An Optimal Controller Design for BLDC Motor Drive with Transit Search Optimization Algorithm

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Abstract - The use of BLDC motors has been on the rise, requiring efficient speed control techniques. This paper proposes a transit search to designing optimal parameters for the PI controller, utilizing Transit Search optimization (TSO) algorithm. Traditional methods for PI controller parameter design can be complex and may result in large overshoot. Although PSO-based methods are commonly used to optimize PI control parameters for BLDC motor speed control, they require proper setting of several algorithm control parameters to achieve better performance. Therefore, this paper proposes a new method based on transit search optimization for optimal parameter design of the PI controller for BLDC motor speed control. The PI control parameters' optimum values are necessary to achieve the desired motor speed under any dynamic condition. To evaluate the proposed algorithm's performance, a MATLAB/Simulink model of the BLDC motor is utilized.

Keywords - BLDC Motor, PI Controller, Particle Swarm Optimization (PSO), Transit Search Optimization (TSO)

I. INTRODUCTION

In contrast to these traditional methods, soft computing techniques have gained popularity in recent years due to their ability to efficiently tune controller parameters with less mathematical complexity. These techniques include metaheuristic algorithms such as particle swarm optimization (PSO), teaching-learning-based optimization (TLBO), and differential evolution (DE), among others. These techniques aim to balance exploration and exploitation to find the optimal values of controller parameters for the BLDC motor control system[5-7].

Among these soft computing techniques, transit search optimization (TSO) is a new optimization method inspired by galaxysystem[1]. In TSO, a population of solutions is generated and categorized into different groups or parties. These parties compete with each other, and the best solutions are chosen from each party to form a new population. This process is repeated until convergence is achieved. TSO has been successfully applied to various optimization problems and has shown promising results in terms of efficiency and accuracy.

Therefore, in this paper, the authors propose using TSO to optimize the PI controller for BLDC motor speed control10]. The aim is to achieve more accurate speed control under all dynamic conditions while avoiding the complexity of traditional tuning methods[9].

TSO is a novel metaheuristic optimization technique that is inspired by political election processes. The TSO algorithm is based on the behavior of stars.The main idea of the TSO algorithm is to use a set of movement of stars to represent the planet position, and the stars represent the fitness values. The TSO algorithm uses a set of stars population to change the positions of the planets and eventually converge to the optimal solution.

In this paper, the TSO algorithm is used to optimize the PI controller parameters for the speed control of the BLDC motor. The proposed method is compared with other soft computing techniques like PSO, DE[10], and TLBO[11]. The simulation results show that the proposed TSO-based technique outperforms the other methods and provides more accurate speed control under all dynamic conditions. The TSO algorithm has better convergence properties and can find the optimal solution faster than other techniques. Moreover, the TSO algorithm is easy to implement, and it requires only a small number of parameters to be tuned.

II. MODELING OF BLDC MOTOR

The BLDC motor is a type of self-synchronous rotating motor that is similar in construction to the permanent magnet synchronous motor[2]. It offers better speed versus torque characteristics and has a superior dynamic response. One of the most attractive features of the BLDC motor is its straightforward structure and lower cost compared to other motors. Additionally, it is the ideal choice for applications that require less space and weight.The main difference between a BLDC motor and a DC motor is that in a BLDC motor, the main flux is produced by a permanent magnet, while in a DC motor, the field flux is produced by DC current through the field coil of the stator. Additionally, instead of a commutator and brushes, BLDC motors use hall effect sensors to sense the rotor position, which is then used by the electronic commutation controller to control the power state of the windings. This continuous commutation allows the rotor to move without the need for a mechanical commutator. The torque and speed of the BLDC motor are influenced by the back emf.

