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An adaptive decreasing sigmoid convergence factor for enhancing Grey Wolf Optimizer performance in high-dimensional optimization problems

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Abstract

Optimization algorithms require an effective balance between exploration and exploitation to achieve fast convergence and high solution quality. The Grey Wolf Optimizer (GWO) has demonstrated promising performance in various engineering applications; however, its conventional linear convergence factor often leads to premature convergence or insufficient exploitation, particularly in high-dimensional search spaces. To address this limitation, this study proposes an adaptive decreasing sigmoid convergence factor that dynamically regulates the transition between exploration and exploitation throughout the optimization process. Unlike the standard linear reduction scheme, the proposed sigmoid-based mechanism maintains stronger exploration during the early search stages and accelerates exploitation in later iterations through a controlled nonlinear decline. The proposed approach was evaluated using four widely adopted benchmark functions, namely Sphere, Rosenbrock, Rastrigin, and Griewank, under different dimensionalities, population sizes, and iteration limits. Experimental results demonstrate that the proposed method improves performance in most benchmark scenarios compared with the standard GWO. The best performance was obtained with a sigmoid parameter n = 0.75, which yielded near-optimal solutions for the Sphere and Griewank functions while maintaining stable convergence for the Rosenbrock function. The results further indicate that the proposed strategy scales effectively across medium- and high-dimensional optimization problems. These findings confirm that the adaptive decreasing sigmoid convergence factor provides a simple yet effective enhancement to GWO, offering improved convergence behavior and optimization accuracy across benchmark optimization problems.

Keywords:
Grey Wolf Optimizer;
Metaheuristic Optimization;
Convergence Factor;
Sigmoid Function;
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INTRODUCTION

Optimization has become a fundamental component of modern engineering systems, playing a critical role in improving efficiency, reliability, adaptability, and decision-making quality. The increasing complexity of cyber-physical systems, autonomous platforms, smart manufacturing environments, renewable energy networks, and intelligent transportation systems has intensified the need for advanced optimization techniques capable of handling nonlinear, multimodal, and high-dimensional search spaces [1][2]. In many real-world applications, suboptimal parameter settings may lead to increased energy consumption, reduced operational efficiency, degraded control performance, and instability. Consequently, optimization algorithms are increasingly integrated into control systems, robotics, power systems, machine learning, and industrial automation to enable adaptive and intelligent decision-making under dynamic conditions [3][4].

Among numerous metaheuristic optimization algorithms, the Grey Wolf Optimizer (GWO), originally proposed by Mirjalili et al., has attracted considerable attention due to its simplicity, low computational complexity, and competitive optimization performance [5][6]. Inspired by the leadership hierarchy and cooperative hunting behavior of grey wolves, GWO employs a population-based search mechanism that naturally balances exploration and exploitation through the interaction among alpha, beta, delta, and omega wolves. Because of these advantages, GWO has been successfully applied to a wide range of engineering problems, including controller parameter tuning, feature selection, power system optimization, robotic path planning, and energy management systems [7, 8, 9]. Recent surveys indicate that GWO remains one of the most actively investigated swarm intelligence algorithms due to its scalability and robustness across diverse optimization domains [8][9].

Despite its success, the standard GWO still suffers from several limitations that restrict its effectiveness when solving complex optimization problems. One of the most critical components influencing GWO performance is the convergence factor (*a*), which controls the transition between exploration and exploitation during the optimization process. In the original GWO formulation, the convergence factor decreases linearly from 2 to 0 throughout the search process [10][11]. Although computationally simple, this linear reduction mechanism may not adequately reflect the dynamic search requirements encountered in different optimization stages. A rapid decrease may prematurely suppress exploration and cause the algorithm to become trapped in local optima, whereas a slow decrease may delay exploitation and reduce convergence speed. These issues become increasingly significant in multimodal and high-dimensional optimization problems where an effective balance between global exploration and local exploitation is essential for achieving high-quality solutions [12, 13, 14].

To overcome these limitations, numerous studies have attempted to redesign the convergence control mechanism of GWO. Adaptive approaches based on population diversity and variance information have been proposed to dynamically regulate the search process, improving convergence stability but often introducing additional computational overhead. Other researchers have investigated nonlinear reduction strategies, including exponential, logarithmic, and polynomial decay functions, to provide more flexible transitions between exploration and exploitation [15, 16, 17, 18, 19]. Chaotic maps have also been incorporated to enhance population diversity and prevent premature convergence [20, 21, 22]. Furthermore, exploration-enhanced mechanisms, random-walk strategies, and hybrid algorithms that combine GWO with other metaheuristics, such as Particle Swarm Optimization (PSO), have demonstrated improved optimization performance [23, 24, 25]. While these approaches have achieved varying degrees of success, several important limitations remain. Adaptive mechanisms frequently require additional monitoring parameters and computational resources. Nonlinear decay schemes often exhibit strong sensitivity to parameter settings, and hybrid methods increase algorithmic complexity, making implementation and scalability more challenging.

The above observations reveal an important research gap. Existing convergence-control strategies generally attempt to improve either exploration capability or exploitation efficiency, but many fail to achieve a consistent balance between both objectives while maintaining algorithmic simplicity. Moreover, most studies rely on predefined decay profiles whose transition characteristics cannot adapt smoothly to different optimization phases. To the best of our knowledge, the use of a decreasing sigmoid convergence factor as a dedicated convergence-control mechanism for GWO has received very limited attention in the literature. A sigmoid function offers several desirable properties, including a naturally smooth nonlinear transition, controllable inflection behavior, and the ability to maintain strong exploration during the early search stage while rapidly strengthening exploitation as convergence approaches. These characteristics make the sigmoid function a promising candidate for improving convergence regulation without introducing additional algorithmic complexity.

