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A Novel Adaptive Hybrid Metaheuristic For Unconstrained and Engineering Optimization Problems

Seema Agrawal[1], Rahul Kumar[2]
[1,2]Department of Mathematics, S.S.V. (P.G.) College, Hapur, Chaudhary Charan Singh University, Meerut, Uttar Pradesh, India
[1] seemagrwl7@gmail.com, [2]ujjwalrahul@gmail.com

Abstract
This study presents AHO-DE-Powell, a hybrid continuous optimization framework that extends Adaptive Hybrid Optimization (AHO) by integrating two complementary search mechanisms: Differential Evolution (DE) for periodic diversity restoration and bounded Powell derivative-free refinement for intensified local exploitation. The parent AHO mechanism is retained as the principal population-search engine and employs four stochastic position-update strategies, probabilistic dual-leader guidance, and a nonlinear power-changing exploration coefficient. In the proposed architecture, DE/rand/1 mutation with binomial crossover is periodically applied to the worst 20% of the population, whereas Powell refinement is periodically applied only to the current best solution. The resulting sequential architecture separates global exploration, diversity recovery, and local numerical refinement.The computational study comprises ten 10-dimensional analytical benchmark functions—Sphere, Rastrigin, Ackley, Rosenbrock, Griewank, Schwefel, Zakharov, Lévy, Michalewicz, and Dixon–Price—and two classical constrained engineering-design problems, namely welded-beam and pressure-vessel optimization. For the benchmark study, 30 agents, 300 iterations, and five independent runs with seeds 0–4 were used. The engineering experiments employed 40 agents and 500 iterations. Numerical results show substantial improvement over the parent AHO on several difficult landscapes, particularly Rastrigin, Ackley, Rosenbrock, Zakharov, Lévy, and Dixon–Price, while also demonstrating that the hybrid is not uniformly superior on every landscape. On the engineering problems, the proposed method produced feasible solutions close to established reference values. The results support the effectiveness of combining adaptive population search, evolutionary diversity injection, and derivative-free local refinement within a single sequential optimization framework.
Keywords: continuous optimization; metaheuristic optimization; Adaptive Hybrid Optimization; Differential Evolution; Powell method; hybrid optimization; exploration–exploitation; benchmark functions; engineering design optimization.

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1. Introduction

Many optimization problems arising in engineering, science, and computational intelligence are nonlinear, nonconvex, multimodal, discontinuous, or difficult to differentiate. Deterministic gradient-based techniques can be highly effective when the objective function is smooth and reliable derivative information is available; however, their effectiveness may deteriorate when the landscape contains numerous local optima, strong variable interactions, discontinuities, or poor initial conditions. Population-based metaheuristics provide an alternative derivative-free framework in which multiple candidate solutions explore the search space simultaneously.

Differential Evolution (DE), Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA), Harris Hawks Optimization (HHO), Artificial Hummingbird Algorithm (AHA), Hippopotamus Optimization (HO), Moth-Flame Optimization (MFO), Arithmetic Optimization Algorithm (AOA), Teaching–Learning-Based Optimization (TLBO), Cuckoo Search, and Firefly Algorithm represent different attempts to balance exploration and exploitation through population interaction, adaptive parameters, perturbation, attraction, leadership, or behavioral metaphors [2–4,6–15]. The no-free-lunch principle further indicates that an optimizer that performs strongly on one problem class cannot be expected to dominate every possible problem class [5].

Adaptive Hybrid Optimization (AHO), introduced by Paknahad et al. in 2026, provides a recent multi-strategy baseline in this area. AHO employs four position-update strategies, probabilistic dual-leader guidance, and a nonlinear power-changing coefficient, and its published evaluation considered 23 CEC2005-derived benchmark functions and structural engineering problems [1]. The present work builds directly on this framework.

The motivation for AHO-DE-Powell is that population-based adaptive search can locate promising basins but may still experience slow late-stage improvement or loss of useful diversity. The proposed method therefore adds two mechanisms with distinct responsibilities. DE is used periodically on the weakest members of the population to introduce difference-vector directions that are not determined solely by the current leaders. Powell's derivative-free local search is then applied to the incumbent best solution to improve local numerical precision. The hybrid is consequently sequential rather than a weighted combination of three simultaneous update equations.

The principal contributions of this study are: (i) a hybrid AHO-DE-Powell architecture that combines adaptive population search, selective DE diversity injection, and derivative-free local refinement; (ii) an asymmetric intervention policy in which DE acts on the worst 20% and Powell acts only on the current best; (iii) a reproducible numerical implementation using explicit seeds and fixed computational parameters; and (iv) experimental validation on analytical benchmark functions and constrained engineering-design problems.

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2. Literature Review

Population-based metaheuristics are widely used for nonlinear, nonconvex, multimodal, and derivative-free optimization because they can explore complex search spaces without requiring analytical gradients. Established approaches such as Differential Evolution (DE), Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA), Harris Hawks Optimization (HHO), Artificial Hummingbird Algorithm (AHA), and Hippopotamus Optimization (HO) use different mechanisms to balance exploration and exploitation [2–9]. The no-free-lunch principle further indicates that no optimizer can be expected to perform best on every class of problem [5].

