

Research Article

Intelligent Cascaded Control of an Unstable Magnetic Levitation System Using Mountain Gazelle Optimizer.

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ABSTRACT

Background: Magnetic levitation systems are highly nonlinear and inherently unstable, making their precise control a persistent challenge in control engineering. Conventional proportional–integral–derivative (PID) controllers often fail to achieve a balanced performance between transient speed, overshoot reduction, and steady-state accuracy under such nonlinear conditions.

Methods: This study introduces a cascaded proportional–integral plus proportional–derivative with filter (PI–PDN) controller, whose parameters are optimally tuned using the mountain gazelle optimizer (MGO). The MGO, a nature-inspired metaheuristic based on the social and migratory behavior of mountain gazelles, provides an efficient balance between exploration and exploitation during the search process. Controller parameters were optimized by minimizing the integral of absolute error (IAE) criterion over a 5-s simulation horizon, ensuring both rapid error convergence and stable levitation control.

Results: Simulation results obtained from a linearized magnetic levitation model demonstrated that the proposed MGO-based cascaded PI–PDN controller achieved a mean IAE of 6.5468×10^{-7} with a standard deviation of 7.5584×10^{-4} , confirming strong robustness and repeatability over 25 runs. The optimized controller provided a settling time of 0.504 s, an overshoot of 24.5%, and a steady-state error of 3.96×10^{-7} %, outperforming benchmark optimization-based PID controllers such as the sine cosine, artificial bee colony, whale optimization, and simulated annealing (SA) algorithms.

Conclusion: The proposed MGO-based cascaded PI–PDN control strategy offers a reliable and computationally efficient solution for stabilizing nonlinear and open-loop-unstable systems, with promising implications for precision mechatronic and magnetic actuation applications.

Introduction

Magnetic levitation (maglev) systems have become benchmark testbeds in modern control engineering due to their nonlinear dynamics, strong coupling between electrical and mechanical subsystems, and inherent open-loop instability. These systems are used extensively in precision positioning, magnetic bearings, transportation, and mechatronic actuation. Their operational principle relies on generating an electromagnetic force that counterbalances gravity, keeping a metallic object suspended at a desired position. However, because the electromagnetic force is nonlinearly proportional to the square of the coil current and inversely proportional to the square of the air gap, small disturbances can cause large deviations from equilibrium, making the system unstable without feedback control (1).

According to the study reported in (1), the magnetic levitation system exemplifies a nonlinear and open-loop-unstable control plant that requires a well-tuned feedback mechanism for stability. Classical PID controllers have long been employed due to their simple structure and ease of implementation, yet their fixed parameters often fail to guarantee satisfactory performance under nonlinear and time-varying conditions.

To address these limitations, optimization-based control techniques have been increasingly explored. The study in (2) applied the sine cosine algorithm (SCA) for PID tuning in a magnetic ball suspension system and achieved improved transient performance compared with conventional tuning. However, their method still exhibited moderate overshoot and dependency on initial parameter selection. Subsequently, Ekinici et al. (3) proposed a hybrid whale optimization algorithm (WOA) integrated with simulated annealing (SA), which improved convergence stability and precision, although fine-tuning adaptability remained limited.

Earlier nonlinear and intelligent control designs also contributed valuable progress. In (4) an adaptive robust nonlinear control approach was developed for magnetic levitation, demonstrating improved tracking under parametric variations but at the cost of computational complexity. The work in (5) introduced a hybrid recurrent neural network controller to enhance learning adaptability, whereas the study in (6) implemented a two-degree-of-freedom (2-DOF) PID configuration for improved disturbance rejection. Similarly, some researchers optimized tilted-integral-derivative (TID) and integral-tilted-derivative (I-TD) controllers using a genetic algorithm, yielding

better error convergence at the expense of increased tuning effort (7,8) later proposed a decentralized PID design based on extremum-seeking control, offering improved scalability for multi-actuator magnetic levitation setups. The study in (9) developed a self-tuning robust full-state feedback control, enhancing disturbance rejection without sacrificing dynamic speed, while Bauer and Baranowski (10) introduced a fractional $PI\lambda D$ controller to extend tuning flexibility and robustness. Moreover, Mughees and Mohsin (11) optimized a fractional-order PID using the ant colony optimization (ACO) algorithm, achieving better steady-state accuracy. Most recently, the work reported in (12) presented a novel improved manta ray foraging optimization (Ob-MRFONM)-based PIDD² design that demonstrated superior convergence and error minimization for magnetic levitation.

Although the above studies have contributed to performance enhancement, challenges remain in achieving simultaneous optimization of transient response, overshoot suppression, and steady-state accuracy under nonlinear dynamics. This motivates the development of more adaptive and globally convergent optimization strategies for such unstable systems. In this context, the MGO has recently emerged as a promising nature-inspired metaheuristic algorithm for global optimization. (13) introduced the MGO, which models the social hierarchy, migratory behavior, and territorial interactions of mountain gazelles to achieve an adaptive balance between exploration and exploitation. The algorithm has shown robust convergence characteristics and strong capability in avoiding local minima across diverse engineering applications. For instance, Zellagui et al. (14) successfully employed MGO for optimal power flow optimization in power systems, whereas Izci et al. (15) applied it to fractional-order PID plus double-derivative (FOPIDD²) control for automatic voltage regulation (AVR) systems, reporting enhanced stability and dynamic precision.