Motivated by this gap, this study proposes a novel Adaptive Decreasing Sigmoid Convergence Factor (ADSCF) for the Grey Wolf Optimizer. The proposed mechanism replaces the conventional linear convergence schedule with a sigmoid-based nonlinear strategy that dynamically regulates the exploration–exploitation balance throughout the optimization process. The main contributions of this study are threefold. First, a new sigmoid-based convergence-control framework is introduced to enhance the search dynamics of GWO. Second, the effectiveness of the proposed strategy is systematically evaluated using four widely adopted benchmark functions representing both unimodal and multimodal optimization landscapes. Third, the robustness and scalability of the proposed approach are investigated under different dimensionalities, population sizes, and iteration settings. The results demonstrate that the proposed sigmoid-based mechanism improves convergence behavior, solution accuracy, and optimization robustness while preserving the simplicity and computational efficiency that characterize the original GWO.

METHOD

Standard Grey Wolf Optimizer

The Grey Wolf Optimizer (GWO), introduced by Mirjalili et al., is a swarm-based metaheuristic algorithm inspired by the social hierarchy and cooperative hunting behavior of grey wolves. In a wolf pack, individuals are categorized into four hierarchical groups: alpha (α), beta (β), delta (δ), and omega (ω). The α wolf represents the best candidate solution, followed by β and δ wolves, while the remaining wolves update their positions according to these three leading wolves.

In the process of hunting, to surround the prey, it is necessary to calculate the distance between the current grey wolf and the prey and then update the position accordingly. The behavior of grey wolves rounding up prey is defined as follows:

$$X_i = \{X_i^1, X_i^2, \dots, X_i^d\}, i = 1,2,\dots,N \tag{1}$$

$$X(t+1) = X_p(t) - A \times D \quad (1)$$

and

$$D = |C \times X_p(t) - X(t)| \tag{2}$$

where (1) is the updating formula of the grey wolf's position and (2) is the calculation formula of the distance between the grey wolf individual and prey. Variable t is the current iteration number, *Xp(t)* and *X(t)* are the current position vectors of the prey and the grey wolf at iteration *t*, respectively. *A* and *C* are coefficient vectors calculated by (3) and (4), respectively.

$$A = 2 \times a \times r_1 - a \tag{3}$$

$$C = 2 \times r_2 \tag{4}$$

and

$$a = 2 - 2 \times \frac{t}{t_{max}} \tag{5}$$

where a is the convergence factor, and a linearly decreases from 2 to 0 as the number of iterations increases. r_1 and r_2 are random vectors in [0, 1]. Equation (5) is the calculation formula a and t_{max} indicate the maximum number of iterations.

In an abstract search space, the position of the optimal solution is uncertain. In order to simulate the hunting behavior of grey wolves, α, β, and δ wolves are assumed to have a better understanding of the potential location of prey. α wolf is regarded as the optimal solution, β wolf is regarded as the suboptimal solution, and δ wolf is regarded as the third optimal solution. Other grey wolves update their positions based on α, β, and δ wolves, and the calculations (6), (7), and (8) are as follows:

$$\begin{aligned} D_\alpha &= |C_1 \times X_\alpha - X_t| \\ D_\beta &= |C_2 \times X_\beta - X_t| \\ D_\delta &= |C_3 \times X_\delta - X_t| \end{aligned} \tag{6}$$

and

$$\begin{aligned} X_1 &= X_\alpha - A_1 \times D_\alpha \\ X_2 &= X_\beta - A_2 \times D_\beta \\ X_3 &= X_\delta - A_3 \times D_\delta \end{aligned} \tag{7}$$

then

$$X(t+1) = (X_1 + X_2 + X_3)/3 \tag{8}$$

where D_α represents the distance between the current grey wolf and α wolf; D_β represents the distance between the current grey wolf and β wolf; D_δ represents the distance between the current grey wolf and δ wolf; and X_α, X_β, and X_δ represent the position vectors of α wolf, β wolf, and δ wolf, respectively. *X(t)* is the current position of the grey wolf. *C* are random vectors, calculated by (4). A_1, A_2, and A_3 are determined by (3). Equation (7) represents the step length and direction of grey wolf individuals to α, β, and δ wolves, and (8) is the position-updating formula of grey wolf individuals.

Adaptive Decreasing Sigmoid Convergence Factor (ADSCF)

The performance of GWO strongly depends on the convergence factor *a*. In the standard formulation, a linear decrease from 2 to 0 throughout the optimization process. Although computationally efficient, this linear schedule imposes a constant transition rate between exploration and exploitation.

In practical optimization problems, the search process rarely evolves linearly. During the early iterations, broader exploration is desirable to investigate diverse regions of the search space. Conversely, in the later stages, stronger exploitation is required to refine promising solutions. A fixed linear decay cannot fully accommodate these changing search requirements.

As a consequence, premature convergence may occur when exploration is suppressed too early, whereas excessive exploration may delay convergence and reduce optimization efficiency. These limitations become more pronounced in multimodal and high-dimensional optimization problems.

Therefore, a nonlinear convergence control strategy is required to dynamically regulate the exploration–exploitation balance throughout the search process.

To overcome the limitations of linear convergence control, this study proposes an Adaptive Decreasing Sigmoid Convergence Factor (ADSCF). The function is expressed as (9).

$$a(t) = a_{min} + \frac{a_{max} - a_{min}}{1 + \exp\left(\lambda(t - nT)\right)} \quad (9)$$

where a_{max} is the initial exploration strength, a_{min} is the final exploitation strength, n is the transition location, and λ is the transition steepness. The function is depicted in Figure 1.

The proposed Adaptive Decreasing Sigmoid Convergence Factor (ADSCF) regulates the exploration - exploitation balance through a smooth nonlinear transition mechanism. During the early stage of the optimization process, when the iteration number satisfies ($t < nT$), the convergence factor remains close to its maximum value (a approx a_{max}). Under this condition, the coefficient vector (A) exhibits larger fluctuations, allowing wolves to explore wider regions of the search space. Consequently, population diversity is maintained at a high level, enabling stronger global exploration and reducing the risk of premature convergence to local optima.