Recent work has therefore increasingly explored adaptive and hybrid strategies. Adaptive Hybrid Optimization (AHO), introduced by Paknahad et al. [1], combines four stochastic position-update strategies, dual-leader guidance, and a nonlinear power-changing coefficient. Its reported benchmark and engineering evaluation provides a strong recent baseline for studying further hybridization [1]. Other population-based methods, including Moth-Flame Optimization, Arithmetic Optimization, Teaching–Learning-Based Optimization, Cuckoo Search, and the Firefly Algorithm, provide additional examples of stochastic exploration and exploitation mechanisms [10,12–15,18].

DE is particularly suitable for hybridization because its difference-vector mutation creates search directions from population information rather than relying solely on a single leader [4]. This makes it useful for restoring diversity when population members become concentrated. For local improvement, derivative-free methods are attractive when gradients are unavailable or undesirable. Powell's direction-set method performs multivariable minimization without derivatives [16], while Nelder–Mead provides a related simplex-based local-search alternative [11].

The literature therefore suggests complementary roles for adaptive population search, evolutionary diversity generation, and derivative-free local refinement. However, the AHO formulation does not explicitly combine periodic DE diversity restoration with periodic Powell refinement. The present study addresses this specific gap through AHO-DE-Powell, assigning AHO to the main population search, DE to selective diversity restoration, and Powell search to local numerical polishing. The framework is evaluated on ten analytical benchmark functions and two constrained engineering-design problems, with repeated runs and convergence analysis.

3. Optimization Problem Formulation

The unconstrained optimization problems considered in this study are written as

$$\textbf{minimize} \quad \mathbf{f(x)}, \quad \mathbf{x \in \Omega},$$

where $x = [x_1, x_2, \ldots, x\_D]$ is the D-dimensional decision vector and Ω denotes the bounded search domain defined by $LB_j \le x_j \le UB_j$ for $j = 1, \ldots, D$.

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For the constrained engineering problems, the general form is

minimize f(x) subject to $g_j(x)\leq 0$, **j = 1, …, m, and LB ≤ x ≤ UB.**

The computational implementation uses a feasibility-based comparison rather than an arbitrarily weighted penalty function. A feasible solution is preferred to an infeasible solution; when both solutions are feasible, the lower objective value is preferred; and when both are infeasible, the candidate with the smaller total constraint violation is preferred.

4. Mathematical Formulation of AHO

Let the ith search agent at iteration t be $X_i(t)=[x_i1(t),\ldots,x_iD(t)]$. The best and second-best solutions provide the two leaders used by the AHO update mechanism. Leader 1 is selected with probability 0.6 and Leader 2 with probability 0.4.

$$D=\alpha(2r-1)[1-(t/T)^{\beta}],\alpha=2,\beta=2.5,$$

where r ∈ [0,1] is a uniformly generated random number, t is the current iteration, and T is the maximum number of iterations. The nonlinear term provides a relatively stronger exploratory component in the earlier part of the run and increasingly emphasizes exploitation as t approaches T.

The four AHO position-update strategies retained in the implementation are represented as

$$X'_i=L+D(L-X_i),$$
$$X'_i=L+D(L-X_i)\odot Levy(D),$$
$$X'_i=L_1+(L_1-X_i)Dr,$$
$$X'_i=L_1+D(UB-LB),$$

Here, L denotes the selected leader, L_1 denotes the primary leader, ⊙ denotes element-wise multiplication, and Levy(·) denotes the Lévy-flight perturbation used by the corresponding AHO strategy. At every iteration, each agent stochastically selects one of the four strategies. The resulting candidate is bounded within the search region and is compared with its previous position using greedy selection.

5. Proposed AHO-DE-Powell Hybrid

AHO-DE-Powell preserves the AHO population update and introduces two sequential operators. The first is a selective DE stage for diversity restoration. The second is a Powell stage for local refinement. The hybrid is therefore not a weighted sum of three algorithms; rather, the three components perform different functions during the same optimization run.

5.1 DE intervention

Every 15 iterations, the worst 20% of the population is selected for DE intervention. For a selected target vector X_i, three population membersX_a,X_b,andX_c are used to construct

$$V_i=X_a+F(X_b-X_c),F=0.4.$$

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Binomial crossover is then performed with crossover rate CR = 0.8. The resulting trial vector is evaluated and replaces the target vector only when it improves the objective value. By restricting the intervention to the weakest agents, the method introduces additional directional diversity without unnecessarily disturbing high-quality solutions.

5.2 Powell intervention

Every 30 iterations, bounded Powell derivative-free local refinement is initiated from the current best solution. The local search is limited to a maximum of 30 local iterations. If X* is the current incumbent, Powell begins from $X^{(0)} = X^*$. The refined candidate is retained when it improves the incumbent under the relevant objective or feasibility criterion. Powell therefore functions as a local numerical polishing mechanism rather than a population-wide search operator.