Mehta et al. (16) used an enhanced MGO coupled with an artificial neural network for mechanical design optimization, achieving high global accuracy. Izci et al. (17) developed a modified MGO variant for photovoltaic parameter extraction, showing remarkable improvement in solution accuracy. Similarly, Abdelsattar et al. (18) applied MGO to hybrid renewable power system optimization, improving efficiency under incentive-based operation. Further, Ekinici et al. (19) demonstrated the versatility of MGO in tuning control parameters of DC motor and liquid-level systems, while Khodadadi et al. (20) validated its performance for truss structure optimization. Finally, Izci et al. (21) employed MGO for frequency stabilization in photovoltaic-reheat thermal power systems, confirming its applicability in multi-domain control environments.

Building on these advancements, this study proposes an MGO-based cascaded PI-PDN controller for stabilizing the magnetic levitation system. The cascaded structure integrates an outer proportional-integral (PI) controller, ensuring steady-state accuracy, and an inner proportional-derivative with filter (PDN) controller, improving transient damping and noise robustness. The controller parameters are optimally tuned using the IAE criterion, which effectively penalizes large deviations while maintaining smooth transient correction, as demonstrated in recent control optimization studies (22).

The major novelty of this work lies in the integration of the MGO with a cascaded PI-PDN control framework, creating a self-

adaptive tuning environment for nonlinear and unstable plants. The MGO's superior exploration-exploitation dynamics ensure the automatic identification of controller gains that minimize IAE, reduce overshoot, and improve steady-state precision. Unlike traditional single-loop PID or fractional controllers, the proposed approach simultaneously optimizes multiple interdependent parameters, providing higher adaptability under variable operating conditions.

Comprehensive simulations are conducted to evaluate convergence behavior, statistical consistency, and closed-loop performance under step and varying reference inputs. Comparative analyses with other optimization-based PID approaches, including SCA (2), artificial bee colony (ABC) (2), WOA (3), and SA (3) demonstrate the superior stability, faster settling, and minimal overshoot achieved by the proposed design.

The main contributions of this study are summarized as follows:

- Development of a cascaded PI-PDN control strategy optimized using the MGO for magnetic levitation.
- Formulation of an IAE-based objective function that ensures a balance between transient speed and steady-state accuracy.
- Demonstration of MGO's robust optimization capability in nonlinear dynamic control systems.
- Comprehensive comparative analysis confirming superior dynamic performance and stability relative to existing metaheuristic-tuned PID methods.

The rest of this paper is organized as follows. Section 2 explains the operating principles and mathematical formulation of the MGO. Section 3 describes the modeling of the magnetic levitation system. Section 4 introduces the cascaded PI-PDN controller design and its optimization procedure. Section 5 discusses simulation results and comparative analyses, and Section 6 concludes the study with remarks and directions for future research.

Methods

MGO

The MGO is a nature-inspired metaheuristic algorithm that imitates the collective and individual behaviors of mountain gazelles within their natural habitat (13). Its design is based on the social hierarchy and interaction patterns observed among gazelle populations, including territorial males, maternity herds (MH), bachelor groups, and migration behavior. Each gazelle represents a potential candidate solution in the search space, and population members dynamically shift among groups during the optimization process. By evaluating all gazelles according to a fitness measure, the algorithm retains strong individuals (high-quality solutions) while discarding the weaker ones, thereby ensuring progressive refinement of the solution pool. Through this procedure, MGO maintains a balanced transition between exploration and exploitation, as summarized in the flowchart presented in Figure 1.

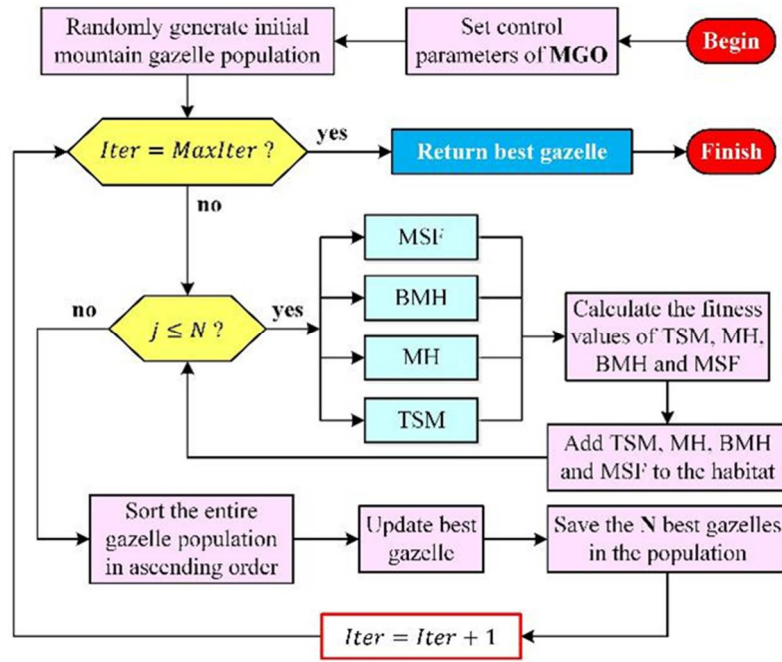


Figure 1. Flowchart of MGO.