This behavior is particularly beneficial for multimodal optimization problems where multiple candidate regions must be investigated before promising solutions can be identified.

As the optimization progresses toward the midpoint of the search process ($t \approx nT$), the sigmoid function enters its inflection region and produces a rapid yet smooth decline in the convergence factor. This phase represents a controlled transition from exploration to exploitation. Unlike the conventional linear reduction strategy, which decreases exploration capability at a constant rate throughout the search process, the sigmoid-based mechanism preserves exploratory behavior for a longer period and then gradually redirects the search toward solution refinement. Such a transition improves the adaptability of the optimizer to different search stages and enhances the balance between diversification and intensification.

During the final stage of optimization, when ($t > nT$), the convergence factor approaches its minimum value ($a \approx a_{min}$). As a result, the movement of wolves becomes increasingly concentrated around the leading solutions represented by the alpha, beta, and delta wolves. The search process shifts from global exploration to local exploitation, allowing more intensive refinement of candidate solutions. This behavior accelerates convergence and improves solution accuracy by focusing computational effort on promising regions of the search space. Therefore, the proposed ADSCF provides a dynamic and adaptive search mechanism that maintains exploration when diversity is needed and strengthens exploitation when convergence becomes the primary objective. The proposed ADSCF does not modify the fundamental hunting mechanism of GWO. Instead, the conventional linear convergence factor in (5) is replaced by the proposed sigmoid-based convergence factor.

Therefore, position updating equations remain unchanged, hunting behavior remains unchanged, and computational complexity remains unchanged. The modification only affects the dynamic regulation of exploration and exploitation. This simplicity represents a major advantage over hybrid and multi-operator GWO variants.

Algorithm 1 summarizes the implementation procedure of the proposed ADSCF-GWO. Figure 2 illustrates the overall workflow of the proposed Adaptive Decreasing Sigmoid Convergence Factor Grey Wolf Optimizer (ADSCF-GWO).

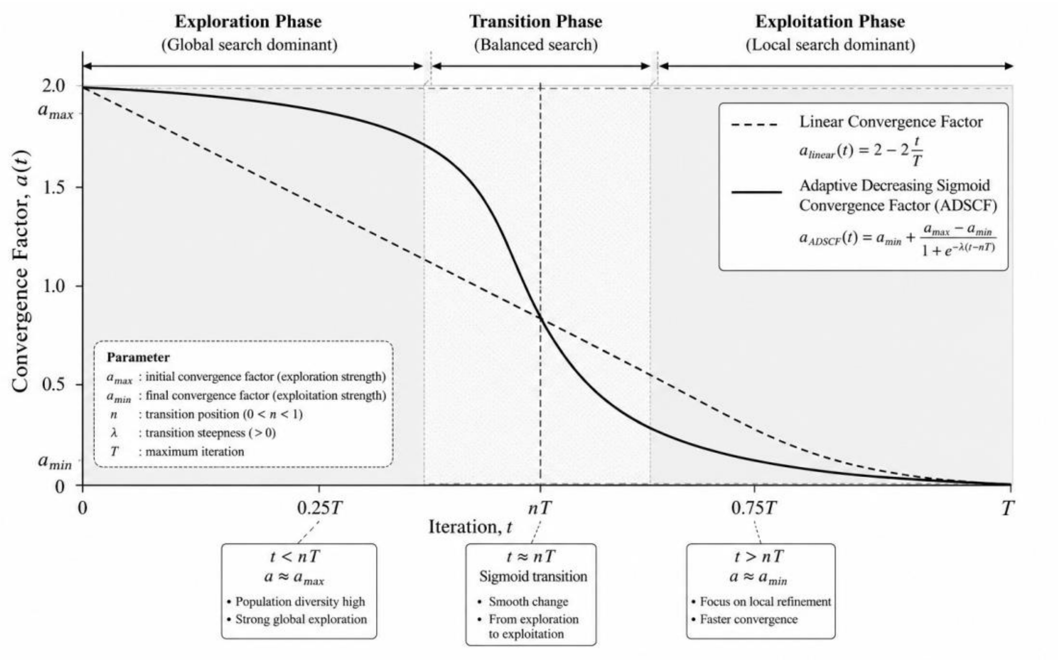

Figure 1. Linearly Decreasing and Sigmoid Convergence Factor

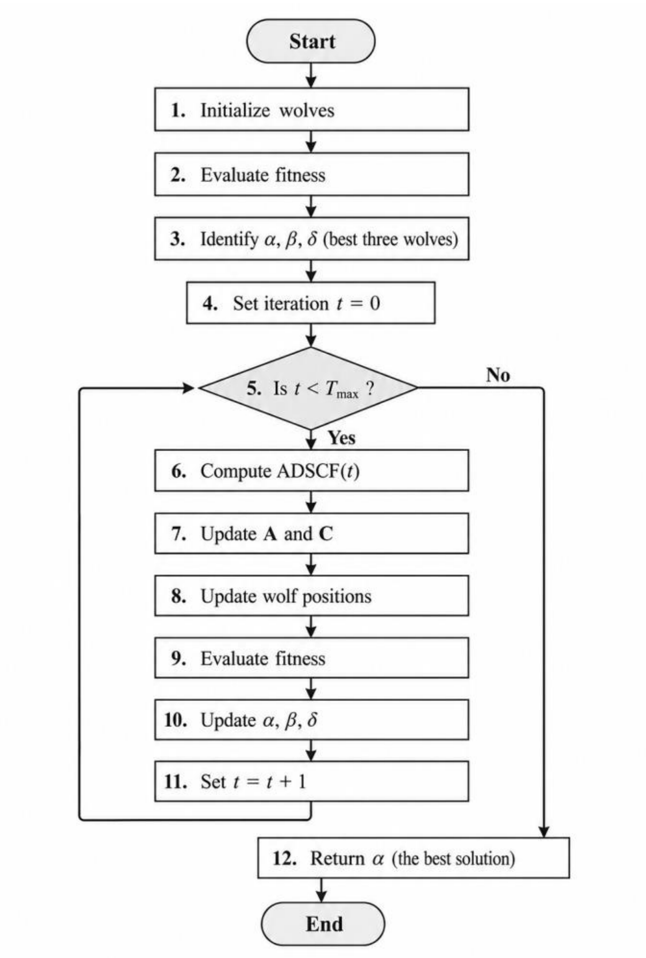

Figure 2. Adaptive Decreasing Sigmoid Convergence Factor Grey Wolf Optimizer (ADSCF-GWO) Flowchart