5.3 Computational workflow

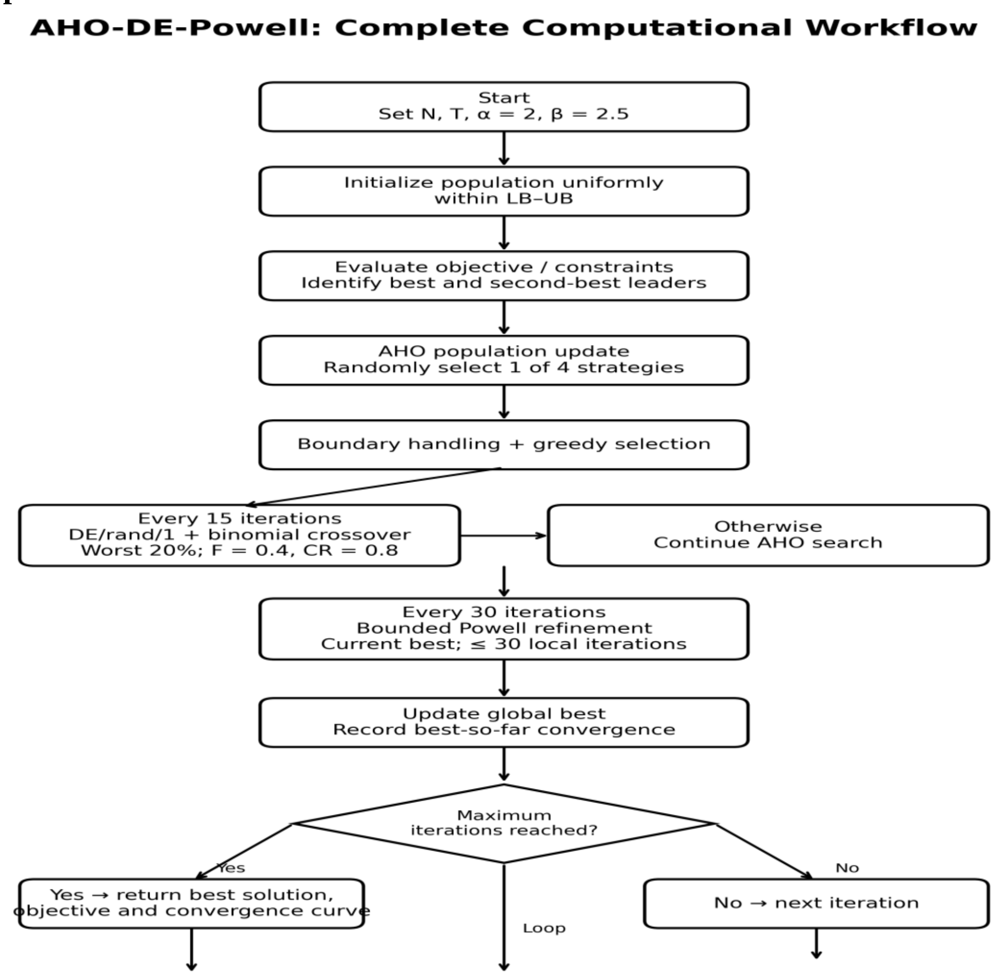

Figure 1. Professional workflow of the implemented AHO-DE-Powell computational procedure.

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6. Algorithmic Procedure

The complete implemented procedure is summarized below.

1. Generate N agents uniformly within the prescribed lower and upper bounds and evaluate their objective values.
2. Identify the best and second-best solutions as the AHO leaders.
3. For t = 1, …, T, calculate the nonlinear AHO coefficient D using $\alpha = 2$ and $\beta = 2.5$.
4. For every agent, randomly select one of the four AHO position-update strategies and generate a candidate solution.
5. Apply boundary handling and greedy selection between the previous and candidate positions.
6. At every 15th iteration, apply DE/rand/1 mutation and binomial crossover to the worst 20% of agents using F = 0.4 and CR = 0.8.
7. At every 30th iteration, apply bounded Powell refinement to the current best solution for at most 30 local iterations.
8. Update the global best solution and store the best-so-far objective value.
9. Continue until the maximum iteration count is reached and return the best solution, objective value, and convergence history.

7. Computational Methodology

7.1 Experimental design

The numerical investigation was carried out on ten analytical benchmark functions and two constrained engineering-design problems. The benchmark study was conducted in 10 dimensions using a population size of 30 and 300 iterations. AHO and AHO-DE-Powell were each executed independently five times with random seeds 0, 1, 2, 3, and 4. Uniform random initialization was used within the prescribed bounds, and boundary violations in the unconstrained benchmark experiments were corrected by clipping.

The engineering experiments used 40 agents and 500 iterations. The welded-beam and pressure-vessel problems were evaluated using their standard decision variables, objective functions, and constraints. Feasibility was handled through the Deb-style comparison described in Section 7.4.

