

Study on an Improved Harris Hawks Optimization Algorithm for Control Parameter Tuning

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ABSTRACT

To address the characteristics of control parameter tuning problems, such as narrow feasible regions, strong boundary sensitivity, significant objective-function nonlinearity, and high requirements for late-stage high-precision search, this paper proposes an improved Harris Hawks Optimization (HHO) algorithm for engineering-oriented tuning tasks. Built upon the standard HHO framework, the proposed method introduces three major improvements: initialization enhancement, stagnation recovery, and late-stage refinement. First, a hybrid initialization strategy that integrates global random sampling, prior-region guidance, and opposition-based learning is adopted to improve the coverage of the initial population over narrow feasible regions and boundary-adjacent high-quality areas. Second, a stagnation-awareness mechanism is constructed based on both the improvement magnitude of the best fitness and population diversity, and a directed escape strategy is incorporated to restore search activity in the middle stage of evolution. Finally, an elite-guided local refinement mechanism is introduced, where coordinate-diagonal hybrid search and random perturbation polishing are employed to enhance final solution accuracy and result stability. The proposed algorithm is validated on two representative control tuning problems, namely LLC and AVR, and its generalization capability is further examined on the supplementary THIRD and MMS scenarios. The results show that the improved HHO achieves better median performance and lower tail risk in both LLC and AVR cases. It is particularly suitable for control parameter tuning problems characterized by narrow feasible regions, pronounced boundary high-quality solutions, and strong demands for terminal refinement.

KEYWORDS

Harris hawks optimization; Control parameter tuning; Hybrid initialization; Stagnation awareness; Local refinement

1 Introduction

Controller parameter tuning is one of the key issues in the design of power electronic systems, automatic control systems, and complex industrial plants. For representative systems such as LLC resonant converters and automatic voltage regulators (AVR), parameter selection directly affects response speed, overshoot, steady-state error, and robustness. Since the relationship between control parameters and dynamic response is usually highly nonlinear, nonconvex, and strongly coupled, control parameter tuning is essentially a complex black-box optimization problem^[1].

In recent years, swarm intelligence algorithms such as Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Harris Hawks Optimization (HHO) have been widely applied to control parameter tuning. Among them, HHO simulates the cooperative hunting behavior of Harris hawks and realizes a dynamic transition between global exploration and local exploitation through the prey escape energy. It features a clear structure, rich behavioral mechanisms, and simple implementation. However, when the standard HHO is directly applied to control parameter tuning, several limitations remain. First, standard random initialization has a low hit rate in narrow feasible regions and boundary-adjacent high-quality areas, which results in an insufficient number of effective initial samples. Second, the population tends to contract rapidly during the middle stage of iteration, which may lead to local stagnation. Third, for low-dimensional but highly sensitive control parameter spaces, the late-stage search of standard HHO still mainly depends on the original exploitation mechanism, leaving room for improvement in final accuracy and stability^[2-3].

To address these issues, this paper proposes an improved HHO algorithm tailored for control parameter tuning tasks. The algorithm is designed around three stages, namely initialization enhancement, stagnation recovery, and late-stage refinement, with the aim of improving early effective search capability, mid-stage stagnation recovery ability, and late-stage local approximation accuracy. Experimental results demonstrate that the proposed method achieves better typical performance and lower tail risk on control tuning problems such as LLC and AVR, while maintaining good overall competitiveness on supplementary complex scenarios.

2 Basic Principles of Standard HHO

The HHO algorithm approximates the optimal solution iteratively by simulating the process of prey searching, encircling, and attacking performed by a hawk population. Its search process can be divided into two stages, namely global exploration and local exploitation, and the transition between the two stages is controlled by the prey escape energy^[4]. The escape energy is defined as

$$E = 2E_0 \left(1 - \frac{1}{T}\right) \quad (1)$$

where $E_0 \in [-1, 1]$ is a random initial value, t is the current iteration number, and T is the maximum number of iterations.

When $|E| \geq 1$, the algorithm tends to perform global exploration; when $|E| < 1$, it enters the local exploitation stage^[5].

To characterize the overall distribution of the population, the population mean is defined as

$$X_m(t) = \frac{1}{N} \sum_{i=1}^N X_i(t) \quad (2)$$

where N is the population size, and $X_i(t)$ denotes the position of the i -th individual at iteration t .

During the exploration stage, individuals update their positions according to either a randomly selected reference individual or the population mean, which can be expressed as

$$X_i(t+1) = \begin{cases} X_{rand}(t) - r_1 |X_{rand}(t) - 2r_2 X_i(t)|, & q \geq 0.5 \\ (X_{best}(t) - X_m(t)) - r_3 (LB + r_4 (UB - LB)), & q < 0.5 \end{cases} \quad (3)$$

where $X_{rand}(t)$ is the position of a randomly selected individual, $X_{best}(t)$ is the current best individual, LB and UB are the lower and upper bounds of the variables, respectively, and r_1, r_2, r_3, r_4, q are random numbers.

