

Optimal Control of DC Motor Using Multiverse Optimization Algorithm

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Abstract- Regulating the PID controller's parameters is a significant challenge in DC motor control operation. Multiverse Optimization Algorithm (MVO), a new metaheuristic algorithm, is used to overcome this challenge and is designed for driving a DC motor to find the best possible solution globally in the search space. The suggested controller can be used to adjust the PID controller's parameters to their optimum value. The outcomes of the simulation demonstrate that the suggested controller is capable of efficiently looking for the best PID controller. According to the simulation results, the development of the speed loop response stability has improved, the steady state error has decreased, the rising time has been perfected, and disturbances have no effect on the driving motor's performance with no overtaking.

Keywords— Multiverse Optimization Algorithm, DC motor, PID controller, Parameter Optimization.

I. Introduction

There is scarcely an industrial application today that does not make use of DC motors [1, 2]. This is true because brushless DC motors in particular are simple to regulate, require little maintenance, are inexpensive, and are robust in a variety of applications. Machine tools, paper mills, the textile sector, electric traction, and robotics are a few notable industrial applications where DC motors are utilized often.

The ability to manage the armature winding and field winding individually gives DC motor controller designs more flexibility [3]. The current in the field winding is often maintained constant while the current in the armature winding is adjusted, or vice versa, which provides good speed control performance across a large range of desired values. The goal of these applications is to maintain output speed at the desired level while tracking speed commands in order to accomplish target speed or position control in the shortest amount of time possible without experiencing significant overshoots and settling delays [4, 5].

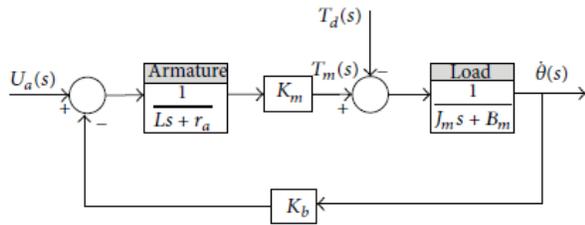
There are numerous types of controllers that can be used in control applications, including lead, lag, LQR (linear quadratic regulator), PID, and sliding-mode control [6–8]. Due to its effectiveness and simplicity of use, the PID controller—one of

the few types of controllers mentioned—is one of the earliest and best understood controllers and is used in practically every industrial control application [9]. Although there are many well-known and simple to use classical techniques for designing and tuning PID controller parameters (K_p , K_i , and K_d), one of their main drawbacks is the need for expertise and experience when tuning PID controller using these methods. This is true since these techniques only serve as a starting point, necessitating trial-and-error parameter fine adjustment to achieve desired performance. Due to its dynamic character, metaheuristic methods might be an excellent alternative.

Numerous metaheuristic and stochastic optimization approaches have been created over time and are now used in all areas of life [10–12]. Depending on the swarm intelligence, evolutionary, or foraging behavior of various animals, these strategies are nature-inspired. The genetic algorithm (GA), particle swarm optimization (PSO), and simulated annealing (SA) are a few of the often-utilized methods. The findings acquired through these techniques have demonstrated their superiority over the classical methodologies, and these metaheuristic algorithms have been successfully implemented in a number of control system disciplines [13–18]. A PID controller design for DC motor speed management is provided in this study, and recently developed equilibrium optimization algorithm was utilized to fine-tune the PID controller's parameters.

II. Mathematical Model of DC Motor

The dynamic behavior of DC motor is given by following set of relations [19] and its block diagram is shown in Figure 1.



A simplified linear model is presented for this work ignoring the nonlinearities like the backlash and dead zones to simplify the application of metaheuristic techniques. Consider

$$T_m(s) = k_m I_a(s)$$

$$U_a(s) = (r_a + Ls) I_a(s) + U_b(s)$$

$$U_b(s) = ,$$

$$\dots (1)$$

where U_a is armature applied voltage, U_b is back-emf, K_m is motor constant, K_b is back emf constant, J_m is inertia of rotor, B_m is viscous damping, T_m is developed motor torque, T_l is torque delivered to load, T_d is disturbance torque, r_a is armature resistance, L is armature inductance, I_a is armature current, and s is s-plane.