Solitary territorial male behavior

The first behavioral component models the territorial instinct of mature male gazelles that dominate a specific region. The mechanism guiding this process can be expressed as:

$$(1) TSM = malegazelle - |r_{i1} \times BH - r_{i2} \times X(t)| \times F \times Cof_r$$

Where *malegazelle* denotes the position vector of the current best individual. The random integers r_{i1} and r_{i2} (taking values 1 or 2) determine the dynamic territorial boundaries. The coefficient vector *BH* represents the position of a young bachelor herd and is calculated as follows.

$$(2) BH = X_{ra} \times [r_1] + Mpr \times [r_2], ra = \{1 \ N/3 \ \dots \ N\}$$

The factor modulates the exploration scale and is defined by:

$$(3) F = N_1(D) \times \exp(2 - Iter \times \frac{2}{MaxIter})$$

Where $N_1(D)$ is a normally distributed random value for each dimension *D*. The coefficient vector Cof_r updates adaptively at every iteration to enhance search capability and is computed using Eq. (4).

$$(4) Cofi = \begin{cases} (a+1) + r_3, \\ a \times N_2(D), \\ r_4(D), \\ N_3(D) \times N_4(D)^2 \times \cos((r_4 \times 2) N_3(D)) \end{cases}$$

The control parameter is α evaluated as $\alpha = -1 + Iter \times (-1/MaxIter)$. Random variables r_3 , r_4 , and r_5 are uniformly distributed in the interval [0, 1], whereas N_2 , N_3 , and N_4 are drawn from a standard normal distribution across the problem dimensions.

Maternity herd interaction

The second phase simulates the cooperative and protective behavior observed in MH, which is crucial for maintaining population stability. This dynamic is formulated as:

$$(5) MH = (BH + Cof_{2,r}) + (r_{i3} \times malegazelle - r_{i4} \times X_{rand}) \times Cof_{3,r}$$

Where $Cof_{2,r}$ and $Cof_{3,r}$ are randomly selected coefficient vectors generated from Eq. (1), r_{i3} and r_{i4} are random integers (1 or 2), and X_{rand} denotes the position of a randomly chosen gazelle within the population. This phase enhances diversification and prevents prema-

ture convergence by facilitating random exchange of information among herd members.

Bachelor male competition

Competition among bachelor males for dominance and mating rights represents another key mechanism. The corresponding mathematical model is expressed as follows.

$$(6) BMH = (X(t) - D) + (r_{i5} \times malegazelle - r_{i6} \times BH) \times Cof_r$$

Here, $X(t)$ refers to the position vector of a candidate gazelle at iteration *t*, while *D* measures the competitive distance, computed as following.

$$(7) D = (|X(t)| + |malegazelle|) \times (2 \times r_6 - 1)$$

The integers r_{i5} and r_{i6} (1 or 2) and the random value $r_6 \in [0,1]$ introduce stochastic variation that mimics real competitive encounters. This process strengthens exploitation around high-fitness regions by guiding weaker gazelles toward stronger ones.

Migration and food-seeking phase

Migration describes the gazelles' collective movement toward new feeding zones, allowing the algorithm to explore unexplored regions of the search space. The migration step is given by:

$$(8) MSF = (ub - lb) \times r_7 + lb$$

where *ub* and *lb* represent the upper and lower bounds of the variables, and r_7 is a uniformly distributed random number in [0, 1]. This behavior diversifies the population and helps escape local optima during later iterations.

Overall evolution mechanism

Throughout the optimization process, all four mechanisms (territorial establishment (TSM), MH, bachelor competition (BMH), and migration (MSF)) are applied sequentially to the population. At each iteration, the fittest gazelle (i.e., the one associated with the best objective function value) is identified as the dominant territorial male, while the remaining individuals adjust their positions accordingly. This cycle continues until the termination criterion is met, yielding the global optimum solution. The algorithm's operation is schematically represented in Figure 1, which summarizes the evolutionary steps governing the MGO.