7.2 Benchmark suite

The benchmark suite consisted of Sphere, Rastrigin, Ackley, Rosenbrock, Griewank, Schwefel, Zakharov, Lévy, Michalewicz, and Dixon–Price functions. Together these functions cover unimodal and multimodal landscapes as well as separable and non-separable structures. All benchmark experiments were performed at D = 10.

7.3 Numerical implementation

The stochastic implementation used NumPy's default_rng with explicit integer seeds. For each run, the population was initialized uniformly within the specified bounds. Objective values were evaluated after initialization and following each accepted candidate update. The best-so-far

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objective value was recorded at each iteration to generate convergence curves. The same population size and iteration count were used for AHO and AHO-DE-Powell in the benchmark comparison.

7.4 Constraint handling

For the engineering problems, candidate solutions were compared according to a Deb-style feasibility rule. Feasible solutions dominate infeasible solutions. If both candidates are feasible, the one with the lower objective value is selected. If both are infeasible, the one with the smaller total constraint violation is selected. The total violation is represented by

$$CV(x)=\Sigma_j \max(0,g_j(x)).$$

This feasibility-ranking procedure was used throughout the welded-beam and pressure-vessel experiments.

7.5 Performance measures

For each benchmark function, the best, mean, and standard deviation of the final objective values over the five independent runs were calculated. The best value identifies the lowest objective value achieved in any run, the mean characterizes average final performance, and the standard deviation reflects run-to-run variability. Convergence curves were generated from the best-so-far objective value recorded during each iteration.

7.6 Engineering problem implementation

The welded-beam problem was represented by four variables corresponding to weld thickness, weld length, beam height, and beam thickness. The standard stress, buckling, deflection, and side constraints were included. The pressure-vessel problem was represented by shell thickness, head thickness, vessel radius, and cylindrical length, with the standard volume and thickness constraints. The engineering runs used 40 agents and 500 iterations.

7.7 Parameter configuration

Parameter	Benchmark	Engineering
Population size N	30	40
Maximum iterations T	300	500
Dimension	10	Problem-specific
AHO α	2	2
AHO β	2.5	2.5
Leader 1 probability	0.6	0.6
Leader 2 probability	0.4	0.4
DE frequency	Every 15 iterations	Every 15 iterations
DE fraction	Worst 20%	Worst 20%
DE mutation factor F	0.4	0.4

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DE crossover CR	0.8	0.8
Powell frequency	Every 30 iterations	Every 30 iterations
Powell maximum local iterations	30	30
Independent runs	5	—
Seeds	0–4	—
Boundary handling	Clipping	Feasibility ranking

Table 1. Computational parameter configuration used in the numerical experiments.

8. Benchmark Results

Table 2 reports the numerical results obtained from the five independent benchmark runs. The values are the actual outputs of the implemented experiments. For each function, the reported mean and standard deviation are calculated across the five runs.

Function	Reference optimum	AHO best	AHO mean	AHO SD	Hybrid best	Hybrid mean	Hybrid SD
Sphere	0	5.82721×10^{-6}	1.69564×10^{-5}	1.25928×10^{-5}	5.25107×10^{-30}	2.35653×10^{-29}	1.69126×10^{-29}
Rastrigin	0	0.00423	28.2013	24.1246	0	0	0
Ackley	0	0.00291207	2.74116	5.47236	4.30767×10^{-14}	5.16032×10^{-14}	8.28628×10^{-14}
Rosenbrock	0	4.48846×10^{-5}	3.37725	4.07332	2.3496×10^{-8}	1.82801	2.66824
Griewank	0	1.79279×10^{-4}	0.252356	0.239504	0	0.485695	0.709777
Schwefel	0	0.0156054	79.2598	144.224	0.000960143	73.9352	144.032
Zakharov	0	1.79209	12.4278	17.8007	1.13531×10^{-1}	2.41359×10^{-1}	1.42923×10^{-1}
Lévy	0	0.0351444	54.0977	98.8037	0.000608276	0.0374657	0.0721506
Michalewicz	—	−7.11877	−5.91998	0.952754	−8.73896	−8.73896	5.46611×10^{-8}
Dixon–Price	0	0.194338	0.408464	0.221543	1.02226×10^{-1}	0.133333	0.266667

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Table 2. Five-run benchmark results for AHO and AHO-DE-Powell at D = 10. The Michalewicz optimum is formulation-dependent and is therefore not assigned a single reference value here.