By using (1) the transfer function of DC motor is
 $\dots (2)$

Table 1: DC motor parameters

Motor parameters	Value
r_a	2.0 ohms
L	0.5 Henry
	0.1 N·m/A
	0.1 N·m/A
	0.02 Kg·m ² /rad
	0.2 N·m

III. IMPLEMENTATION

Fitness Function: for optimal control of dc motor using Pid controller we used two fitness functions. Fitness function for first case is Integral of absolute error and is given as:

$$\dots (3)$$

Fitness function for second case is Integral of absolute time error and is given as:

$$\dots (4)$$

IV. MULTI VERSE OPTIMIZER (MVO)

Seyedali Mirjalili discovered the Multi Verse Optimizer algorithm [19], which is based on three ideas: the black hole,

the white hole, and the wormhole seen in Fig. 2. Wormholes connect various parts of the universe and serve as time- and space-travel conduits through which objects can easily move between any corners of a universe. The white hole is thought to be the original part of the universe and the first big bang that caused the creation of the universe, while the black hole attracts everything due to its powerful gravitational pull. Every universe experience inflation, which results in its expansion through space. As a result, the speed of an inflation is crucial for the creation of other universes and the stability of the one we live in. In order to evaluate exploitation, exploration, and local search, respectively, these notions are mathematically modelled [19]. Each variable in the solution is an object in the equivalent universe, and we moreover assign each solution an inflation rate corresponding to its fitness.

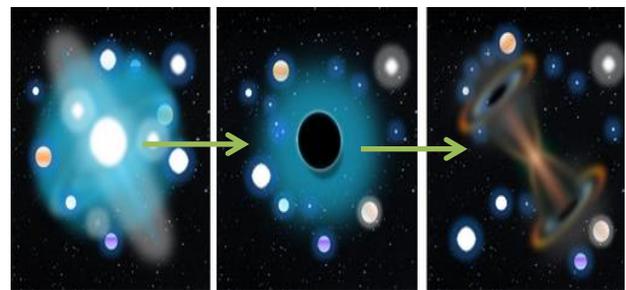


Figure 2. The three concepts of MVO algorithm

Rules of MVO algorithm:

- The higher the inflation rate, the higher the likelihood of having a white hole; conversely, the higher the inflation rate, the lower the likelihood of having a black hole.
- White holes are often used to send items through universes with high rates of inflation.
- More items enter black holes in universes with lower rates of inflation.
- The objects from every universe could move at random in the direction of the best universe or through wormhole universes.

All of these laws are shown in Fig. 3, where shifting objects between universes with high and low inflation rates causes the average inflation rate of the entire universe to increase over time. Each time, a white hole is chosen from among the

universes by applying the roulette wheel principle and storing them according to their inflation rates as follows: [19]

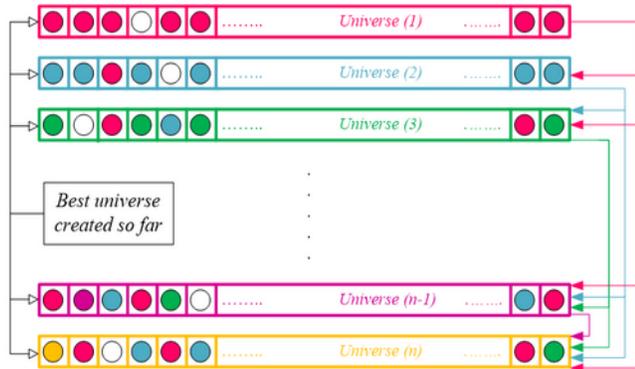


Figure 3. Basic principle of MVO algorithm (5)

where, d represents the number of variables and n is the number of candidate solutions:

$$x_i^j = \begin{cases} x_i^j; & r1 < NI(U_i) \\ x_k^j; & r1 \geq NI(U_i) \end{cases}$$