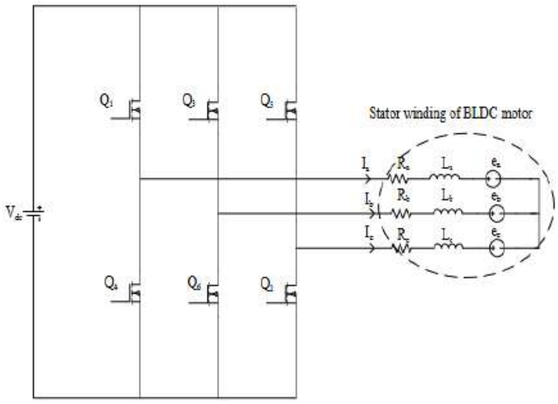

Fig.1: Stator of BLDC motor connected to a three-phase inverter

The phase to phase stator voltage equation of BLDC motor can be written as;

$$V_{xy} = R(i_x - i_y) + L\frac{d}{dt}(i_x - i_y) + e_x - e_y \quad (1)$$

$$e_x = \frac{k_e}{2}\omega_m F(\Theta_e - \Phi_x) \quad (2)$$

$$T_e\omega_m = \sum e_x i_x \quad (3)$$

$$T_e = k_f\omega_m + J\frac{d\omega_m}{dt} + T_L \quad (4)$$

III. Transit search algorithm

In this section, details of the proposed algorithm are presented.In the algorithm structure, two parameters are defined: the number of host stars (n_s) and the signal-to-noise ratio (*SN*). The *SN* parameter is determined based on the transit model. Furthermore, the noise is estimated using the standard deviation of the observations obtained outside the transit. In practice, there is always the possibility of noise in the photons received from stars images shows an optional transit for different amounts of signal-to-noise ratio. It should be noted that the product of the two parameters of the proposed algorithm (*ns* and *SN*) is equal to the amount.

There are five phases for implementing the TS, which include the phases of galaxy, star, transit, planet, neighbor, and exploitation. In this section, details of each of these phases are provided.

3.1. Galaxy phase:

The algorithm starts by selecting a galaxy. For this purpose, a random location in the search space is chosen as the galaxy center. Once this location is determined, it is necessary to identify the habitable zones of the galaxy (life belt). To do this, n_s*SN random regions L_R, are evaluated by Eqs. (1) to find the situations having the potential for the best stellar systems (the regions with a high probability of the host of life). Finally, n_s of them that have the best fitness are selected. The selected regions have the potential to be the host of life, and the next steps of the algorithm begin with these regions.

$$L_{R,l} = L_{Galaxy} + D - Noise\, ; l = 1, \dots, (n_s \times SN \qquad (1)$$
$$Noise = c_2^3 L_r$$

3.2. Transit phase:

In order to detect the transit, it is necessary to re-measure the amount of light received from the star to detect its possible reduction in the received light signals. In the TS algorithm, L_S and its corresponded fitness (f_S) have two meanings (M_1 and M_2) which are presented in . In cases where the goal is to use the location of the star to determine and update the location of a planet, M_1 is used. In cases where the goal is to determine the brightness received from the star and update it, M_2 is used. Accordingly, in the case of M_2 a change in L_S means a new specification of the light signal, while in the case of M_1, a change in L_S means a change in the location of the star.

$$L_i = \frac{\frac{R_i}{n_s}}{d_i^2}; \qquad \mathrm{I} = 1, \dots, \mathrm{ns} \qquad (2)$$
$$d_i = \sqrt{(L_S - L_T)^2}$$

3.3. Planet phase:

By specifying the value of P_T in the previous phase, if the transit is observed (P_T= 1), the planet phase is implemented in the TS algorithm. In this phase, first, the initial location of the detected planet is determined. Given that the light received by the observer (telescope) is received from the star, so a decrease in the amount of this light (occurrence of transits) occurs when the planet has passed between the star and the telescope. Based on this, the initial location of the detected planet (L_z) can be determined. In the TS algorithm, this is done.

$$L_z = (c_3 L_T + R_L L_{s,i})/2 \qquad i = 1, .., n_s \qquad (3)$$

3.4. Neighbour phase:

If there is no transit for a star in the current observation, the neighbourhood planets of the previously detected planet for the star will be studied. In other words, if the neighbour has better conditions than the current planet (it has better conditions to host life), it will be replaced with the current planet of the star. This is done in the TS algorithm in the neighbour phase using. First, the initial location of the neighbour (L_z) is estimated with consideration of its host star ($L_{S,ew}$) and a random location (L_R). Then, the final location of the neighbour planet (L_N) is determined. The coefficients c_4 and c_5 in Eq. (5) deal with a random number between 0 and 1.