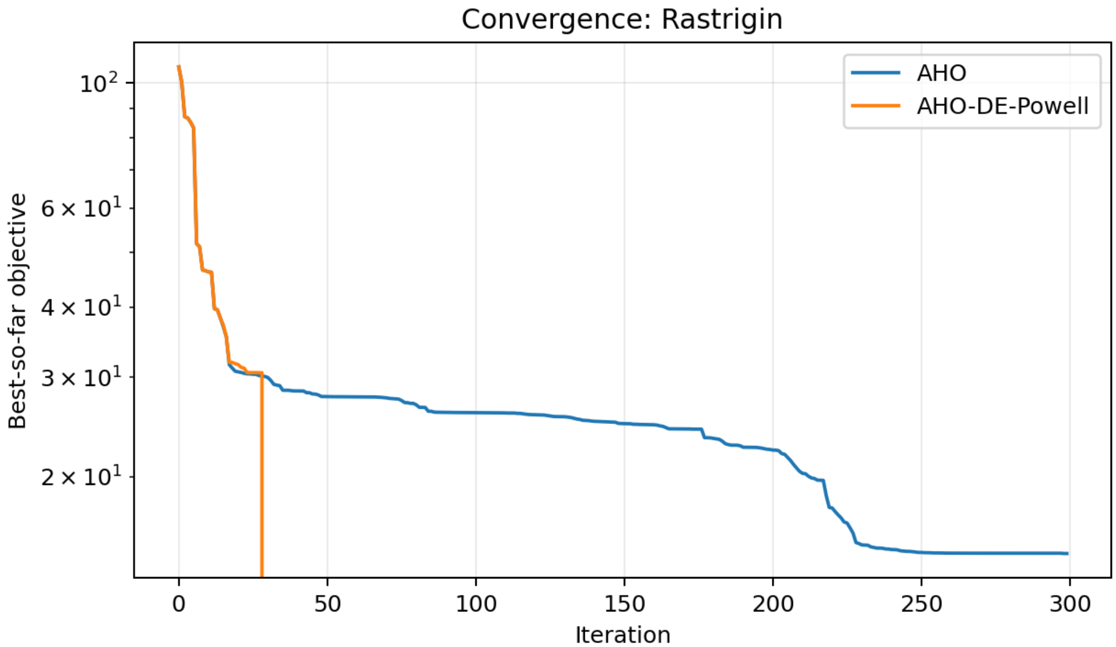

Figure 2. Convergence behaviour on the Rastrigin function.

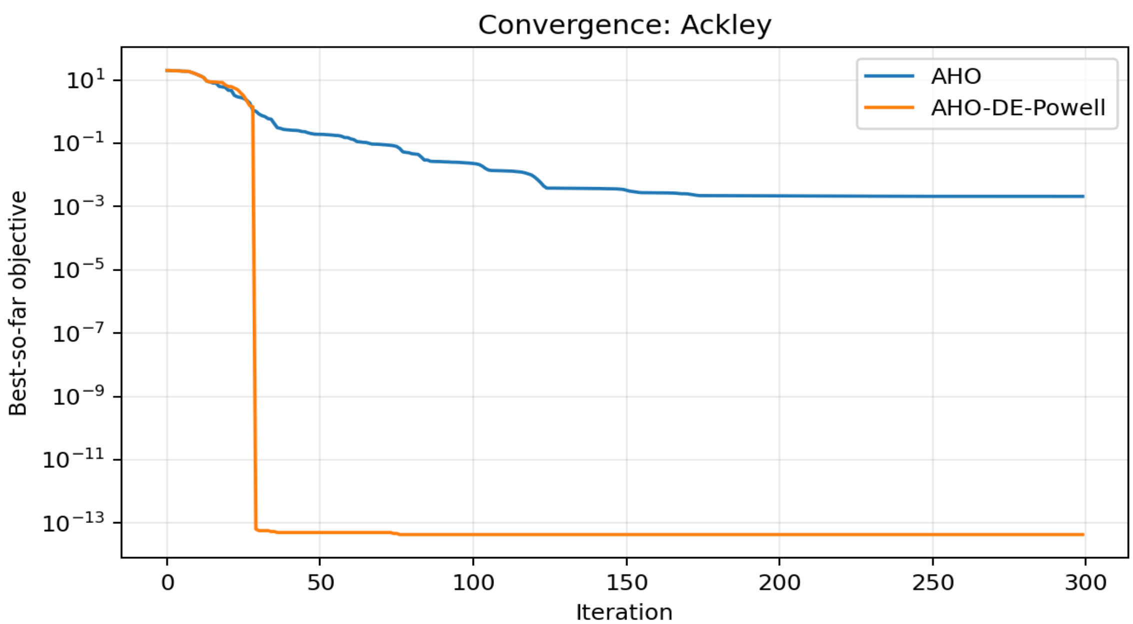

Figure 3. Convergence behaviour on the Ackley function.