(6)

where: x_{ij} represents the i th variable of i th universe. U_i is the i th universe, $NI(U_i)$, is the normalized inflation rate of i th, universe, $r1$ is a random number in the range $[0,1]$, and x_{kj} , represents the j th variable of k th universe chosen by using roulette wheel. Updating the universe positions and giving the possibility of improving the inflation rate by worm holes, these particular wormholes tunnels are always established between a universe and the best universe found so far, which can be described as follows:

$$x_i^j = \begin{cases} X_j + XTDR \times ((ub_j - lb_j) \times r4) & r3 < 0.5 \quad r2 < W \\ X_j + XTDR \times ((ub_j - lb_j) \times r4) & r3 < 0.5 \quad r2 < W \\ x_i & r2 \geq WEP \end{cases}$$

(7)

where X_j shows j th variable of fittest universe created until now, L_{bj} , U_{bj} indicate the lower /upper limits of j th variable, of i th universe, and $r1, r4$ are random numbers in $[0,1]$. It can be conducted by the calculation of wormhole existence probability (WEP) and travelling distance rate as chief coefficients defined as follows:

$$WEP = \min + t \times \left(\frac{\max - \min}{t_{MAX}} \right)$$

(8)

$$TDR = 1 - \frac{l^{1/p}}{L^{1/p}}$$

(9)

where t represents the current run, t_{max} the maximum number of iterations, \min the minimum (in this case, 0.2), \max the maximum (in this case, 1), l the current iteration, and L the maximum iterations are shown. where t represents the current run, t_{max} the maximum number of iterations, \min the minimum (in this case, 0.2), \max the maximum (in this case, 1), l the current iteration, and L the maximum iterations are shown. Where, \max is the maximum of WEP and \min is the minimum (which in this paper is chosen to be 0.2). P is the precision of the exploitation across iterations (taken as 6). The MVO algorithm depends on a variety of factors, including the number of candidate solutions, the number of runs, the roulette wheel, and the sorting mechanism.

V. RESULTS & DISCUSSIONS

MVO is used to find K_p, K_i, K_d gains for PID control of dc motor. The number of populations used for MVO was 20 and maximum number of iterations performed were 40.

Test case I: Neglecting Disturbance Torque.

For this case dc motor parameters used are given in table 1. Unit step signal was given as input to simulation model given in fig.4. First the simulation was run with IAE as fitness function and then with IATE as fitness function.

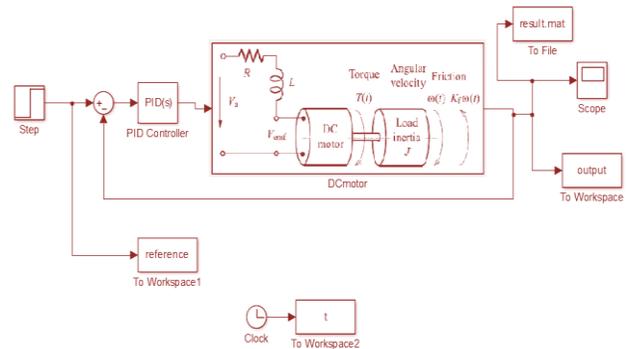


Fig.4. Simulation model of DC motor PID control

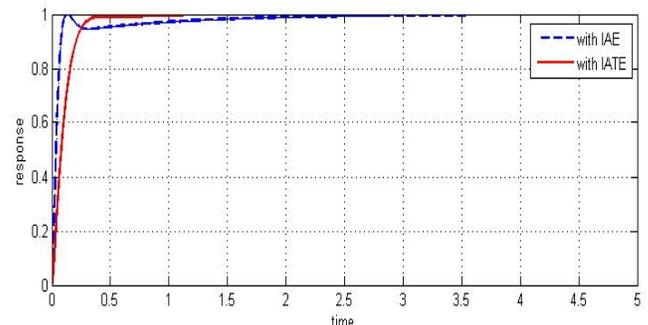


Fig.5. Simulation Results of DC motor PID control

Parameter	P	I	D
Fitness function (IAE)	40	40	1.8221
Fitness function (IATE)	12.9293	40	0.734391

Parameter	IAE	IATE
Rise Time	0.0660	0.1865
Settling Time	1.3423	0.3153
Settling Min	0.9019	0.9007
Settling Max	0.9997	1.0000
Overshoot	0.0259	0
Undershoot	0	0
Peak	0.9997	1.000
Peak Time	0.1310	0.4

Table2. Results for Test Case-I

Simulation results clearly reveal that MVO is performing good on tuning of PID parameters for DC motor control. Output results with IAE and IATE as fitness function were compared and clearly IATE is better choice for fitness function.