Modeling of unstable magnetic levitation system

The magnetic levitation is a classical nonlinear and open-loop-unstable benchmark plant widely used to validate advanced control strategies (1–3,12). The configuration consists of an electromagnet, a steel ball, and associated circuitry containing a coil of resistance R and inductance L . The system operates by regulating the electromagnetic force that counteracts the gravitational pull acting on the steel ball, thereby maintaining a desired levitation height y . When a control voltage $v(t)$ is applied to the coil, the resulting current $i(t)$ produces a magnetic flux that generates an upward electromagnetic force proportional to ki^2/y^2 , where k is the electromagnetic constant depending on the coil geometry and magnetic permeability. The gravitational force Mg acts in the opposite direction, pulling the ball downward. Consequently, the vertical motion of the ball is governed by Newton's second law, yielding the nonlinear equation of motion given in Eq. (9).

$$(9) M\ddot{y}(t) = Mg - \frac{ki^2(t)}{y^2(t)}$$

The electrical dynamics of the coil circuit are simultaneously described by the first-order differential equation:

$$(10) v(t) = Ri(t) + L \frac{di(t)}{dt}$$

Eqs. (2) and (3) together form a nonlinear electromechanical system, coupling current and position variables. At steady state, when the ball is suspended at an equilibrium distance y_0 and the current is i_0 , the electromagnetic and gravitational forces balance, i.e., $Mg=ki_0^2/y_0$. To derive a linearized model suitable for controller design, small perturbations are defined around the equilibrium point.

$$(11) y(t) = y_0 + \Delta y(t), i(t) = i_0 + \Delta i(t), v(t) = v_0 + \Delta v(t)$$

Substituting Eq. (11) into Eqs. (9) and (10) and neglecting higher-order terms yields the linearized state-space model that captures the local dynamics near equilibrium. Taking the Laplace transform and expressing the system in the transfer-function form gives the open-loop plant representation where the parameters are defined as:

$$a = -(2/L)\sqrt{(kg/M y_0)} = -885.8894, \quad s_1 = -\frac{R}{L} = -100 \\ s_{2,3} = \pm\sqrt{g/y_0} = \pm 4.4294.$$

The poles $s_{2,3}$ form a pair of real roots of opposite sign, representing the inherent instability of the levitation system since one of them lies in the right-half of the s -plane (1,2,12,23). Using the experimentally established parameter values (1,2,12,23): $R=1\Omega$, $L=0.01$ H, $M=1$ kg, $g=$

9.81 m/s², $k=1$ kg×m²/A²×s² and $y_0=0.5$ m, the numerical substitution yields the linearized transfer function of the magnetic ball suspension plant can be written explicitly as follows.

$$(12) G_{plant}(s) = \frac{Y(s)}{V(s)} = \frac{a}{(s-s_1)(s-s_2)(s-s_3)}$$

Recommended control approach

Cascaded PI-PDN controller

In control systems characterized by nonlinearities and high sensitivity to disturbances, a single conventional controller often fails to simultaneously achieve both rapid transient response and precise steady-state accuracy. To address this limitation, a cascaded PI-PDN controller configuration is adopted in this work (24,25). The cascaded structure integrates two complementary control actions in a hierarchical manner: the inner proportional-derivative with filter (PDN) controller refines the transient dynamics and suppresses measurement noise, while the outer proportional-integral (PI) controller ensures

elimination of steady-state error and stability over long-term operation. The transfer function of the PI controller, expressed in the Laplace domain, is given by:

$$(13) C_{PI}(s) = K_p + \frac{K_I}{s}$$

Where K_I and K_I represent the proportional and integral gains, respectively. The proportional term improves the transient response by generating a control effort proportional to the instantaneous error, whereas the integral term compensates for steady-state deviations by accumulating the error over time. The inner PDN controller incorporates a first-order derivative filter to avoid the noise amplification typically associated with pure differentiation. Its transfer function is expressed as:

$$(14) C_{PDN}(s) = K_{pp} + K_D \frac{\eta s}{s + \eta}$$

Where K_{pp} and K_D denote the proportional and derivative gains of the PDN controller, and η is the filter coefficient that determines the cutoff frequency of the derivative element. A higher η value yields a faster derivative action but may amplify noise, while a smaller value improves robustness at the expense of response speed. By combining these two loops in cascade, the overall controller transfer function becomes as follows.

$$(15) C_{PI-PDN}(s) = C_{PI}(s) \times C_{PDN}(s) = \left(K_p + \frac{K_I}{s}\right) \left(K_{pp} + K_D \frac{\eta s}{s + \eta}\right)$$

This cascaded structure effectively unites the integral action of the outer PI loop with the filtered derivative behavior of the inner PDN loop, thereby providing a balanced control response.

