Advanced Tuning of the PID Controller for a Mobile Robot

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Abstract. This work deals with the automatic tuning of a PID controller for regulating the angular velocity of a DC motor integrated into the drive wheels of an electric wheelchair. The system is modeled using the motor's electromechanical equations in order to obtain a transfer function used in the closed-loop simulation. The PID gains are optimized by the Arithmetic Optimization Algorithm (AOA) by minimizing the Integral of Time-weighted Absolute Error (ITAE). The performance of the AOA-PID-ITAE controller is compared to two competing metaheuristics, Artificial Bee Colony (ABC) and Corona Virus Search Optimizer (CVSO), under the same simulation conditions. The results show that the AOA achieves the lowest ITAE of 0.078262 with fast and steady convergence, while the ABC and CVSO stagnate at higher values of 0.19862 and 0.18077, respectively. In terms of transient response, the proposed controller significantly reduces stabilization time and overshoot, with t_s = 0.78925s and M_p = 0.34876%, respectively.

Nomenclature

ABC	**Artificial Bee Colony**	c_b	**Back-emf constant**
AOA	Arithmetic Optimization Algorithm	C_{bm}	Coefficient of friction
ArOA	Archimedes Optimization Algorithm	C_{Jm}	Motor inertia
BA	Bat Algorithm	c_t	Torque constant
CHR	Chien-Hrones-Reswick	f_{em}	Counter-electromotive force
CVSO	Corona Virus Search Optimizer	i_a	Current in the armature
FFA	FireFly Algorithm	K_d	Derivative gain
GA	Genetic Algorithm	K_i	Integral gain
ITAE	Integral Time Absolute Error	K_p	Proportional gain
MOA	Math Optimizer Accelerated	L_a	Armature inductance
MOP	Math Optimizer probability	M_p	maximum overshoot
PID	Proportional-Integral-Derivative	R_a	Armature resistance
PSO	Particle Swarm Optimization	T_m	Motor torqua
SMA	Slime Mould Algorithm	t_p	Peak time
ZN	Zeigler-Nichols	t_r	Rise time
t_s	Settling time	u_{in}	Input voltage
ω_m	Angular velocity		

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Introduction

The integration of mobile robots into everyday tasks is increasing rapidly, especially in the medical field, where it indicates a growing trend toward more automation and the rapid acceptance of modern technology [1]. These robotic systems, in numerous forms, are utilized to increase service quality while helping to minimize expenses. Among the most prevalent platforms in this context, wheelchairs have a crucial role [2]. They play an essential role in supporting the independence of people with disabilities, helping them to carry out various activities of daily living, including certain spiritual practices.

Designing a PID regulator that is both accurate and well-suited to the process remains a major challenge for researchers in this field [3]. In an industrial context, it is generally possible to successfully design and implement fixed-gain controllers for linear systems with invariant parameters [4]. The literature gives various traditional approaches to PID gain adjustment, including the Cohen-Coon [5], Ziegler-Nichols [6], and Chien-Hrones-Reswick methods [7]. However, these strategies are restricted when it comes to adjusting a PID regulator for nonlinear systems with time-varying parameters, which is the case with electric wheelchairs.

Authors in [8] focus their work on the adaptation of the PID regulator tuning for the motors of an electric wheelchair through the bat algorithm (BA) which is a nature-inspired optimization strategy derived from the echolocation behavior of bats. They benchmark the outcome with a PSO-based tuning. The experimental evidence shows that the BA method provides much better and higher quality control at the same time considerably reducing the computation time as compared to the PSO method. Nonetheless, the authors admit that the time of stabilization and the overshoot rate still represent large values. Taking this paper as a starting point, the authors of [9] advocate augmenting the PID control of electric wheelchairs by means of a multi-metaheuristic optimization which in their case consists of the Firefly Algorithm (FFA), Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Grey Wolf Optimizer (GWO). A series of comparative tests reveal that the GWO-PID controller leads to a faster system response when it is utilized for controlling this nonlinear system with time-varying parameters.