The pseudocode of full ADCSF-GWO is as follows:

```
Algorithm 1 ADSCF-GWO

Initialize wolf population
Evaluate fitness
Determine α, β, and δ wolves
for t = 1 to $T_{max}$
   Compute ADSCF(t)
   Update A and C
   Update wolf positions
   Evaluate fitness
   Update α, β, and δ
end for
Return α wolf as the best solution
```

Experimental Setup

The proposed ADSCF-GWO was evaluated using four widely adopted benchmark functions representing different optimization characteristics. The first function is the Sphere function given as:

$$f_0(x) = \sum_{i=1}^{n} x_i^2 \tag{10}$$

where x = [x1, x2, …, xn] is an n-dimensional real-valued vector. Then, the second function is the Rosenbrock function given as:

$$f_1(x) = \sum_{i=1}^{n} (100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2) \tag{11}$$

After that, the third function is the generalized Rastrigin function formulated as:

$$f_2(x) = \sum_{i=1}^{n} (x_i^2 - 10\cos(2\pi x_i) + 10) \tag{12}$$

Finally, the fourth function is the generalized Griewank function shown as:

$$f_3(x) = \frac{1}{400}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} \cos(\frac{x_i}{\sqrt{i}}) + 1 \tag{13}$$

These functions represent both unimodal and multimodal landscapes and a valley-shaped function, making them suitable for evaluating exploration and exploitation balance. Each function was tested with three different dimensionalities (5, 10, and 20). For each case, the maximum number of generations was set to 50, 100, and 200, respectively. To evaluate scalability, different population sizes (20, 30, and 50) were used. The proposed sigmoid-based convergence factor was varied using three different shape parameters (n = 0.25, 0.5, and 0.75). Each experiment was conducted under identical parameter settings, and the best fitness value obtained was used as the primary performance indicator for comparing convergence behavior among different convergence-factor configurations.

RESULTS AND DISCUSSION

Based on the experimental setup described in the previous section, a series of tests was conducted on four benchmark functions, Sphere, Rosenbrock, Rastrigin, and Griewank, under varying dimensions, population sizes, and iteration limits. The experiments were designed to rigorously evaluate the performance of the proposed sigmoid-based convergence factor compared to the standard GWO. By systematically adjusting the sigmoid constant (n = 0.25, 0.5, 0.75), the study aimed to observe how different shapes of the decreasing curve affect the trade-off between exploration and exploitation. The inclusion of multiple dimensions and population sizes further allowed us to assess the scalability and robustness of the method across different levels of problem complexity. In the following subsections, the results are presented and analyzed in terms of solution accuracy, convergence speed, and convergence behavior under different optimization settings, providing a comprehensive view of the strengths and limitations of the proposed approach.

The test results consist of the best fitness values for each operation process shown in Table 1, Table 2, Table 3, and Table 4 for each function of Sphere, Rosenbrock, Rastrigin, and Griewank. In addition, convergence graphs for each equation are shown in Figure 3, Figure 4, Figure 5, and Figure 6.

As shown in Table 1, the Decreasing Sigmoid approach applied to the Sphere function, particularly with sigmoid constants n = 0.5 and n = 0.75, produces the most optimal fitness values in many scenarios when compared to the linear GWO variant. For instance, in a configuration with dimension 20, population size 50, and 200 generations, the fitness value achieved with n = 0.75 is as low as 7.42E-07, significantly outperforming the linear approach.

The superior performance of the ADSCF-GWO with n = 0.75 can be explained by the delayed transition from exploration to exploitation introduced by the sigmoid convergence factor. Unlike the linear schedule, which continuously reduces the exploration capability throughout the search process, the sigmoid profile maintains a relatively high convergence factor during the early iterations.

Table 1. The best fitness values for the Sphere function

Population Size	Dim	Gen	Linear	Decreasing Sigmoid		
				***n* = 0.25**	***n* = 0.5**	***n* = 0.75**
20	5	50	3.49E+05	2.59E-02	1.40E+07	3.82E+03
	10	100	1.75E+06	2.28E-03	2.28E+06	7.27E+02
	20	200	1.92E+02	3.33E-03	1.30E+05	3.19E-02
30	5	50	3.52E+04	1.47E-03	6.54E+06	2.46E+02
	10	100	4.45E+04	1.17E-03	6.35E-04	6.40E+01
	20	200	1.37E+00	1.05E-04	2.35E+04	3.27E-02
50	5	50	9.72E+02	7.57E-04	8.17E+05	1.68E+01
	10	100	7.09E-01	7.91E+08	1.23E+02	1.71E-01
	20	200	3.51E-03	1.73E+09	1.42E+02	7.42E-07