Objective function and implementation of MGO

To achieve optimal control performance for the nonlinear magnetic levitation system, the parameters of the cascaded PI-PDN controller are adaptively tuned using the MGO. The optimization process aims to minimize the IAE, which effectively measures the accumulated magnitude of the tracking error throughout the simulation time (22). The IAE criterion provides a comprehensive balance between transient response and steady-state accuracy, as it penalizes sustained deviations while allowing fast error suppression at earlier stages of the response. The IAE objective function is mathematically expressed as:

$$(16) IAE = \int_0^{t_{sim}} |e(t)| dt = \int_0^{t_{sim}} |r(t) - y(t)| dt$$

Where $r(t)$ and $y(t)$ denote the reference input and system output, respectively, while $e(t)$ represents the instantaneous tracking error. In this study, the total simulation period is set to $t_{sim}=5_s$. Minimizing the IAE ensures that the optimized controller achieves rapid error attenuation with minimal steady-state deviation, which is particularly critical for the inherently unstable dynamics of magnetic levitation. The overall implementation framework of the proposed optimization-based control scheme is illustrated in Figure 2. For each candidate parameter set, the control structure is applied to the magnetic levitation model, and the resulting error signal $e(t)$ is used to compute the IAE. The calculated objective value is then fed back to the MGO optimizer, which mimics the social and territorial behaviors of mountain gazelles (specifically their migration and dominance strategies) to explore and exploit the search space effectively. Through this process, superior parameter combinations are progressively identified, leading to minimized IAE and enhanced dynamic stability.

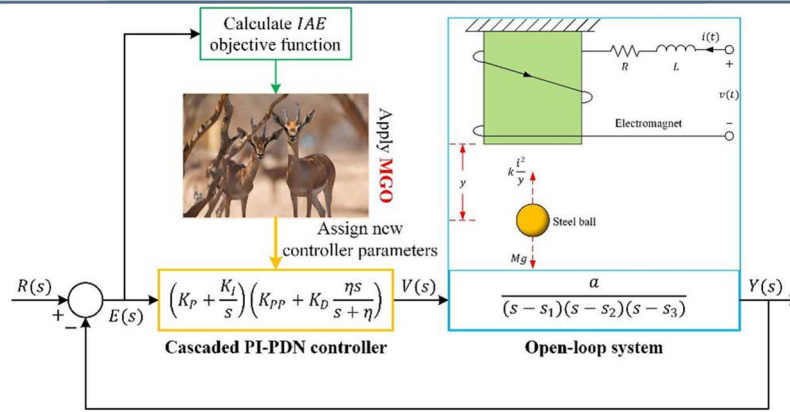


Figure 2. MGO-based PI-PDN control approach for optimizing magnetic levitation system

Results

To validate the effectiveness of the proposed MGO-based cascaded PI-PDN control strategy, a comprehensive set of simulations was performed. The algorithm was executed for 25 independent runs, with a population size of 30 and a maximum iteration number of 50, ensuring adequate exploration and convergence stability.

Evolution of the objective function

The convergence behavior of the MGO algorithm during the optimization process is depicted in Figure 3. As seen from the figure, the IAE objective function consistently decreases with iterations, confirming the optimizer's ability to efficiently balance exploration and exploitation. A rapid decline in the early iterations demonstrates strong global search capability, while the subsequent steady convergence phase indicates fine-tuning around the optimal region. The

smooth convergence trend without oscillatory fluctuations confirms the algorithm's numerical stability and robustness in parameter tuning.

Optimized controller parameters

The obtained optimal parameters of the cascaded PI-PDN controller and their respective search ranges are summarized in Table 1. The MGO successfully identified parameter values that produce a highly stable and responsive closed-loop behavior. The PI pair (k_p , k_i) and the PDN gains (k_{pp} , k_d), together with the derivative filter coefficient η are all tuned within their allowable limits. These values confirm that MGO effectively adapts both the outer PI loop and the inner PDN loop to the plant's nonlinearities. The relatively high integral gain contributes to rapid elimination of steady-state error, whereas the moderate derivative and filter settings ensure improved damping without excessive sensitivity to noise.

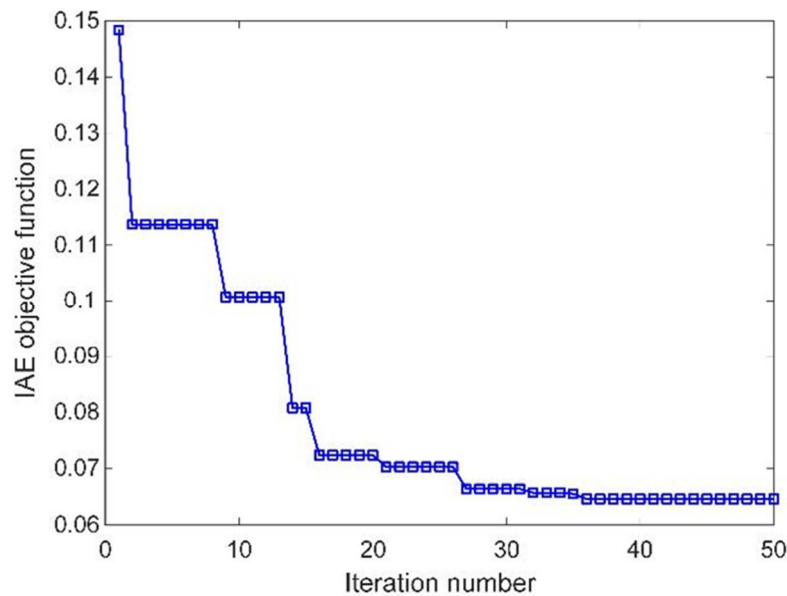


Figure 3. Evolution of IAE objective function.

