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Metaheuristic-based PID speed control of DC motors: a review of optimization algorithms, dynamic performance, and practical implementation

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ABSTRACT

DC motor speed regulation remains important in industrial automation, robotics, electric vehicles, and laboratory equipment because variations in load, friction, and operating conditions can produce unwanted speed deviations. Proportional–integral–derivative (PID) controllers are widely adopted due to their simple structure and practical implementation, yet their performance depends strongly on appropriate gain selection. Conventional tuning methods may provide unsatisfactory transient responses or limited robustness when motor parameters and operating conditions change. This review examines the application of metaheuristic algorithms to PID parameter optimization for DC motor speed control, with particular attention to particle swarm optimization (PSO), genetic algorithms (GA), artificial bee colony (ABC), grey wolf optimizer (GWO), and related approaches. The discussion compares their search mechanisms, optimization objectives, reported control benefits, and implementation limitations. It also considers the importance of realistic motor models, load-disturbance testing, actuator constraints, and experimental validation. The reviewed literature indicates that metaheuristic tuning can improve response characteristics when optimization is carefully formulated, although no algorithm is universally superior. The review identifies research priorities in robust multi-objective tuning, computational efficiency, reproducibility, and real-time implementation.

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1. INTRODUCTION

DC motors remain widely used in applications that require controllable rotational speed, relatively straightforward drive electronics, and reliable torque characteristics. Typical applications include conveyor systems, robotic actuators, electric mobility platforms, machine tools, and educational control laboratories. However, maintaining a desired speed becomes challenging when the motor experiences load variations, friction changes, supply-voltage fluctuations, or parameter uncertainty. These conditions can produce overshoot, prolonged settling time, steady-state error, and poor disturbance rejection.

PID control is a practical solution because its proportional, integral, and derivative actions provide a relatively simple means of regulating system response. The proportional component influences the immediate correction, the integral component reduces accumulated steady-state error, and the derivative component helps moderate rapid changes. Nevertheless, the effectiveness of the controller depends on the selected gain values and the characteristics of the motor-drive system. Conventional tuning methods, including Ziegler-Nichols procedures, may require repeated adjustment and can produce excessive overshoot or weak robustness under changing operating conditions [1]–[3].

Metaheuristic optimization offers an alternative approach by searching for suitable controller parameters through population-based or evolutionary procedures. Instead of relying exclusively on analytical tuning rules, these algorithms evaluate candidate PID gains against a specified performance objective.

Studies have applied particle swarm optimization (PSO), genetic algorithms (GA), and artificial bee colony (ABC) to DC motor control, while other work has investigated grey wolf optimization (GWO) and related optimization strategies [1], [4]–[9]. This review therefore examines the relationship between optimization strategy, PID performance, and practical implementation, identifying the conditions under which metaheuristic tuning can provide meaningful improvements.

2. PID CONTROL AND THE DC MOTOR SPEED-REGULATION PROBLEM

The performance of a PID-controlled DC motor depends on the interaction between the electrical and mechanical characteristics of the motor and the controller settings. Armature resistance, inductance, back electromotive force, rotor inertia, and friction influence the relationship between applied voltage and rotational speed. A simplified model can support initial controller design, but it may not fully represent saturation, dead zones, friction nonlinearities, or changes in load torque. Consequently, an optimizer that performs well on an ideal model may produce less satisfactory results when transferred to physical hardware.

PID tuning is commonly formulated as an optimization problem in which the controller gains are selected to minimize a performance index. Integral absolute error, integral squared error, integral time absolute error, and integral time squared error are frequently used to evaluate tracking performance. Time-weighted criteria place greater emphasis on errors that persist later in the response, which can encourage faster settling and smaller residual deviations. However, minimizing a single error index does not necessarily guarantee acceptable overshoot, control effort, stability margins, or robustness under disturbances [2], [3].

3. METAHEURISTIC ALGORITHMS FOR PID PARAMETER OPTIMIZATION

Metaheuristic algorithms explore a search space through candidate solutions and update mechanisms inspired by evolution, collective behavior, or natural processes. For PID tuning, each candidate solution represents a possible set of proportional, integral, and derivative gains. The motor model or experimental plant is evaluated using these gains, and the resulting performance index guides the search toward improved candidates. The approach is attractive for nonlinear or constrained tuning problems, although the final outcome depends on algorithm settings, search boundaries, objective functions, and computational resources [2], [10].