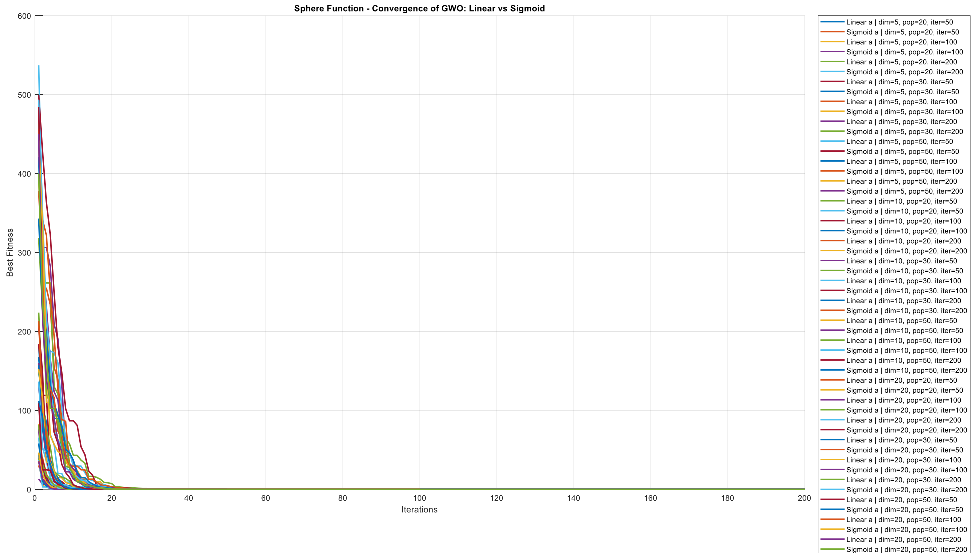

Figure 3. Convergence for Sphere Function

This behavior enables wolves to explore a wider search region and increases the probability of locating promising areas near the global optimum. Once the search enters the later iterations, the convergence factor decreases rapidly, intensifying exploitation around the best solutions. As a result, ADSCF-GWO achieves both strong global search capability and efficient local refinement, leading to faster convergence and lower fitness values on the unimodal Sphere function.

In the case of the Rosenbrock function, as presented in Table 2, the Decreasing Sigmoid approach with n = 0.75 again delivers generally lower fitness values. For example, at dimension 20, population 30, and generation 200, it achieves a fitness of 1.66E+01, compared to 1.71E+01 using the linear method. The Rosenbrock function is characterized by a narrow-curved valley that often causes optimization algorithms to experience slow convergence and premature stagnation. The ADSCF mechanism with n = 0.75 appears to improve navigation through this valley by preserving exploration during the early search phase while gradually strengthening exploitation near convergence. This balanced transition prevents excessive oscillation around suboptimal regions and enables a smoother search trajectory toward the global optimum. Consequently, the convergence behavior becomes more stable than that of the standard linear GWO.

Turning to the Rastrigin function (Table 3), the use of n = 0.75 within the Decreasing Sigmoid model proves effective under low-dimensional, small-population settings. An example is the configuration with dimension 10, population 20, and generation 100, where it reaches a fitness value of 1.27E-04. The inconsistent performance observed on the Rastrigin function suggests that the effectiveness of ADSCF strongly depends on the landscape characteristics of the optimization problem. Rastrigin contains a large number of regularly distributed local optima, making it highly sensitive to the exploration–exploitation balance.

Table 2. The best fitness values for the Rosenbrock function

Population Size	Dim	Gen	Linear	Decreasing Sigmoid		
				***n* = 0.25**	***n* = 0.5**	***n* = 0.75**
20	5	50	2.25E+00	4.24E+00	1.80E+00	2.24E+00
	10	100	8.10E+00	8.55E+00	7.94E+00	7.12E+00
	20	200	1.80E+01	1.91E+01	1.71E+01	1.76E+01
30	5	50	2.36E+00	4.08E+00	2.85E+00	2.14E+00
	10	100	7.83E+00	8.21E+00	7.93E+00	7.09E+00
	20	200	1.71E+01	1.85E+01	1.88E+01	1.66E+01
50	5	50	1.99E+00	2.34E+00	2.22E+00	1.94E+00
	10	100	7.03E+00	7.64E+00	7.51E+00	7.06E+00
	20	200	1.62E+01	1.84E+01	1.65E+01	1.72E+01