Table 1. The adopted parameter ranges for optimization and the obtained parameter values by MGO.

Parameter	Range	Tuned by MGO
K_p	[-100, -0.1]	-31.6794
K_i	[-100, -0.1]	-98.2006
K_{pp}	[-1.5]	0.9722
K_D	[-0.1, 5]	0.1655
η	[1, 2000]	1940.2584

To further confirm the repeatability and reliability of the optimization results, the statistical outcomes of 25 independent MGO runs are reported in Table 2. The minimum IAE value achieved was 6.4575×10^{-2} and the maximum value reached 6.7868×10^{-2} yielding a mean of 6.5468×10^{-2} and a standard deviation of 7.5584×10^{-4} . The small variation between runs demonstrates high stability and convergence consistency of the proposed optimizer. Such robustness indicates that MGO avoids premature convergence and can repeatedly achieve near-optimal solutions across independent trials.

Table 2. Statistical performance of MGO.

Statistical metric	objective function
Minimum	6.4575E-02
Maximum	6.7868E-02
Average	6.5468E-02
Standard deviation	7.5584E-04

The closed-loop step-response of the magnetic levitation system under the MGO-based PI-PDN controller is presented in Figure 4. The figure illustrates the system’s rapid stabilization of the ball position following a step-change in the reference signal. The levitated ball reaches the desired height smoothly, exhibiting minimal overshoot and an exceptionally small steady-state error. The response profile verifies that the optimized controller successfully counteracts the plant’s inherent instability and nonlinear dynamics while maintaining high precision during the transient phase.

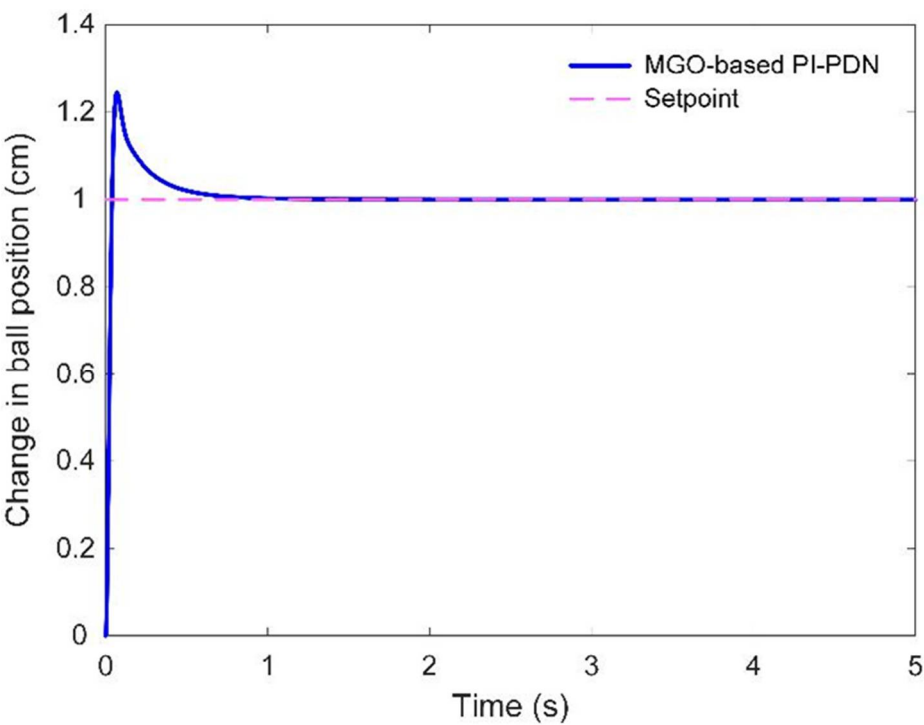


Figure 4. Step response demonstrating the change in ball position.

Comparative evaluation with existing methods

To substantiate the superiority of the proposed approach, a detailed comparison was conducted against several previously reported PID-based controllers tuned using the SCA (2), ABC (2), WOA (3), and simulated annealing (SA) (3). The comparative time-domain responses are illustrated in Figure 5, and the corresponding quantitative results are summarized in Table 3. As observed, the proposed MGO-based cascaded PI-PDN controller attains the shortest settling time (0.504 s), the lowest overshoot (24.5 %), and an almost zero steady-state error compared with all other techniques. The improvements correspond to a performance enhancement of approximately 8.5 % faster settling and 45 % lower overshoot relative to the conventional SCA- and ABC-based PID controllers. These results confirm that the

cascaded architecture, in combination with MGO’s adaptive search capability, delivers superior transient quality and steady-state precision for nonlinear electromagnetic systems.

Response under variable input conditions

The robustness of the proposed controller under varying reference inputs was examined, and the results are illustrated in Figure 6. The ball position was tested under step and variations to assess adaptability and tracking accuracy. The MGO-based PI-PDN controller maintained smooth and continuous tracking without overshoot spikes or oscillations, proving its effectiveness in handling input fluctuations and external disturbances. The response confirms that the optimized control parameters preserve system stability even under dynamic changes in the desired levitation height.