Firefly (FF) and Genetic Algorithm (GA) have been employed in [10] to adjust the gain parameters of a PID controller in order to ensure that the mobile robot is accurately controlled and guided to the set target. Simulation outcomes reveal that the PID controller adjusted through the Firefly algorithm (FF-PID) leads to a closed-loop reaction that complies with the performance criteria, hence it can be used for controlling the mobile robot. Moreover, the paper [11] has outlined a control method for a wheeled electric wheelchair with the Archimedes Optimization Algorithm (ArOA). The latter is employed to tune the gains of the PID controller used for regulating a DC motor that is part of the drive wheels. The effectiveness and reliability of the approach presented in this paper have been confirmed through simulations. Additionally, the results demonstrate that the ArOA-PID controller achieves better performance in terms of transient response quality when compared to other metaheuristics, such as SCA-PID (sine-cosine algorithm) and SMA-PID (Slime Mould algorithm) controllers.

The combination of metaheuristics for tuning the gains of a PID controller is a good way to create a system that can be adjusted and controlled easily, even if the system is nonlinear and its parameters change with time. Several optimization methods have been discussed before in the literature, such as genetic algorithms (GA), particle swarm optimization (PSO), firefly algorithms (FA), and other similar techniques [12].

Recent work has shown how metaheuristics can play a vital role in the automatic adjustment of the gains of a PID controller to mitigate the shortcomings of manual or empirical settings (operator dependency, variable performance, and sensitivity to disturbances). Still, a number of these methods are plagued by slow convergence, a possibility of being trapped in local minimum, or most of the time they lack a fair comparison between algorithms. This work sets out to utilize a

new metaheuristic, the Arithmetic Optimization Algorithm (AOA), for PID tuning in a DC motor speed control problem (electric wheelchair application), using a single performance criterion (ITAE) and a homogeneous comparison protocol. Then the AOA-PID controller's performance is measured and compared to that of other methods based on ABC [13] and CVSO [14] metaheuristics, thus the results of the paper clearly demonstrate the effectiveness of the proposed method for accuracy, overshoot, and stabilization speed.

The primary contributions of this document are as follows:

- Mathematical modeling of the wheel electric wheelchair.
- AOA is suggested to adjust the PID gains regulator to control the system under study.
- A comparison between AOA-PID and other approaches was performed to validate its effectiveness and superiority based on system convergence and transient response criteria.

The following section is devoted to presenting the electric wheelchair system with wheels studied. Section 3 describes in detail the proposed approach for optimizing the gains of the PID regulator. The simulation and its analysis are presented in Section 4. Finally, we conclude this work and suggest several avenues for further research.

Modelisation of the studied system

The electric wheelchair under study uses two independent drive wheels, each equipped with a DC motor. The side and top views of the system under consideration are depicted in Figure 1 below:

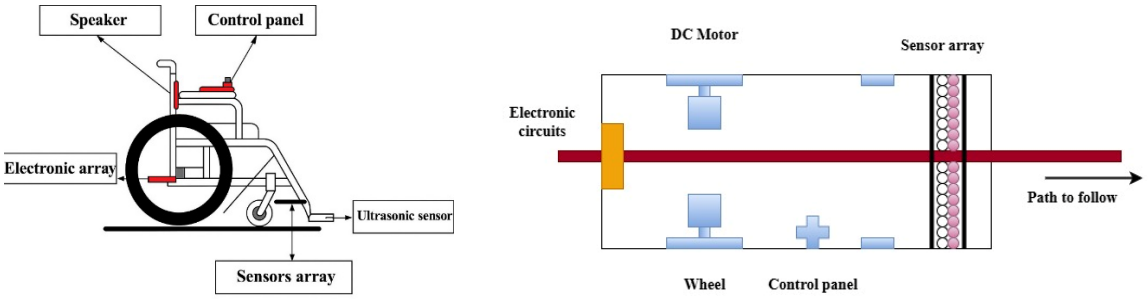
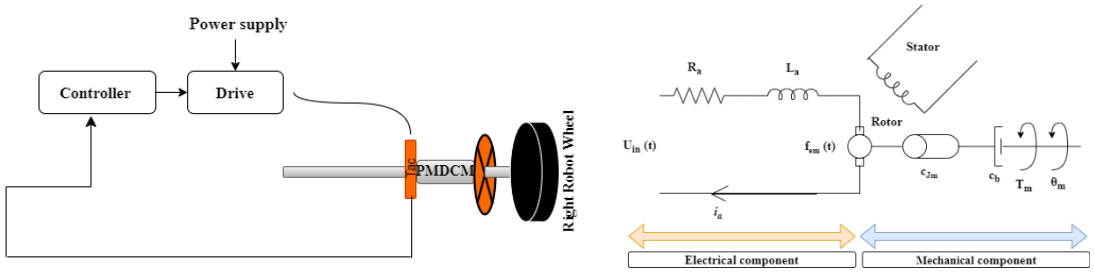