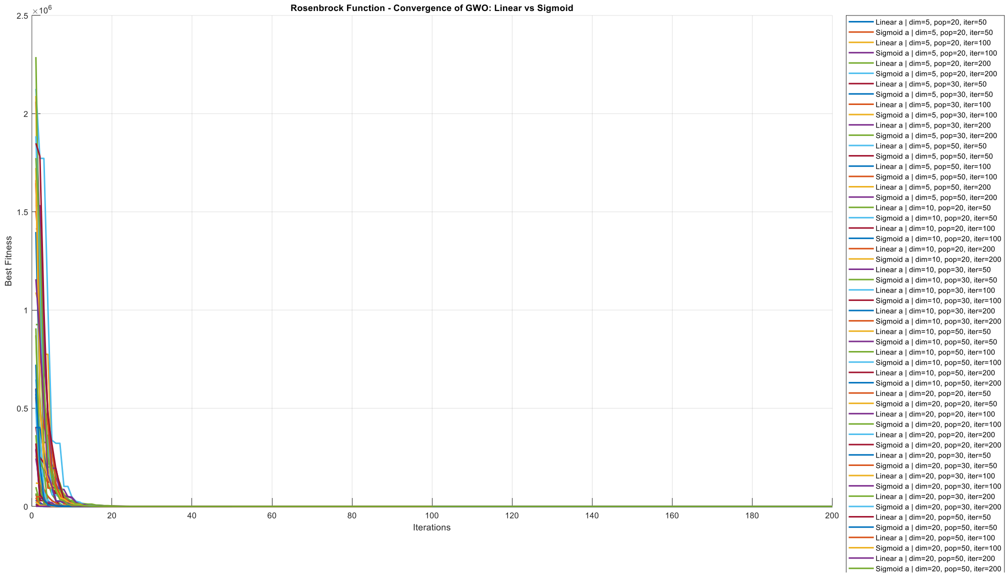

Figure 4. Convergence for Rosenbrock Function

Table 3. The best fitness values for the Rastrigin function

Population Size	Dim	Gen	Linear	Decreasing Sigmoid		
				***n* = 0.25**	***n* = 0.5**	***n* = 0.75**
20	5	50	2.61E+00	2.55E+01	5.20E+00	4.86E-01
	10	100	4.01E+00	4.17E+01	7.55E+00	1.27E-04
	20	200	4.56E+00	2.32E+01	1.83E+01	3.85E+00
30	5	50	2.63E+00	4.05E+00	9.09E+00	2.93E+08
	10	100	4.02E+00	4.21E+01	5.15E+09	1.16E+01
	20	200	6.91E+00	6.73E+01	4.84E+01	4.55E+01
50	5	50	4.98E+00	1.50E+01	4.98E+00	2.26E+08
	10	100	5.62E+00	9.67E+00	1.13E+01	3.31E-01
	20	200	6.52E+00	2.23E+01	1.84E+09	1.00E+03

When the sigmoid parameter is not properly selected, the convergence factor may decrease too rapidly, causing the search process to concentrate prematurely around local optima. This behavior explains the occurrence of several exceptionally large fitness values in certain configurations. Therefore, although ADSCF improves convergence in many scenarios, its parameterization must be carefully adjusted when dealing with highly multimodal optimization landscapes

Finally, Table 4 and Figure 6 reveal that the Griewank function benefits significantly from the Decreasing Sigmoid approach with n = 0.75. In several configurations, this setting results in the best and most stable outcomes. A notable case is dimension 20, population 50, and generation 200, where the fitness reaches 0, the optimal solution.

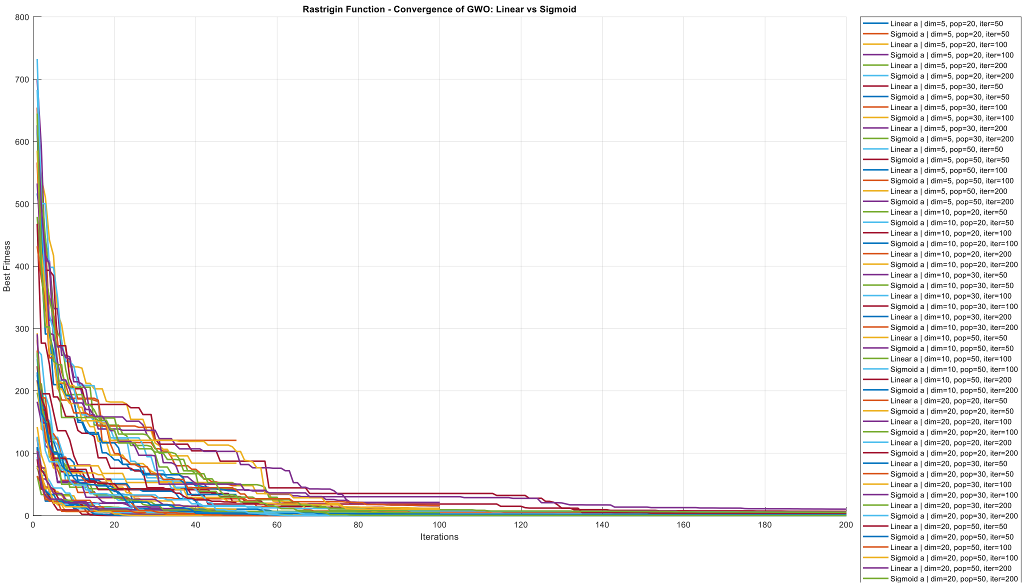

Figure 5. Convergence for Rastrigin Function

Table 4. The best fitness values for the Griewank function

Population Size	Dim	Gen	Linear	Decreasing Sigmoid		
				***n* = 0.25**	***n* = 0.5**	***n* = 0.75**
20	5	50	4.31E-02	1.86E-01	2.28E-02	9.40E-02
	10	100	7.80E-02	1.20E-01	4.95E-01	2.72E-01
	20	200	1.25E-02	2.62E-04	2.26E-02	1.30E-02
30	5	50	2.51E-02	1.56E-01	1.02E-01	7.60E-02
	10	100	2.40E-02	1.14E-01	1.74E-01	1.27E-01
	20	200	2.52E+00	1.97E+09	6.99E+02	3.46E-03
50	5	50	2.71E-01	3.19E-01	9.17E-02	8.83E-02
	10	100	1.13E-01	2.04E-01	1.77E-01	3.20E-02
	20	200	0	5.37E+06	9.04E+00	0