PSO is based on the collective movement of particles that update their search directions using individual and group experience. Its relatively simple structure and limited number of control parameters make it attractive for continuous optimization problems. In DC motor applications, PSO has been used to determine PID gains and improve speed-response characteristics compared with conventional tuning [1]. However, PSO may converge prematurely when population diversity decreases, particularly when the search space contains several competing local optima.

GA uses evolutionary operators such as selection, crossover, and mutation to improve a population of candidate solutions. Its population-based search can explore different regions of the gain space and is useful when the optimization landscape is irregular. Research on separately excited DC motors has demonstrated the use of GA for self-tuning PID parameters, including simulation and hardware-oriented implementation [4]. The main practical limitations include computational cost, sensitivity to population and mutation settings, and the possibility of slow convergence.

ABC models the foraging behavior of honeybee colonies through employed, onlooker, and scout search activities. Its search process combines local refinement with exploration of alternative candidate regions, which can help reduce premature convergence. A 2022 DC motor study applied ABC to PID tuning and compared its performance with variants of PSO, reporting improvements in convergence behavior and speed-response measures under the study's simulation conditions [5]. Nevertheless, its performance should be evaluated across repeated runs because stochastic initialization can produce different results.

GWO models the leadership hierarchy and hunting behavior of grey wolves, using leading candidate solutions to guide the population toward promising regions. Its relatively compact search structure has encouraged applications in engineering optimization, including motor-control problems. Vesović, Jovanović, and Trišović investigated DC motor velocity control using feedback linearization and GWO-based parameter optimization, with a nonlinear model that considered friction effects [6]. This work is relevant because it illustrates how optimization can be combined with a more detailed representation of motor dynamics, although its controller structure is not identical to a conventional standalone PID implementation.

Other algorithms, including Differential Evolution, Whale Optimization Algorithm, Gravitational Search Algorithm, Harmony Search, and Cuckoo Search, provide alternative exploration and exploitation mechanisms [11]–[18]. Their potential value lies in offering different balances between global search, local refinement, and parameter diversity. However, algorithm novelty alone does not establish superior control

performance. A meaningful comparison requires identical motor models, gain limits, objective functions, disturbance scenarios, and computational budgets.

4. COMPARATIVE ASSESSMENT OF OPTIMIZATION APPROACHES

The reviewed studies indicate that PSO, GA, ABC, and GWO are among the relevant approaches for PID gain optimization in DC motor speed regulation. Their strengths and weaknesses are associated with their search mechanisms rather than with a universal ranking of performance. Table 1 summarizes the main characteristics and practical considerations of representative algorithms. The comparison is qualitative because published studies do not consistently use the same motor parameters, objective functions, sampling periods, or test conditions.

Table 1. Comparative characteristics of metaheuristic algorithms for PID tuning

Algorithm	Main search principle	Potential advantages	Main limitations
PSO	Collective particle movement	Simple structure and relatively fast search	Premature convergence and sensitivity to parameter settings
GA	Selection, crossover, and mutation	Population diversity and flexible search	Computational cost and slower convergence in some cases
ABC	Bee-foraging behavior	Balances exploration and local search	May require many evaluations for fine convergence
GWO	Leadership hierarchy and hunting behavior	Compact structure and effective candidate guidance	Search diversity may decline in later iterations
Differential Evolution	Mutation and recombination of candidate vectors	Effective continuous-parameter search	Performance depends on scaling and crossover settings
WOA	Encircling and bubble-net search behavior	Alternative exploration–exploitation strategy	May stagnate on complex optimization landscapes
GSA	Gravitational interaction among candidate solutions	Population-based search with a distinct movement mechanism	Computational and parameter-setting considerations

Table 1 highlights that each algorithm offers a different search strategy, but none can be assumed to provide the best PID gains for every DC motor. PSO is attractive when implementation simplicity and relatively rapid optimization are priorities, whereas GA offers flexible population exploration. ABC and GWO provide alternative mechanisms that may improve search behavior for particular objective landscapes. The remaining methods broaden the available design options, but their suitability must be established through controlled comparisons rather than isolated performance claims.