In the local exploitation stage, to simultaneously account for encircling and surprise pounce behaviors, the update rule can be simplified as

$$X_i(t+1) = X_{best}(t) - E |JX_{best}(t) - X_i(t)| + S \cdot Levy(D) \quad (4)$$

where J denotes the jump strength, S is the step-size coefficient, and $Levy(D)$ denotes a D -dimensional Lévy flight perturbation. This mechanism allows the algorithm to contract around the current promising region while retaining a certain ability to escape local optima through random pouncing.

Although standard HHO exhibits good flexibility in continuous optimization, it still suffers from insufficient initial coverage, pronounced mid-stage stagnation, and limited late-stage refinement capability when applied to control parameter tuning problems with narrow feasible regions, strong boundary sensitivity, and high precision requirements. Therefore, targeted improvements are necessary^[6].

3 Design of the Improved HHO Algorithm

3.1 Improvement Strategy for Control Tuning Problems

Unlike conventional benchmark functions, control parameter tuning problems usually exhibit the following characteristics. First, the feasible region is often narrow, and high-quality solutions are frequently located near boundaries or within narrow band-like regions. Second, the objective function is typically composed of multiple dynamic performance indices, and significant conflicts may exist among these indices. Third, the relationship between parameters and performance is highly nonlinear and strongly coupled, leading to numerous local optima and near-optimal regions. These problem characteristics make it difficult for standard HHO to simultaneously achieve adequate early-stage coverage, mid-stage recovery, and late-stage refinement when directly applied to control tuning tasks.

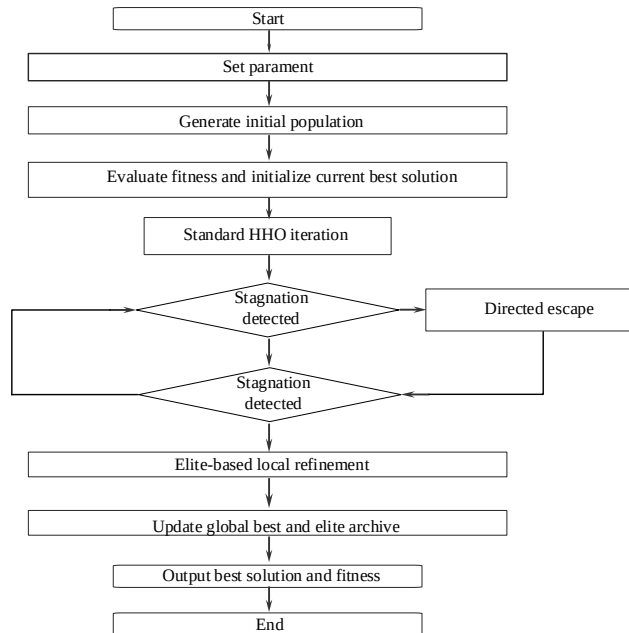


Figure 1 Flowchart of the Proposed Improved HHO Algorithm

To address these issues, this paper constructs an improved HHO framework from three stages. In the initialization stage, hybrid initialization is used to increase the proportion of effective initial samples. In the main iteration stage, stagnation awareness and directed escape are introduced to restore search activity. In the late exploitation stage, elite-

guided local refinement is employed to improve solution accuracy and stability.

3.2 Hybrid Initialization Strategy

To improve the hit rate of the population in narrow feasible regions and boundary high-quality areas during the initial stage, a hybrid initialization strategy integrating global random sampling, prior-region guidance, and opposition-based learning is adopted.

The globally random samples are generated as

$$X_i^{(g)} = LB + r \odot (UB - LB) \quad (5)$$

where r is a uniformly distributed random vector and denotes element-wise multiplication. These samples are used to ensure basic coverage of the search space.

If a prior region $[LB_p, UB_p]$ can be determined based on engineering experience or existing design parameters, the prior-guided samples are generated as

$$X_i^{(p)} = LB_p + r \odot (UB_p - LB_p) \quad (6)$$

This strategy causes part of the initial samples to concentrate in regions that are more likely to yield feasible or high-quality solutions, thereby improving the effectiveness of the initial population.

To further enhance the coverage of boundary and symmetric regions, opposition-based learning samples are introduced as

$$X_i^{(o)} = LB + UB - X_i \quad (7)$$

The hybrid initialization strategy thus balances global exploration and prior guidance. It not only prevents the initial population from being overly confined to local regions, but also increases the probability of early access to high-potential areas.

3.3 Stagnation Awareness and Directed Escape Mechanism

As the iteration proceeds, the population often experiences diversity loss, rapid aggregation, and long periods during which the best solution no longer improves. To accurately identify this state, where individuals still move but effective search is nearly halted, a stagnation criterion is constructed by jointly considering the change in the best fitness and the population diversity.