$$L_S = (c_4 L_{s,new} + c_5)/2 \qquad (4)$$

3.5. Exploitation phase:

In the previous phases, the best planet is determined for each star. As mentioned earlier, discovering a planet alone does not matter. In fact, it is necessary to study the characteristics of the planet and the conditions to host life. In the TS algorithm, this is done in the Exploitation phase. In this phase, a new definition for the L_P is expressed. In other words, L_P in the current phase (L_E) refers to the characteristics of the planet (such as its density, materials, atmosphere, etc.). Then, by adding new knowledge (K), the final characteristics of the planet are modified SN times (j= 1,..., SN). In this equation, c_5 is a random number between 0 and 2, and c_{16} is a random number between 0 and 1. Also, c_{17} is a random vector between 0 and 1. The parameter P indicates a random power between 1 and (n_s* SN). In this equation, c_k is a random number (1, 2, 3, or 4) and indicates the knowledge index.

IV. OPTIMAL PARAMETER DESIGN OF PI CONTROLLER USING TRANSIT SEARCH OPTIMIZER:

The control signal u(t) from the PI controller[3] is generated form proportional and integral action on error signal e(t).

$$u(t) = K_p(e(t) + \frac{1}{T_1}\int_0^t e(t)\,dt)$$

where $K_p$is the proportional coefficient, T_1 is the integral coefficient. Whereas the discrete model of the PI controller used in the digital controller is

$$u(k) = K_p(e(k) + \frac{T}{T_1}\sum_{j=0}^{k} e(j))$$

where $K_p$is the proportional coefficient, T is the sampling period, and$e(k)$is the deviation values at thek_{th} sampling time.

The important aspect of solving the parameter design of the PI controller with the PO algorithm is the selection of objective function. Integral of absolute error gives a satisfactory transient response. Whereas the integral of the square of control signal prevents excessive control action. Hence the linear combination of the above two terms is considered as an objective function for this minimization problem;

$$F = \int_0^\infty (w_1\,|e(t)| + w_2 u^2(t))dt$$

where $e(t)$is the system error, *u(t)*is the controller output, and w_1 and $w_2$are weight values taken from [9].

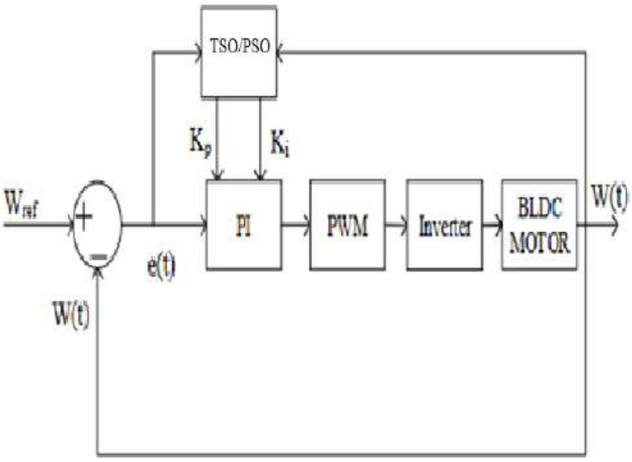

Fig.2: Speed control of BLDC motor

V. SIMULATION CASE STUDY

The performance of the TSO technique for controlling the speed of a BLDC motor was tested using a MATLAB/SIMULINK model with a recommended control system. In order to compare its efficiency with other algorithms, PSO was chosen due to its proven effectiveness.

The study compared speed control characteristics using different techniques and found that all algorithms had satisfactory operating characteristics. However, the algorithms focused on error minimization as the objective function, and the proposed algorithm yielded the least value.

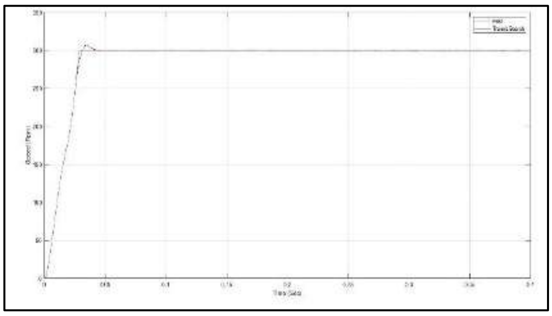

Fig3: Speed response of BLDC motor with TSO and PSO algorithm

Fig 4: Output current and voltage waveforms

VI. CONCLUSION

The paper proposes a new optimization method (TSO) for setting the parameters of a PI controller to control the speed of a BLDC motor, with the aim of achieving more accurate and reliable control under dynamic conditions. The simulation results demonstrate that the proposed method outperforms the existing PSO based technique in terms of performance. As a result, the paper presents an effective method for controlling the speed of a BLDC motor.