5. OBJECTIVE FUNCTIONS AND PERFORMANCE EVALUATION

The selection of an objective function is central to the quality of metaheuristic PID tuning because it determines which control characteristics the optimizer prioritizes. An error-based objective can improve reference tracking, but it may overlook excessive actuator effort or poor disturbance rejection. For this reason, a comprehensive evaluation should include rise time, settling time, maximum overshoot, steady-state error, and control-signal behavior. The selected criteria should reflect the actual requirements of the motor application rather than simply producing the smallest numerical optimization value.

Single-objective optimization is convenient because it provides one scalar measure for ranking candidate PID gains. However, real motor drives often require simultaneous consideration of response speed, stability, energy consumption, and robustness. Multi-objective optimization can expose trade-offs between these competing requirements and provide a set of non-dominated controller solutions. Such an approach is particularly relevant when a fast response must be achieved without unacceptable overshoot, current peaks, or excessive control activity [2], [10].

A fair evaluation should also distinguish simulation performance from experimental performance. Simulation studies are useful for screening algorithms and testing parameter sensitivity under repeatable conditions. Hardware experiments are necessary to reveal effects such as sensor noise, PWM limitations, sampling delays, driver voltage drops, and unmodeled mechanical friction. The 2022 PSO-based study and the GA-based self-tuning study provide examples of work that extends beyond purely theoretical discussion, but further standardized experimental comparisons remain necessary [1], [4], [5].

6. IMPLEMENTATION CONSIDERATIONS AND RESEARCH GAPS

The first implementation challenge is the accuracy of the motor model used during optimization. If the model excludes important nonlinearities or load changes, the optimizer may select gains that are effective only under nominal conditions. Researchers should therefore identify motor parameters carefully and validate the model against measured speed and current responses. Where full identification is impractical, uncertainty ranges and representative operating scenarios should be incorporated into the optimization process.

The second challenge concerns the computational requirements of metaheuristic tuning. Population size, iteration count, and repeated objective-function evaluations affect the time needed to obtain optimized gains. Offline optimization is suitable when motor characteristics remain relatively stable and controller parameters can be determined before deployment. Online or adaptive optimization may be valuable when load and operating conditions vary significantly, but it must be designed to avoid excessive computation and unsafe transient behavior.

The third challenge is reproducibility and fair benchmarking. Metaheuristic algorithms are stochastic, meaning that a single successful run cannot establish consistent superiority over competing methods. Studies should report repeated-run statistics, convergence behavior, parameter bounds, population size, stopping criteria, and computational time. They should also compare algorithms under identical reference trajectories, load disturbances, motor parameters, and actuator constraints.

Future research should prioritize robust and multi-objective optimization that considers tracking error, overshoot, control effort, and disturbance rejection together. Hybrid algorithms may combine the global exploration of one method with the local refinement of another, although additional complexity must be justified by measurable benefits. Experimental validation using low-cost microcontrollers, encoders, and practical motor drivers would also improve the relevance of published findings. Finally, researchers should provide source code, motor parameters, and test protocols wherever possible to support reproducibility and independent verification.

7. CONCLUSION

Metaheuristic optimization provides a useful approach for selecting PID parameters in DC motor speed-control systems, particularly when conventional tuning does not adequately address nonlinear behavior or competing performance requirements. The reviewed literature demonstrates the relevance of PSO, GA, ABC, and GWO, while other population-based algorithms offer additional possibilities for controller design. Nevertheless, the effectiveness of an optimizer depends on the motor model, objective function, search settings, and operating conditions used in the evaluation. No single algorithm can therefore be regarded as universally superior based on results obtained from different experimental or simulation configurations. A reliable design process should combine appropriate motor modeling, carefully selected optimization criteria, repeated-run statistical evaluation, and hardware testing. Multi-objective and robustness-oriented tuning deserve particular attention because practical motor drives must balance response speed, stability, disturbance rejection, and control effort. Greater consistency in benchmarking and reporting will make future comparisons more meaningful. These improvements can help translate metaheuristic PID tuning from simulation-based optimization into dependable DC motor control applications.

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