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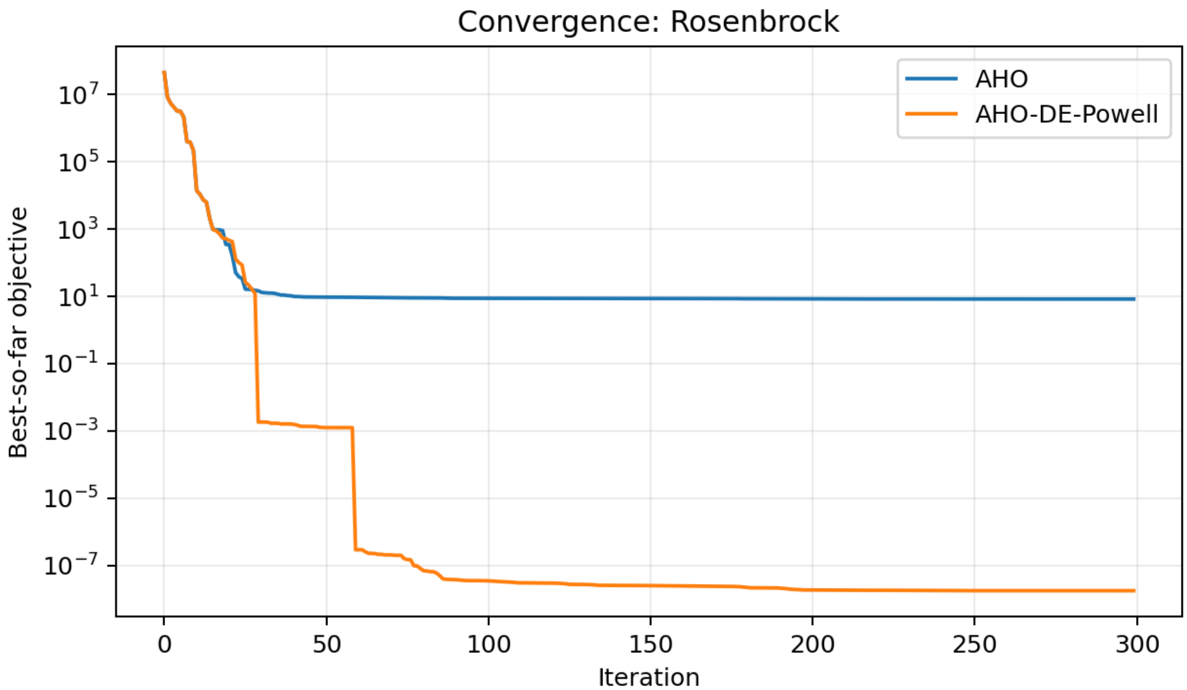

Figure 4. Convergence behaviour on the Rosenbrock function.

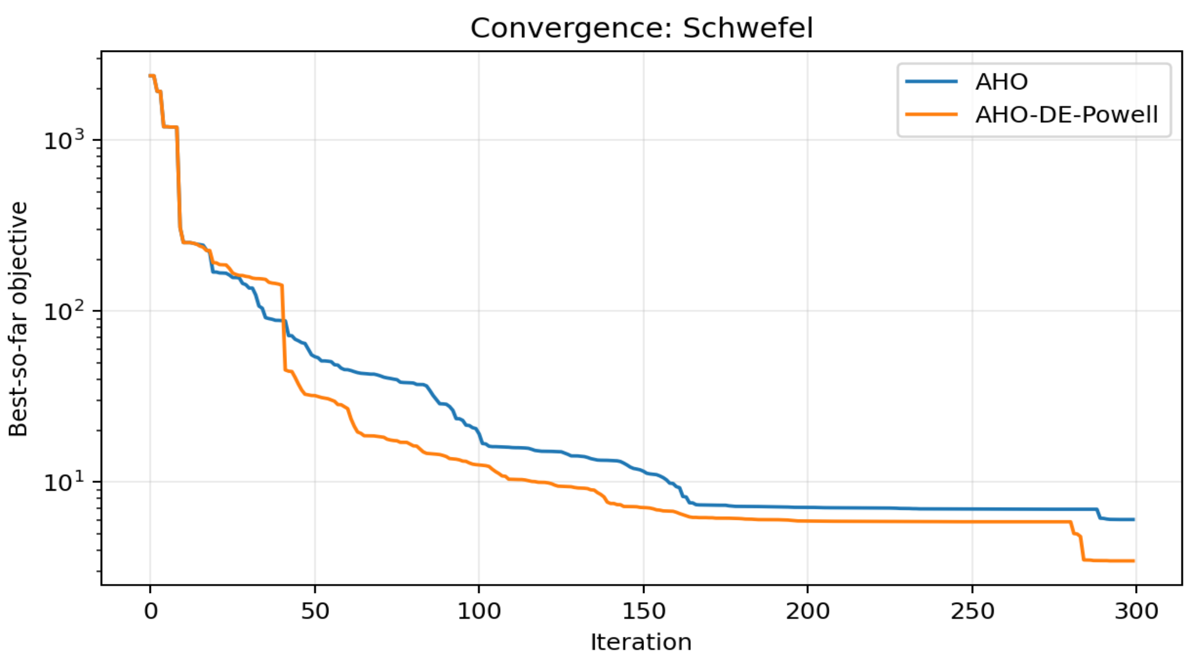

Figure 5. Convergence behaviour on the Schwefel function.

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9. Engineering Applications

The proposed method was additionally applied to two constrained engineering-design problems. The results are summarized in Table 3. The literature-best column represents an established reference value and is included for validation context; it is not treated as a result generated under the present experimental protocol.