REFERENCES

[1] Masoomeh Mirrashid and Hosein Naderpour “Transit Search: An optimization algorithm based on exoplanet exploration,”*Results in control and optimization*, vol.7, 10127, pp.1-37, 2022.

[2] B. Stefán, “BLDC Motor Modelling and Control – AMatlab®/Simulink® Implementation,”Chalmers Tekniska Högskola,Göteborg,Sverige, 2005.

[3] M. Nasri, H. Nezamabadi-pour, and M. Maghfoori, “A PSO-BasedOptimum Design of PID Controller for a Linear Brushless DC Motor,” World Academy of Science, Engineering and Technology, vol. 20, p. 5,2007.

[4] Gwo-Ruey Yu and Rey-Chue Hwang, “Optimal PID speed control ofbrush less DC motors using LQR approach,” in 2004 IEEE International Conference on Systems, Man and Cybernetics (IEEE Cat.No.04CH37583), Oct. 2004, vol. 1, pp. 473–478 vol.1, doi:10.1109/ICSMC.2004.1398343

[5] G. Cheng, “Brushless DC Motor Speed ControlSystem Based on FuzzyPID Controller,” in Network Computing and Information Security, Berlin, Heidelberg, 2012, pp. 287–294, doi: 10.1007/978-3-642-35211-9_37.

[6] M. M. Sabir and J. A. Khan, “Optimal Design of PID Controller for theSpeed Control of DC Motor by Using Metaheuristic Techniques,”Advances in ArtificialNeural Systems,2014.https://www.hindawi.com/journals/aans/2014/126317/.

[7] P. Pal, R. Dey, R. K. Biswas, and S. Bhakta, “Optimal PID ControllerDesign for Speed Control of a Separately Excited DC Motor: A Firefly

Based Optimization Approach," Social Science Research Network,Rochester, NY, SSRN Scholarly Paper ID 3517152, 2015. doi:10.2139/ssrn.3517152.

[8] A. A. A. El-Gammal and A. A. El-Samahy, "A modified design of PIDcontroller for DC motor drives using Particle Swarm Optimization PSO," in 2009 International Conference on Power Engineering, Energy and Electrical Drives, Mar. 2009, pp. 419–424, doi: 10.1109/POWERENG.2009.4915157.

[9] P. Salawria, R. S. Lodhi, and P. Nema, "Implementation of PSO-BasedOptimum Controller for Speed Control of BLDC Motor," InternationalJournal of Electrical, Electronics and Computer Engineering, vol. 6, no.1, pp. 104–109, 2017.

[10] W. Xie, J.-S. Wang, and H.-B. Wang, "PI Controller of SpeedRegulation of Brushless DC Motor Based on Particle SwarmOptimization Algorithm with Improved Inertia Weights," MathematicalProblems in Engineering, 2019. https://www.hindawi.com/journals/mpe/2019/2671792.

[11] H. Jigang, F. Hui, and W. Jie, "A PI controller optimized with modifieddifferential evolution algorithm for speed control of BLDC motor," Automatika, vol. 60, no. 2, pp. 135–148, Apr. 2019, doi: 10.1080/00051144.2019.1596014.

[12] N. Azizi and R. K. Moghaddam, "Permanent Magnet Brushless DCMotor optimal design and determination of optimum PID controllerparameters for the purpose of speed control by using the TLBOoptimization algorithm," AmericanJournal of ResearchCommunication, vol. 1, no. 1, pp.294–313,2013.

[13] Q. Askari, I. Younas, and M. Saeed, "Political Optimizer: A novel socio-inspired meta-heuristic for global optimization," Knowledge-Based Systems, vol. 195, p. 105709, May 2020, doi: 10.1016/j.knosys.2020.105709.