Fig. 1. The side and the upper view of the Electric wheelchair.

The DC motor is a complex system that combines both electrical and mechanical components. In this study, the symmetrical moiety of the robot is built to facilitate analysis and design. Figures 2.a and 2.b show an equivalent depiction of the two motor parts.



(a) (b)

Fig. 2. (a) A half-simplified model of the wheeled electric wheelchair, (b) Equivalent simplified illustration of the engine components.

When tension is applied to the motor coils, usually from an external power source, an electric current flows through the coils. This current creates a magnetic field around the rotor windings. According to Laplace's law, when this magnetic field interacts with the static magnetic field

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generated by the permanent magnets in the stator, a torque is produced. The torque produced by the engine T_m is proportional to current in the armature i_a, with a coupling constant c_t. This is described by Eq. 1:

$$T_m = c_t \times i_a \tag{1}$$

By rotating the motor's armature coils in the stationary magnetic field, a counter-electromotive force f_{em} is generated. This is proportional to the angular velocity of the motor shaft. The following equation can be used to express the Eq. 2:

$$f_{em} = c_b \times \omega_m \tag{2}$$

where $f_{em}(V)$ is the back electromotive force, $c_b(V.s.rad^{-1})$ is a proportionality constant that depends on the specific characteristics of the motor, and $\omega_m(rad.s^{-1})$ is the angular velocity of the motor shaft.

By using Kirchhoff's law on the RL electric part depicted in Figure 2.b, we obtain Eq. 3:

$$u_{in} = R_a \times i_a(t) + L_a \frac{di_a(t)}{dt} + c_b \times \omega_m(t) \tag{3}$$

where $u_{in}(V)$ denotes the input voltage applied to the motor, $R_a(\Omega)$ and $L_a(H)$ represent the resistance and inductance of the armature, respectively.

By taking the transformation of the Laplace to equation (3), we obtain Eq. 4:

$$I_a(p) = \frac{U_{in}(p) - c_b \times \omega_m(p)}{R_a + p \times L_a} \tag{4}$$

The mechanical part of the system is given by Eq. 5:

$$c_t \times i_a(t) - c_{Jm} \frac{d^2\theta_m(t)}{dt^2} - c_{bm} \frac{d\theta_m(t)}{dt} = 0 \tag{5}$$

where $c_{Jm}(Kg.m^2)$ denotes the equivalent inertia of the geared motor, and $c_{bm}(N.m.s)$ represents the viscous damping coefficient.

By taking the Laplace transformation to Eq. 5, we obtain the following relationship:

$$I_a(p) = \frac{c_{Jm}.\theta_m(p).p^2 + c_{bm}.\theta_m(p).p}{c_t} \tag{6}$$

Finally, we get the transfer function derived from Eq. 4 and Eq. 6, which is expressed as follows:

$$G(p) = \frac{c_t}{c_{Jm}.L_a.p^2 + (R_a.c_{Jm} + L_a.c_{bm}).p + R_a \times c_{bm} + c_t \times c_b} \tag{7}$$

Electric wheelchair main parameters are listed in Table 1.

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Table 1. Parameters of DC motor utilized in simulations.