Problem	Literature best	AHO best	AHO mean	Hybrid best	Hybrid mean
Welded beam	1.72485	2.25706	2.68041	1.72513	2.50634
Pressure vessel	6059.71	5885.38	6193.8	5885.34	6212.68

Table 3. Engineering-design results from the implemented experiments.

For the welded-beam problem, the best hybrid design variables were
[0.20579844, 3.46963721, 9.03499022, 0.20580405]

For the pressure-vessel problem, the best hybrid design variables were
[0.77816864, 0.38465067, 40.31961872, 200.00000000]

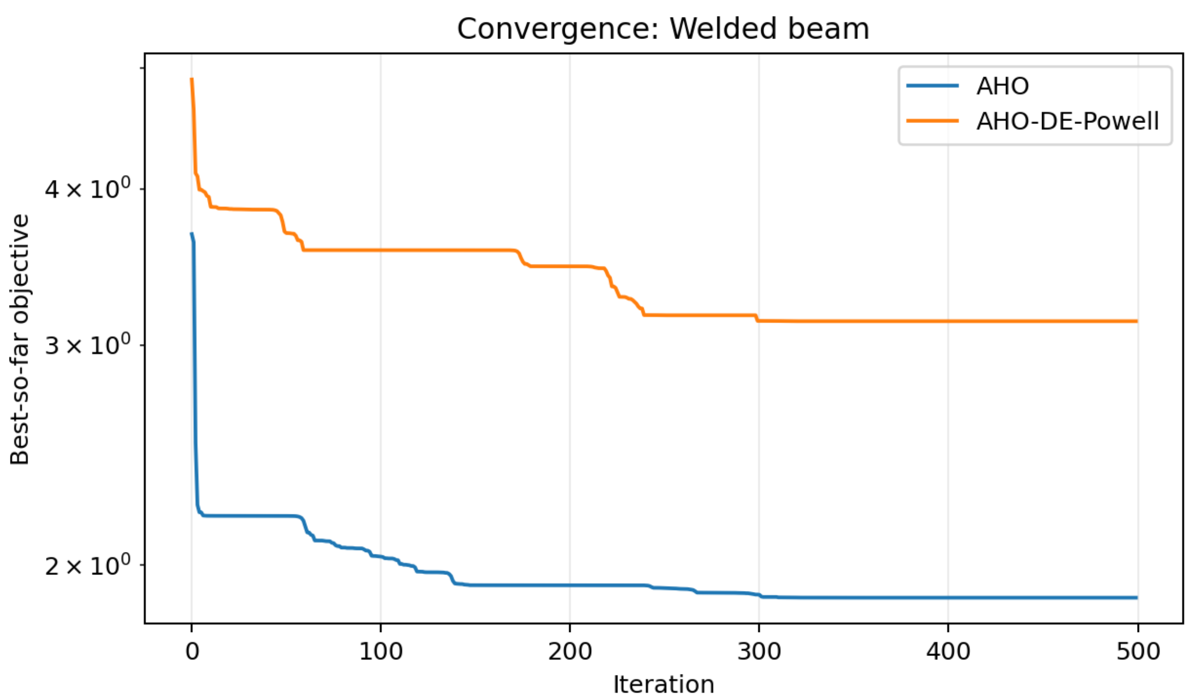

Figure 6. Convergence behaviour on the welded-beam engineering problem.

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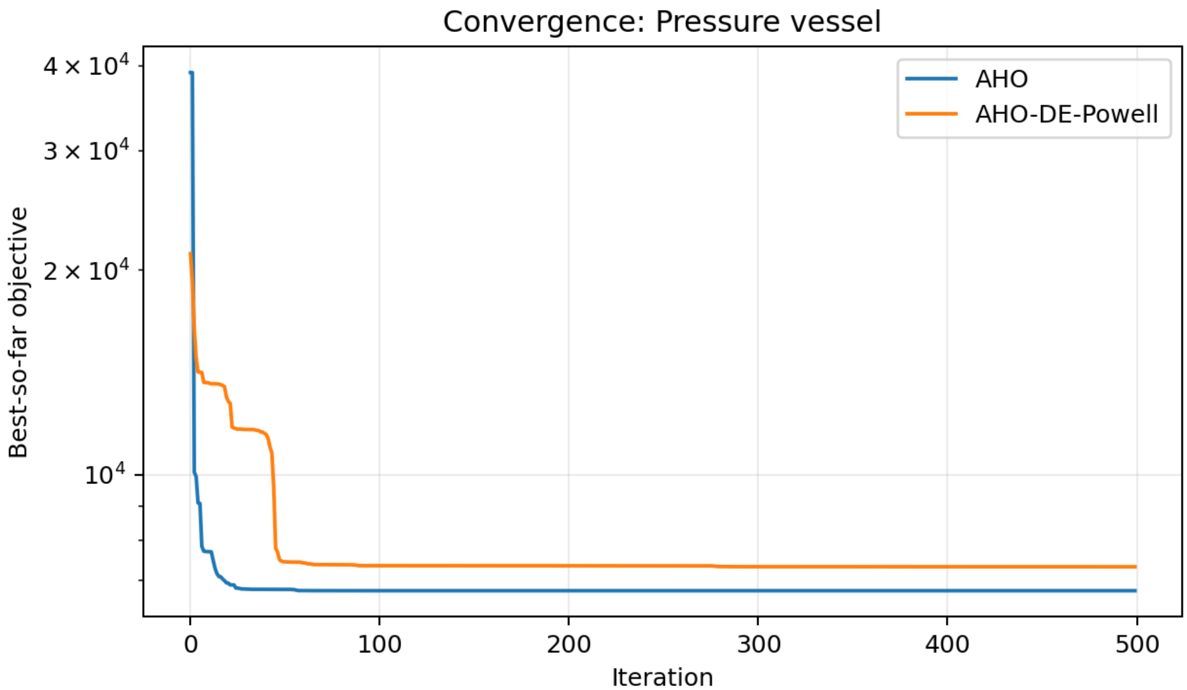