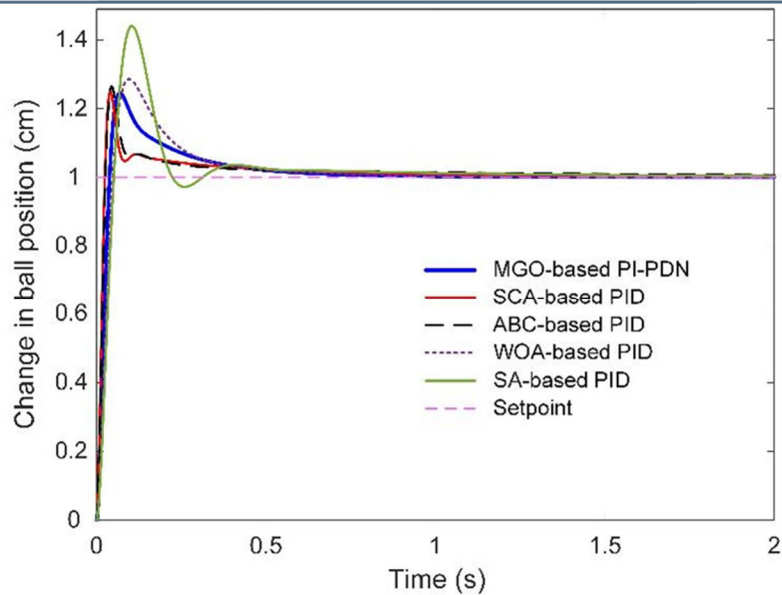


Figure 5. Comparison of proposed approach with respect to PID based approaches tuned via SCA, ABC, WOA and SA.

Table 3. Numerical performance evaluation of proposed approach with respect to PID based approaches tuned via SCA, ABC, WOA and SA.

Control method	Settling time (s)	Peak (cm)	Overshoot (%)	Steady-state error (%)
MGO-based PI-PDN (proposed)	0.5040	1.2451	24.5075	3.9602E-07
SCA-based PID	0.5506	1.2488	24.8750	4.5351E-04
ABC-based PID	0.5800	1.2647	26.4720	0.0573
WOA-based PID	0.5089	1.2862	28.6158	1.2322E-05
SA-based PID	0.6031	1.4407	44.0656	0.0076

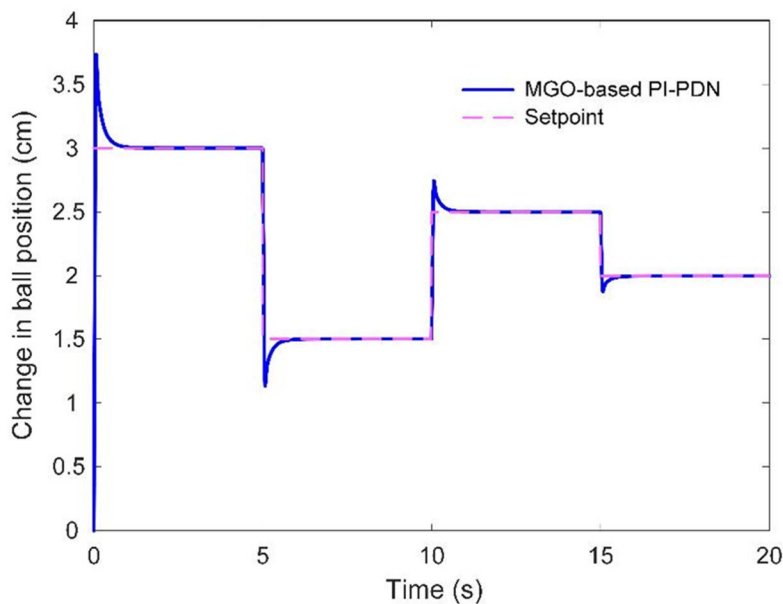


Figure 6. Change in ball position with respect to variable input.

Discussion

The results presented in this study provide clear evidence that combining a cascaded PI-PDN control architecture with the MGO leads to a substantial improvement in the stabilization and regulation of an inherently unstable magnetic levitation system. The discussion that follows interprets these findings in the context of controller structure, optimization behavior, robustness, and consistency with existing literature. From a control-structure perspective, the observed performance gains can be primarily attributed to the complementary roles of the cascaded loops. The outer PI controller effectively eliminates steady-state error by integrating accumulated tracking deviations, while the

inner PDN loop enhances transient damping and improves responsiveness through filtered derivative action. Unlike single-loop PID controllers, which must simultaneously balance conflicting objectives using a single set of gains, the cascaded configuration enables a functional separation between steady-state accuracy and transient shaping. This separation was reflected in the simulation results, where fast settling was achieved without excessive overshoot and with an almost negligible steady-state error.