Parameters	Values
Supply voltage	U_{in} = 12V
Torque constant	c_t = 1.188 N.m/A
Armature resistance	R_a = 0.156 Ω
Armature inductance	L_a = 0.82 mH
Back-emf constant	c_b = 1.185 rad.s^{-1}.V
Motor inertia	C_{Jm} = 0.275 Kg.m^2
Coefficient of friction	C_{bm} = 0.392 N.m.s

We obtain the transfer function used in the simulation by substituting the values mentioned in Table 1 into Eq. 7.

$$G(p) = \frac{1.187}{0.2256\ \mathrm{p}^2 + 0.3645\ \mathrm{p} + 1.468} \tag{8}$$

Proposed PID controller

The primary goal of this paper is to adjust a control strategy for the movement of an electric wheelchair. To do this, a gradual supply voltage $U_{in}(p)$ is delivered to the system, while the velocity is regulated by means of the proposed regulator in a closed feedback loop. The reference and current velocity of the system are compared to obtain the error $e(t)$, which is then fed into the PID regulator responsible for correcting the response dynamics. The parameters of this regulator are then adjusted using the algorithm AOA, adopting as the objective function the integral time of absolute error (ITAE) criterion, defined by Eq. 9:

$$ITAE = \int_0^t t\left|e(t)\right| dt \tag{9}$$

Among the many metaheuristic methods proposed in the literature, the arithmetic optimization algorithm (AOA), introduced by [15], stands out for its use of the distributive behavior of the four fundamental arithmetic operations (addition, subtraction, multiplication, and division). This algorithm was evaluated on several optimization problems to analyze its efficiency, speed of convergence, and complexity of computation. The results show that AOA outperforms eleven classical optimization algorithms in complex optimization tasks. For these reasons, this approach is chosen in this work to address the PID regulator tuning problem, compared with competing metaheuristics.

AOA begins by randomly generating a set of potential solutions. In our application, each solution (S_c) corresponds to the set of three PID regulator parameters, which can be expressed by the matrix (10):

$$S_c = \begin{bmatrix} S_c^{1,1} & S_c^{1,2} & \dots & S_c^{1,n-1} & S_c^{1,n} \\ S_c^{2,1} & S_c^{2,2} & \dots & S_c^{2,n-1} & S_c^{2,n} \\ \dots & \dots & \dots & \dots & \dots \\ S_c^{N-1,1} & S_c^{N-1,2} & \dots & S_c^{N-1,n-1} & S_c^{N-1,n} \\ S_c^{N,1} & S_c^{N,2} & \dots & S_c^{N,n-1} & S_c^{N,n} \end{bmatrix} \tag{10}$$

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At every iteration, the current best potential solution (S_c) is considered the provisional optimum. Before running the AOA-based optimization, the search domain must be specified and the Math Optimizer Accelerated (MOA) term determined. This coefficient is computed according to the following expression:

$$MOA(iter_{cur}) = min + iter_{cur} \cdot \left(\frac{max - min}{iter_{max}} \right) \tag{11}$$

where $MOA(iter_{cur})$ denotes the function value at the actual iteration $iter_{cur}$, with $1 \leq iter_{cur} \leq iter_{max}$. The parameters *min* and *max* correspond to the lower and upper bounds of the MOA, respectively.

During the exploration stage, the AOA uses two mathematical operators ((÷) and (×)) to get the optimum solution. This search phase is conditioned by $rand_1 > MOA(iter_{cur})$, and these two techniques are represented by Eq. 12:

$$S_{c_{i,j}}(iter_{cur}+1) = \begin{cases} (S_{c_j}^{Best}) \div (MOP + \varepsilon) \times (Ub_j \times \mu - Lb_j \times \mu + Lb_j), & rand_2 < 0.5 \\ (S_{c_j}^{Best}) \times MOP \times (Ub_j \times \mu - Lb_j \times \mu + Lb_j), & otherwise \end{cases} \tag{12}$$

where $S_{c_{i,j}}(iter_{cur}+1)$ denotes the j-th component of the i-th solution at the new iteration, and $S_{c_j}^{Best}$ is the j-th component of the best solution found so far. The term ε is a smaller integer, while μ is a control variable that tunes the process. Lb_j and Ub_jcorrespond to the lowest and highest limits of the j-th variable, respectively. The MOP is a coefficient given by the Eq. 13:

$$MOP(iter_{cur}) = 1 - \left(\frac{iter_{cur}}{iter_{max}} \right)^{1/\delta} \tag{13}$$

where $MOP(iter_{cur})$ denotes the value of this function at the actual iteration $iter_{cur}$, $iter_{max}$ is the total iterations, and $\delta = 0.5$ is a parameter controlling the accuracy of the process over the iterations.