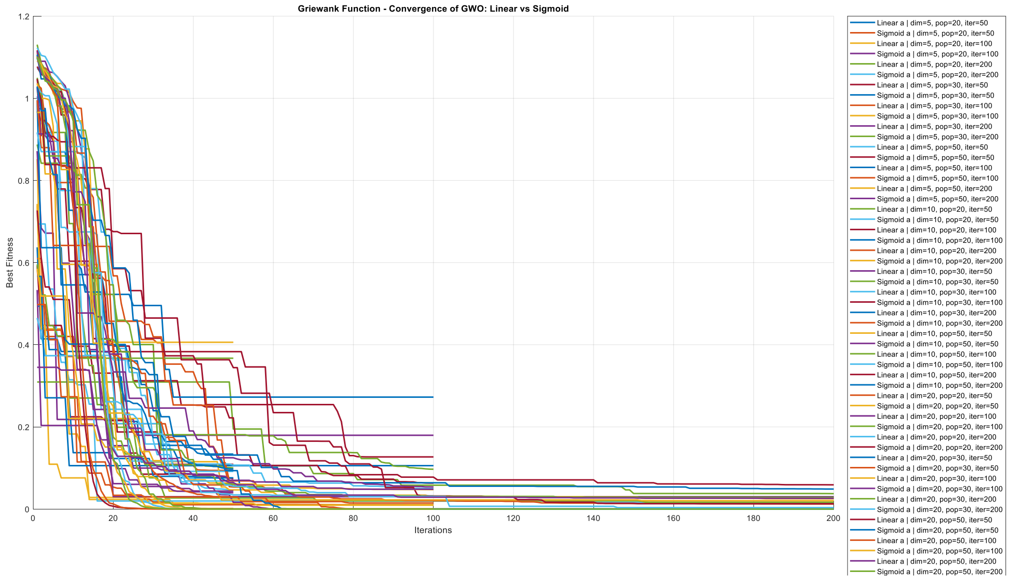

Figure 6. Convergence for Griewank Function

The superior performance of ADSCF-GWO on the Griewank function suggests that the sigmoid-based convergence factor effectively preserves population diversity during the early search phase. Because the Griewank landscape contains many regularly distributed local minima, maintaining exploration is essential to avoid premature convergence. The delayed inflection point associated with n = 0.75 allows wolves to explore more extensively before gradually focusing on exploitation, resulting in more reliable convergence toward the global optimum.

Overall, the Grey Wolf Optimizer (GWO) enhanced with an Adaptive Decreasing Sigmoid Convergence Factor (ADSCF), particularly with a sigmoid constant of n = 0.75, n = 0.75 generally demonstrates superior performance across most benchmark scenarios. This improvement is especially notable in problems with medium (10) and high (20) dimensions, as well as larger population sizes (30–50). The Sphere and Griewank benchmark functions exhibit highly positive responses to this configuration, with best fitness values approaching zero. The convergence graphs also support these findings, showing that n = 0.75 enables faster and more stable convergence compared to the standard linear approach. Specifically, for Sphere and Griewank, this setting promotes effective exploration in the early stages and strong exploitation toward the end. Even on the more complex Rosenbrock function, this variant maintains a smooth and stable convergence trajectory.

Nevertheless, some anomalies were observed in the Rastrigin function, particularly for n = 0.5, where exceptionally large fitness values were obtained. These results indicate that certain sigmoid configurations may preserve exploration excessively, causing wolves to move far from promising regions before convergence is established. Since the coefficient vector A is directly controlled by the convergence factor a, an overly prolonged exploration phase may generate large position updates and unstable search trajectories. Consequently, exploitation is delayed and the algorithm may fail to concentrate around high-quality solutions, resulting in poor final fitness values. This behavior is especially evident in highly multimodal landscapes such as Rastrigin, where an inappropriate exploration–exploitation balance can easily lead to divergence or entrapment in non-promising regions. Therefore, careful selection of the sigmoid parameter remains essential for achieving reliable optimization performance.

From all benchmark functions evaluated in this study, the sigmoid parameter n = 0.75 generally provides the most favorable exploration–exploitation balance. A larger value of n shifts the sigmoid inflection point toward the later stages of the optimization process, allowing the algorithm to maintain exploration for a longer period before entering an intensive exploitation phase. Since the coefficient vector A is directly governed by the convergence factor a, delaying the reduction of a allows larger fluctuations of A during the early iterations, thereby strengthening exploration capability. This delayed transition is particularly beneficial for medium- and high-dimensional search spaces, where premature reduction of exploration often leads to local optimum entrapment. The results therefore, indicate that the position of the sigmoid inflection point plays a critical role in determining the search dynamics and overall optimization performance of ADSCF-GWO.

CONCLUSION

This study introduced a decreasing sigmoid convergence factor to enhance the performance of the Grey Wolf Optimizer (GWO). The experimental results across four benchmark functions demonstrate that the proposed mechanism significantly improves convergence speed, accuracy, and robustness, particularly when the sigmoid constant is set to n = 0.75. Under this configuration, the method in most scenarios outperformed the standard GWO in medium- and high-dimensional problems as well as larger population sizes, achieving near-optimal solutions on the Sphere and Griewank functions and maintaining smooth convergence on the Rosenbrock function.

The findings highlight that the decreasing sigmoid factor provides a systematic and adaptive balance between exploration and exploitation, addressing the limitations of slow convergence and premature stagnation in standard GWO. Although some irregularities were observed in the Rastrigin function for certain parameter values (n = 0.5), the overall results indicate the robustness and scalability of the proposed approach.

In conclusion, the decreasing sigmoid convergence factor provides an effective alternative convergence-control mechanism for GWO, making it more reliable and effective for solving complex, high-dimensional optimization problems. Future work may extend this mechanism to real-world engineering applications and explore hybridization with other metaheuristic frameworks.

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REFERENCES

[1] S. J. Oks, M. Fritzsche, J. J. Weyerer, and M. E. Latoschik, “Cyber-Physical Systems in the Context of Industry 4.0: A Systematic Literature Review,” *Information Systems Frontiers*, vol. 26, no. 2, pp. 533–570, 2024, doi: 10.1007/s10796-022-10252-x.

[2] S. Selvarajan, S. M. M. Roomi, and K. Balasubramanian, “A Comprehensive Study on Modern Optimization Techniques for Engineering Applications,” *Artificial Intelligence Review*, vol. 58, 2025, doi: 10.1007/s10462-024-10829-9.

[3] U. Habiba, I. Ahmed, M. Asif, H. A. Alhelou, and M. A. Khalid, “Review on enhancing energy efficiency and adaptability through system integration for smart buildings,” *Journal of Building Engineering*, vol. 89, Art. no. 109354, 2024, doi: 10.1016/j.jobe.2024.109354.

[4] S. M. Rashid, “Employing advanced control, energy storage, and renewable technologies to enhance power system stability,” *Energy Reports*, vol. 11, pp. 3202–3223, 2024, doi: 10.1016/j.egyr.2024.03.009.