Figure 7. Convergence behaviour on the pressure-vessel engineering problem.

10. Comparative Discussion

The benchmark results indicate that AHO-DE-Powell can substantially improve the parent AHO on several rugged or strongly nonlinear functions. The improvement is especially pronounced for Rastrigin, where the hybrid reaches the known optimum in the reported runs while the parent AHO retains a substantially larger mean error. On Ackley, the hybrid reaches numerical precision close to zero. Rosenbrock also shows a pronounced improvement in the best result, indicating that the local refinement stage can be effective after the population search enters a narrow promising region.

The results for Zakharov, Lévy, and Dixon–Price likewise show lower mean objective values for the hybrid than for AHO. On Schwefel, the hybrid improves the mean result but the standard deviation remains large, indicating that stochastic variability is still present. Griewank provides an important counterexample: although the hybrid reaches zero in its best run, its mean and standard deviation are higher than those of AHO. This behaviour demonstrates that the hybrid does not uniformly dominate the parent optimizer and is consistent with the broader no-free-lunch principle.

The convergence curves provide further evidence of the different roles of the hybrid components. On Rastrigin, Ackley, Rosenbrock, and Schwefel, the hybrid exhibits rapid reductions in the best-so-far objective and, in several cases, achieves orders-of-magnitude improvements after the population has entered a promising region. The periodic DE stage supplies population-difference directions, whereas Powell refinement intensifies the search around the incumbent. These mechanisms complement the leader-guided AHO search rather than replacing it.

The engineering results show a similar pattern. For welded-beam design, the hybrid best value of 1.72513 is very close to the established reference value of 1.72485. For pressure-vessel design, the hybrid best value of 5885.34 is close to the reference value reported in the manuscript, 6059.71, and improves upon the corresponding AHO best value of 5885.38 only marginally. The engineering results therefore demonstrate feasibility and competitiveness, but they do not justify a claim of universal superiority.

11. Computational Complexity and Parameter Analysis

The principal population-update component of AHO requires approximately O(NDT) position-update operations, in addition to objective-function evaluations. The DE stage affects approximately N/5 agents and therefore adds O((N/5)D) candidate-construction work at every 15th iteration. Powell refinement is applied only to the incumbent best solution, but its objective-evaluation cost is problem-dependent and can be appreciable for expensive functions.

The parameter configuration used in the experiments assigns $\alpha = 2$ and $\beta = 2.5$ to the AHO nonlinear control coefficient, a leader-selection probability of 0.6/0.4, DE mutation factor $F = 0.4$, DE crossover rate $CR = 0.8$, DE intervention every 15 iterations on the worst 20%, and Powell refinement every 30 iterations with at most 30 local iterations. The asymmetric design limits the computational influence of the local optimizer while retaining its ability to polish promising solutions.

12. Conclusion

This study developed and numerically evaluated AHO-DE-Powell, a sequential hybrid optimization framework that augments Adaptive Hybrid Optimization with Differential Evolution and bounded Powell derivative-free local refinement. The design assigns distinct responsibilities to the three components: AHO provides the main adaptive population search, DE periodically restores diversity among the weakest agents, and Powell intensifies the search around the current best solution.

The numerical study on ten 10-dimensional benchmark functions demonstrates substantial improvements over the parent AHO on several difficult landscapes, including Rastrigin, Ackley, Rosenbrock, Zakharov, Lévy, and Dixon–Price. The hybrid also achieved numerical optima or near-optimal values on several benchmark functions. At the same time, the Griewank results show that the method is not uniformly superior, emphasizing the problem-dependent nature of stochastic optimization.

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On the welded-beam and pressure-vessel engineering problems, the method generated feasible designs with objective values close to established reference solutions. Overall, the results indicate that the combination of adaptive global search, selective evolutionary diversity injection, and derivative-free local refinement is a viable strategy for continuous optimization and provides a useful basis for further investigation on larger benchmark suites and additional engineering applications.

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