In the exploitation stage, two mathematical operators are employed ((−) and (+)) to refine the current solutions. This phase is activated when $rand_1 < MOA(iter_{cur})$, and the corresponding update rules are given by the following expressions:

$$S_{c_{i,j}}(iter_{cur}+1) = \begin{cases} (S_{c_j}^{Best}) - (Ub_j \times \mu - Lb_j \times \mu + Lb_j) \times MOP, & rand_3 < 0.5 \\ (S_{c_j}^{Best}) + (Ub_j \times \mu - Lb_j \times \mu + Lb_j) \times MOP, & otherwise \end{cases} \tag{14}$$

During the exploration and exploitation stages, the MOA is augmented linearly from 0.2 to 0.9. The pseudo-code of AOA for the PID regulator is shown in Figure 3:

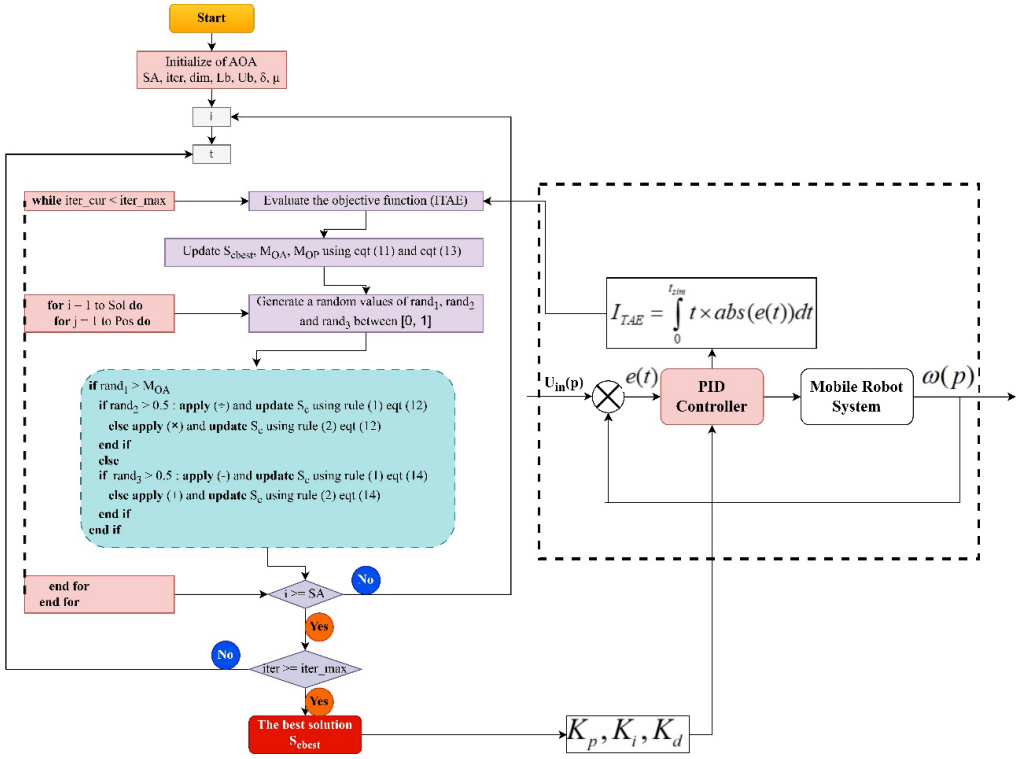


Fig. 3. Flowchart for IR using the AOA algorithm

The control signal *u(t)* generated by the regulator depends on three setting parameters, which are formulated by the following relationship:

$$u(t) = K_p.e(t) + K_i \int_0^t e(\tau).d\tau + K_d.\frac{de(t)}{dt} \tag{15}$$

where K_p is the proportional parameter, K_i is the integral parameter, and K_d is the derivative parameter of the PID controller.