[5] E. H. Houssein, A. G. Gad, D. Oliva, P. N. Suganthan, and B. Abd Elaziz, “Metaheuristics for Solving Global and Engineering Optimization Problems: A Survey and Open Issues,” *Archives of Computational Methods in Engineering*, vol. 32, no. 1, pp. 1–53, 2025, doi: 10.1007/s11831-024-10168-6.

[6] M. H. Nadimi-Shahraki, H. Zamani, Z. A. Varzaneh, A. S. Sadiq, and S. Mirjalili, “A Systematic Review of Applying Grey Wolf Optimizer, Its Variants, and Its Developments in Different Internet of Things Applications,” *Internet of Things*, vol. 26, Art. no. 101135, 2024, doi: 10.1016/j.iot.2024.101135.

[7] A. Maleki, M. Roayai, and S. Mirjalili, “Enhancing leadership-based metaheuristics using reinforcement learning: A case study in grey wolf optimizer,” *Knowledge-Based Systems*, vol. 330, Art. no. 114471, 2025, doi: 10.1016/j.knosys.2025.114471.

[8] S. N. Makhadmeh, M. A. Al-Betar, I. A. Doush, M. A. Awadallah, S. Kassaymeh, S. Mirjalili, and R. A. Zitar, “Recent Advances in Grey Wolf Optimizer, Its Versions and Applications: Review,” *IEEE Access*, vol. 12, pp. 22991–23028, 2024, doi: 10.1109/ACCESS.2024.3366150.

[9] M. Nasir, A. Sadollah, S. Mirjalili, et al., “A comprehensive review on applications of Grey Wolf Optimizer in energy systems,” *Archives of Computational Methods in Engineering*, vol. 32, pp. 2279–2319, 2025, doi: 10.1007/s11831-024-10214-3.

[10] Y. Zhang, “An Improved Grey Wolf Optimizer Based on Attention Mechanism and Nonlinear Convergence Factor,” *Symmetry*, vol. 17, no. 1, Art. no. 50, 2025, doi: 10.3390/sym17010050.

[11] Y. Zhang and Y. Cai, “Adaptive Dynamic Self-Learning Grey Wolf Optimization Algorithm for Solving Global Optimization Problems and Engineering Problems,” *Mathematical Biosciences and Engineering*, vol. 21, no. 3, pp. 3910–3943, 2024, doi: 10.3934/mbe.2024174.

[12] Y. Qiu, X. Yang, and S. Chen, “An improved gray wolf optimization algorithm solving functional optimization and engineering design problems,” *Scientific Reports*, vol. 14, Art. no. 14190, 2024, doi: 10.1038/s41598-024-64526-2.

[13] M. H. Nadimi-Shahraki, S. Taghian, and S. Mirjalili, “An improved grey wolf optimizer for solving engineering problems,” *Expert Systems with Applications*, vol. 166, Art. no. 113917, 2021, doi: 10.1016/j.eswa.2020.113917.

[14] M. Yu, Y. Wang, X. Liu, and Z. Zhang, “Improved multi-strategy adaptive Grey Wolf Optimization for global optimization and engineering design problems,” *Artificial Intelligence Review*, vol. 58, no. 1, 2025, doi: 10.1007/s10462-024-10821-3.

[15] Y. Hou, H. Gao, Z. Wang, and C. Du, “Improved Grey Wolf Optimization Algorithm and Application,” *Sensors*, vol. 22, no. 10, Art. no. 3810, 2022, doi: 10.3390/s22103810.

[16] Y. Li, X. Lin, and J. Liu, “An Improved Gray Wolf Optimization Algorithm to Solve Engineering Problems,” *Sustainability*, vol. 13, no. 6, Art. no. 3208, 2021, doi: 10.3390/su13063208.

[17] A. E. Hassanien and E. Emary, *Swarm Intelligence: Principles, Advances, and Applications*, Boca Raton, FL, USA: CRC Press, 2016.

[18] S. Gupta, K. Deep, H. Moayed, L. K. Foong, and A. Assa, “Sine cosine grey wolf optimizer to solve engineering design

problems," *Engineering with Computers*, vol. 37, pp. 3123–3149, 2021, doi: 10.1007/s00366-020-00996-y.

[19] N. Mittal, U. Singh, and B. S. Sohi, "Modified grey wolf optimizer for global engineering optimization," *Applied Computational Intelligence and Soft Computing*, vol. 2016, Art. no. 7950348, 2016, doi: 10.1155/2016/7950348.

[20] A. Saxena, R. Kumar, and S. Das, "β-chaotic map enabled grey wolf optimizer," *Applied Soft Computing*, vol. 75, pp. 84–105, 2019, doi: 10.1016/j.asoc.2018.10.044.

[21] Y. Bouteraa, A. M. Alimi, and A. Abraham, "Fractal and chaotic map-enhanced grey wolf optimization for deep convolutional neural network architecture optimization," *Scientific Reports*, vol. 15, Art. no. 95519, 2025, doi: 10.1038/s41598-025-95519-4.

[22] Y. Zhang, "An Improved Grey Wolf Optimizer Based on Attention Mechanism and Nonlinear Convergence Factor," *Symmetry*, vol. 17, no. 1, Art. no. 50, 2025, doi: 10.3390/sym17010050.

[23] W. Long, J. Jiao, X. Liang, and M. Tang, "An exploration-enhanced grey wolf optimizer to solve high-dimensional numerical optimization," *Engineering Applications of Artificial Intelligence*, vol. 68, pp. 63–80, 2018, doi: 10.1016/j.engappai.2017.10.024.

[24] S. Gupta and K. Deep, "A novel random walk grey wolf optimizer," *Swarm and Evolutionary Computation*, vol. 44, pp. 101–112, 2019, doi: 10.1016/j.swevo.2018.01.001.

[25] Z. Teng, J. Lv, and L. Guo, "An improved hybrid grey wolf optimization algorithm," *Soft Computing*, vol. 23, pp. 6617–6631, 2019, doi: 10.1007/s00500-018-3310-y.