0253	0.0239
	Peak Undershoot (%)	0.2	0.166	0.1
	Recovery Time (s)	0.2462	0.2344	0.2331
Full Load	Rise Time (s)	0.0291	0.0264	0.0243
	Peak Undershoot (%)	0.4	0.366	0.166
	Recovery Time (s)	0.2572	0.2497	0.2476
Over Load	Rise Time (s)	0.0291	0.0259	0.0249
	Peak Undershoot (%)	0.6	0.533	0.33
	Recovery Time (s)	0.2857	0.2659	0.2585

down to 0.2344 s, and finally with WOA-based controller is utilized the recovery time has come down to 0.243 s.

Likewise under full load condition, with PSO the rise time is detected as 0.0291s, when DE-based controller is placed it has come down to 0.0264 s and while WOA is used it has further come down to 0.0243 s. The under shoot for the full load condition with PSO is obtained as 0.4 s, it has come down to 0.36 6s when DE is placed, finally it has come down to 0.166 s. Also recovery time is obtained as 0.0291 s when PSO is used, while DE is placed in the controller circuit the recovery time comes down to 0.259 s, and finally with WOA-based controller is utilized the recovery time has come down to 0.24p seconds. Here also the WOA has shown its potentiality in getting best results when compared to other techniques.

Equally under over load condition, when PSO is used the rise time is observed as 0.0291s, while DE is used it has come down to 0.0259 s and when WOA-based PI controller is placed in the control circuit it is observed as 0.0249 s. The under shoot for the full load condition with PSO is obtained as 0.6 s, it has come down to 0.5336 s when DE is placed, finally it has come down to 0.33 s. In the same way recovery time is obtained as 0.02857 s when PSO is used, while DE is placed in the controller circuit the recovery time comes down to 0.2659 s, and finally with WOA-based controller is utilized the recovery time has come down to 0.2585 s. The results proven that WOA has effectively worked out in providing better speed characteristics for the BLDC drive when compared to other techniques.

5 Conclusion

In this paper, the settings of the PI controller are tuned using WOA for the speed control of BLDC motor by considering ISE as the objective function. The efficacy of the proposed Whale Optimization Algorithm for the tuning of PI controller gains is tested for different loading conditions of BLDC. The simulation results reveals that the controller with proposed algorithm gave better results when compared to other nature inspired algorithms like PSO and DE.

References

1. Rajashekara, K.: Present status and future trends in electric vehicle propulsion technologies. IEEE J. Emerg. Sel. Top. Power Electron. **1**(1), 3–10 (2013)
2. Jahns, T.M., Blasko, V.: Recent advances in power electronics technology for industrial and traction machine drives. Proc. IEEE **89**(6), 963–975 (2001)
3. Singh, B.: Recent advances in permanent magnet brushless DC motors. Sadhana **22**(6), 837–853 (1997)
4. Bose, B.K.: Power electronics and motor drives - technology advances, trends and applications. In: 2005 IEEE International Conference on Industrial Technology, no. 2000 (2005)
5. Singh, B., Singh, S.: State of the art on permanent magnet brushless DC motor drives. J. Power Electron. **9**, 1–17 (2009)
6. Chaib, L., Choucha, A., Arif, S.: Optimal design and tuning of novel fractional order PID power system stabilizer using a new metaheuristic Bat algorithm. Ain Shams Eng. J. **8**(2), 113–125 (2017)
7. Saad, N.H., El-Sattar, A.A., Marei, M.E.: Improved bacterial foraging optimization for grid connected wind energy conversion system based PMSG with matrix converter. Ain Shams Eng. J. **9**(4), 2183–2193 (2018)
8. Saad, N.H., El-Sattar, A.A., Metally, M.E.: Artificial neural controller for torque ripple control and maximum power extraction for wind system driven by switched reluctance generator. Ain Shams Eng. J. **9**(4), 2255–2264 (2018)
9. Hasanien, H.M.: Design optimization of PID controller in automatic voltage regulator system using Taguchi combined genetic algorithm method. IEEE Syst. J. **7**(4), 825–831 (2013)
10. Hasanien, H.M., Muyeen, S.M.: A Taguchi approach for optimum design of proportional-integral controllers in cascaded control scheme. IEEE Trans. Power Syst. **28**(2), 1636–1644 (2013)

11. Hasanien, H.M.: Particle swarm design optimization of transverse flux linear motor for weight reduction and improvement of thrust force. IEEE Trans. Ind. Electron. **58**(9), 4048–4056 (2011)
12. Saad, N.H., El-Sattar, A.A., Mansour, A.-A.: A novel control strategy for grid connected hybrid renewable energy systems using improved particle swarm optimization. Ain Shams Eng. J. **9**(4), 2195–2214 (2018)
13. El-samahy, A.A., Shamseldin, M.A.: Brushless DC motor tracking control using self-tuning fuzzy PID control and model reference adaptive control. Ain Shams Eng. J. **9**(3), 341–352 (2018)
14. Ibrahim, H.E.A., Hassan, F.N., Shomer, A.O.: Optimal PID control of a brushless DC motor using PSO and BF techniques. Ain Shams Eng. J. **5**(2), 391–398 (2014)
15. Devendra Potnuru, K., Alice Mary, C., Babu, S.: Experimental implementation of Flower Pollination Algorithm for speed controller of a BLDC motor. Ain Shams Eng. J. **10**(2), 287–295 (2019)
16. Gobinath, S., Madheswaran, M.: Deep perceptron neural network with fuzzy PID controller for speed control and stability analysis of BLDC motor. Soft Comput. **24**(13), 10161–10180 (2019)
17. Pillay, P., Krishnan, R.: Modeling of permanent magnet motor drives. IEEE Trans. Ind. Electron. **35**(4), 537–541 (1988)
18. Krishnan, R.: Permanent Magnet Synchronous and Brushless DC Motor Drives. CRC Press (2009)
19. Miller, T.J.E.: Brushless Permanent Magnet and Reluctance Motor Drives. Clarendon Press/Oxford Science Publications (1989)
20. Mirjalili, S., Lewis, A.: The whale optimization algorithm. Adv. Eng. Softw. **95**, 51–67 (2016)
21. Mafarja, M., Mirjalili, S.: Hybrid whale optimization algorithm with simulated annealing for future selection. Neurocomputing **260**, 302–312 (2017)
22. Butti, D., Sivakumar, M.: R Srinivasarao Interconnected multi-machine power system stabilizer design using whale optimization algorithm. Prot. Control Mod. Power Syst. **4**(1), 1–11 (2019)
23. Butti, D., Mangipudi, S.K., Rayapudi, S.R.: An improved whale optimization algorithm for the design of multi-machine power system stabilizer. Int. Trans. Electr. Energy Syst. **30**(5), e12314 (2020)
24. Butti, D., Mangipudi, S.K., Rayapudi, S.R.: Model order reduction based power system stabilizer design using improved whale optimization algorithm. IETE J. Res., 1–20 (2021)
25. Dasu, B., Mangipudi, S., Rayapudi, S.: Small signal stability enhancement of a large scale power system using bio-inspired whale optimization algorithm. Prot. Control Mod. Power Syst. **6**(1), 1–17 (2021)