Test case II: Considering Disturbance Torque.

For this case dc motor parameters used are given in table 1. Unit step signal was given as input to simulation model given in fig.6. The simulation was run with IATE as fitness function.

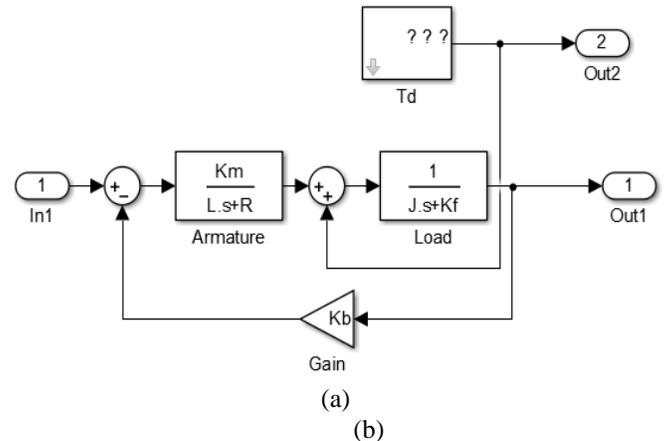
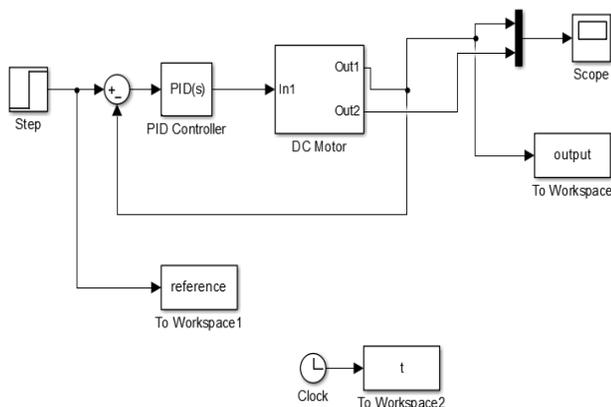


Fig.6. a) Simulation model of DC motor PID control b) Sub model of dc motor with torque disturbance

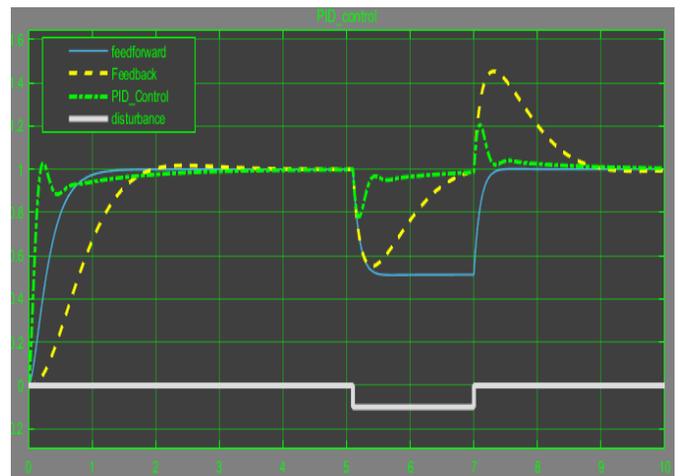


Fig.7. Simulation Results for test case II

Simulation was carried out with feedforward control method, feedback control, PID (tuned with MVO) control. Output results show that PID(MVO) is performing better in rejecting disturbances in torque.

VI. Conclusion

Due to their simple design, often excellent control performance, and ease of use, PID controllers are a common control option. Through modelling of the DC motor speed control system, the Multiverse Optimization Algorithm (MVO) has been used in this work to fine-tune the PID controller. It has been shown that the MVO algorithm approach of tuning a PID controller performs well in terms of the system overshoot, settling time, and rise time as well as in terms of rejecting load torque disturbance.

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