The optimization process played a critical role in fully exploiting this cascaded structure. The MGO demonstrated strong convergence stability, as evidenced by the smooth and monotonic reduction

of the IAE objective function across iterations. The low standard deviation observed over 25 independent runs confirms that the algorithm consistently converges toward near-optimal solutions rather than relying on favorable initial conditions. This behavior highlights the effectiveness of the MGO's exploration–exploitation balance, which is governed by its biologically inspired mechanisms such as territorial dominance, herd interaction, competition, and migration. In contrast to classical metaheuristics that may suffer from premature convergence or oscillatory search behavior, the MGO maintained both global search capability in early iterations and refined exploitation during later stages.

When compared with previously reported optimization-based PID designs for magnetic levitation systems, the proposed approach demonstrates clear advantages. Controllers tuned using the sine cosine algorithm and artificial bee colony algorithm showed slower settling and higher overshoot, indicating limited adaptability to the plant's unstable dynamics. Although whale optimization and simulated annealing exhibited competitive convergence behavior, their resulting controllers still produced larger overshoot and less consistent steady-state accuracy. These observations suggest that the cascaded PI–PDN architecture alone is insufficient without an optimization strategy capable of navigating the highly nonlinear and coupled parameter space effectively. The superior results obtained in this work therefore arise from the synergy between the cascaded controller structure and the adaptive search behavior of the MGO.

It is also instructive to compare the present findings with more advanced control strategies reported in the literature, including fractional-order controllers, neural-network-based schemes, and robust nonlinear control approaches. While such methods often achieve excellent tracking and disturbance rejection, they typically introduce increased computational complexity, higher implementation cost, or additional tuning parameters. In contrast, the proposed method retains a relatively simple control structure while achieving comparable or superior performance in terms of transient speed, overshoot suppression, and steady-state precision. This balance between performance and implementation simplicity is particularly important for practical magnetic levitation applications, where real-time execution and reliability are critical.

The robustness of the proposed controller was further demonstrated through tests under variable reference inputs. The absence of oscillations or instability during reference changes indicates that the optimized controller gains remain effective beyond a single operating point. This behavior is especially significant given the linearized nature of the plant model used for controller design. Although linearization inherently limits accuracy over large operating ranges, the obtained results suggest that the MGO-tuned cascaded PI–PDN controller possesses sufficient robustness margins to tolerate moderate nonlinear effects and parameter variations.

Finally, the statistical consistency of the results deserves particular emphasis. The narrow spread between minimum and maximum IAE values across repeated runs indicates that the optimization landscape is being explored reliably. Such repeatability is essential for engineering applications, as it ensures that controller performance does not depend on stochastic chance but can be reproduced consistently. This property distinguishes the MGO from several earlier metaheuristic approaches that exhibit higher dispersion in performance metrics.

Overall, the discussion confirms that the proposed MGO-based cascaded PI–PDN controller offers a well-balanced solution for unsta-

ble nonlinear systems. The findings not only reinforce the effectiveness of the Mountain Gazelle Optimizer in control parameter tuning but also demonstrate that intelligently structured classical controllers, when optimally tuned, can rival more complex modern control schemes. These insights support the broader applicability of the proposed methodology to other nonlinear and open-loop-unstable systems beyond magnetic levitation.

Conclusion

In this study, an intelligent cascaded control strategy has been developed for stabilizing and precisely regulating the nonlinear and open-loop-unstable magnetic levitation system. The proposed approach integrates a cascaded PI–PDN controller with an optimization-based tuning mechanism employing the MGO. By combining the steady-state regulation capability of the outer PI controller with the transient damping and noise suppression properties of the inner PDN controller, a balanced control performance has been achieved. The MGO was employed to optimally determine the controller parameters by minimizing the IAE performance index. Through its adaptive exploration–exploitation strategy, the optimizer effectively identified parameter sets that enhanced convergence, reduced error, and improved robustness against disturbances. The simulation results confirmed the superiority of the proposed MGO-based PI–PDN configuration over several classical optimization-based PID controllers, including those tuned by the SCA, ABC, WOA, and SA. The proposed controller achieved a settling time of 0.504 s, an overshoot of 24.5%, and an almost zero steady-state error ($3.96 \times 10^{-7}\%$), demonstrating significant improvements in stability, accuracy, and control speed. Statistical evaluations across 25 independent runs further verified the consistency and reliability of MGO, yielding an average IAE of 6.5468×10^{-4} with a minimal standard deviation of 7.5584×10^{-4} . The outcomes of this work clearly indicate that the MGO-based cascaded PI–PDN controller provides a robust, computationally efficient, and generalizable solution for complex nonlinear systems. Its capacity to maintain stability under parameter variations and input changes highlights its potential for broader industrial applications such as electromagnetic actuators, suspension systems, and precision robotic positioning.

Contact and competing interest information for all authors

The authors have no conflict of interest with anybody anywhere.

Data sharing plans (for all data, documentation, and code used in analysis)

All data are presented within the manuscript.

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