Simulation Results

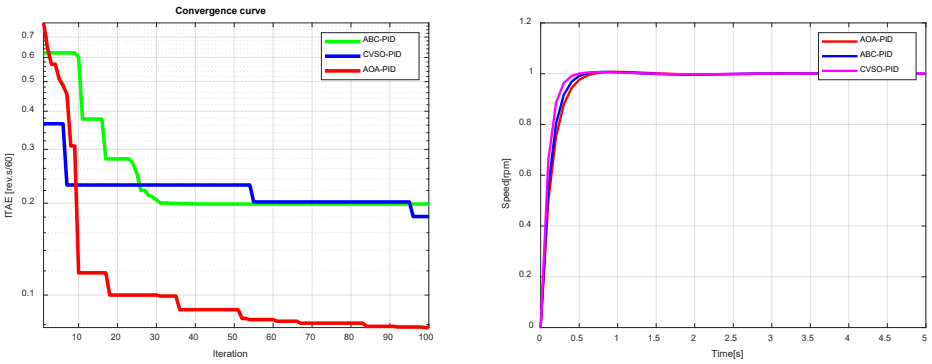
The effectiveness of the AOA-PID is evaluated in terms of transient response and convergence performance and compared with the ABC-PID and CVSO-PID. Simulations were carried out in a MATLAB on a laptop running Windows 10 64-bit, Intel® Core™ i5-6300U CPU @ 2.40GHz 2.50GHz, RAM (8GB). We used the default settings of the selected metaheuristics.

Table 2 highlights the efficiency and superiority of the proposed AOA-PID regulator. The outstanding performance of this regulator is clearly evident in the quality of the transient response. The AOA-PID offers significant improvements in terms of speed, stability, and accuracy compared with other optimizers evaluated, such as ABC-PID and CVSO-PID.

Table 2. Response transient criterion and gains for the regulator.

PID controller	AOA-PID	ABC-PID	CVSO-PID
K_p	9.92588	6.75738	6.19516
K_i	30	27.2335	24.9115
K_d	6.14339	4.18235	3.86144
$t_s(s)$	0.78925	2.7537	3.3921
$M_p(\%)$	0.34876	2.2768	4.32192

Figure 4.a displays the convergence curves of three metaheuristic optimization algorithms used to minimize the objective function ITAE during PID regulator tuning. A comparative analysis of these curves highlights significant performance differences. The AOA demonstrates superior performance with rapid and consistent convergence from the first iterations, achieving a very low ITAE of 0.078262. This indicates its excellent ability to efficiently explore the search space and exploit it effectively, demonstrating robustness against local minima. Conversely, the CVSO algorithm initially converges correctly but quickly stabilizes near an ITAE of 0.18077. Meanwhile, the ABC shows the poorest performance: after an initial improvement, the curve stagnates above 0.19862, suggesting limited optimization ability and a tendency to become trapped in a local minimum. In summary, AOA proved to be the best-performing algorithm among the three tested, due to its speed, stability, and accuracy in optimizing the PID gain parameters.



(a) (b)

Fig. 4. (a) Speed regulation using various control methods, (b) Convergence curve for the optimizers employed.

Figure 4.b illustrates the speed response of a DC motor subjected to three distinct PID control methods: AOA-PID, ABC-PID, and CVSO-PID. Among these approaches, the regulator based on the AOA stands out for its superior dynamic performance. Its curve shows a rapid rise towards the set speed, with very low overshoot, and rapid stabilization without oscillations around the reference value.

Conclusion

This study proposed an automatic PID parameter tuning approach based on the Arithmetic Optimization Algorithm (AOA) for speed control of a DC wheelchair motor. Given the limitations of conventional methods such as Ziegler-Nichols, the AOA was chosen for its ability to balance exploration and exploitation during optimization.

Simulation results demonstrate the superiority of AOA-PID, which achieves the best value of the objective function used with ITAE=0.078262, stable convergence, while significantly improving transient response indicators, stabilization time $t_s = 0.78925s$ and overshoot $M_p = 0.34876\%$, compared to ABC-PID and CVSO-PID approaches.

However, this study remains limited to a purely simulated framework, without taking into account real nonlinearities, friction, or load variations. Future work should focus on experimental validation, robustness testing, embedded implementation, and extension to more advanced control structures such as fractional or adaptive PID.

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