The relative improvement in the best fitness is defined as

$$\delta(t) = \frac{|f_{best}(t) - f_{best}(t-k)|}{\max\{1, |f_{best}(t-k)|\}} \quad (8)$$

where k is the length of the detection window. The normalized population diversity is further defined as

$$Div(t) = \frac{1}{ND} \sum_{i=1}^N \left\| \frac{X_i(t) - X_m(t)}{UB - LB} \right\|_1 \quad (9)$$

$$\delta(t) < \varepsilon_f, Div(t) < \varepsilon_d \quad (10)$$

When the population is regarded as having entered a stagnation state, where and denote the improvement threshold and diversity threshold, respectively.

Once stagnation is detected, a purely random restart can recover diversity but may destroy the useful information already accumulated in high-quality regions. Therefore, this paper employs a directed escape strategy to perturb part of the individuals toward promising regions:

$$X_i^{new} = X_i + \alpha_1 r_1 (X_{best} - X_i) + \alpha_2 r_2 (X_i - X_m) + \alpha_3 \xi \quad (11)$$

where $\alpha_1, \alpha_2, \alpha_3$ are weighting coefficients, and ξ is a random perturbation vector. This expression contains three components: the first drives the individual toward the current promising region, the second expands the search along the direction away from the population center, and the third maintains search flexibility through random perturbation. Compared with a full random restart, this mechanism restores search activity while retaining useful information acquired so far.

3.4 Elite-Guided Local Refinement Mechanism

Although control parameter tuning problems are typically low-dimensional, different parameters often affect system performance in a highly sensitive and strongly coupled manner. In the late stage, standard HHO mainly relies on single-point encircling and pouncing, which limits its ability to fully exploit local high-quality information. To address this issue, an elite-guided local refinement mechanism is proposed, in which multiple promising candidate solutions are refined collaboratively.

For an elite individual, local candidate solutions are generated along coordinate directions or diagonal directions as

$$X_e' = X_e \pm \rho d \quad (12)$$

where ρ is the local search step size and d is the direction vector. When d is chosen as a standard basis vector, the search becomes coordinate-direction scanning, which enables fine adjustment of a single parameter. When d is chosen as a normalized diagonal direction, the search becomes coupled-direction scanning, which captures performance improvements caused by multi-parameter interaction.

Based on the above rule-based directional scanning, a small-scale random perturbation is further introduced in the local promising neighborhood to reduce terminal error:

$$X_{e''} = X_e + \sigma \cdot \mathcal{N}(0, I) \quad (13)$$

where σ denotes the perturbation scale and $\mathcal{N}(0, I)$ denotes a standard Gaussian random vector. If the new solution outperforms the current elite solution, it is accepted. This mechanism enables the algorithm to discover subtle improvement directions beyond regular directional scanning, thereby improving late-stage approximation accuracy and solution stability.

4 Objective Function Construction

The objective of control parameter tuning should not be restricted to a single performance index. Instead, it should comprehensively reflect response speed, smoothness, steady-state accuracy, and operating-condition adaptability. For the LLC-LADRC control tuning problem, a normalized objective function is constructed based on multiple performance indices:

$$J(\theta) = \sum_{i=1}^m w_i \hat{Q}_i^{\gamma_i} \quad (14)$$

where θ is the control parameter vector to be optimized, $\hat{Q}_i$ denotes the normalized performance index, w_i is the weight coefficient, and γ_i is the nonlinear shaping factor. When $\gamma_i > 1$, the objective function penalizes poor solutions more strongly, making the optimization process pay greater attention to high-quality responses and tail-risk control.

In this paper, $\hat{Q}_i$ may include steady-state error, overshoot, settling time, error integral index, and robustness-related terms. Among them, the error integral term may be formulated using the ITAE criterion to enhance sensitivity to late-stage errors and steady-state convergence quality.

Engineering constraints are common in control tuning problems, including parameter bounds, peak response limits, and steady-state error tolerances. To avoid excessive compression of high-quality boundary solutions caused by the fixed large-penalty method, a feasibility-first principle is adopted. The total constraint violation is defined as

$$V(\theta) = \sum \max(0, g_j(\theta)) \quad (15)$$

where g_j denotes the j -th constraint. When comparing two candidates, feasible solutions are preferred. If both are feasible, their objective function values are compared. If both are infeasible, their total constraint violations are compared. This strategy preserves finer discrimination near the constraint boundary and helps the algorithm approach high-quality solutions near the feasible boundary more robustly.

5 Experimental Design

5.1 Experimental Environment

All experiments in this paper were conducted on the MATLAB platform. The hardware platform was a multi-core server equipped with an E5-2680v4 CPU, supporting 56-thread task scheduling, and 64 GB of memory. To improve the efficiency of repeated independent experiments, parallel computing was employed. System simulation, objective-function evaluation, algorithm iteration, and statistical analysis were all implemented in a unified environment to ensure fair comparison among different algorithms.

5.2 Comparative Algorithms and Test Scenarios

To verify the effectiveness and task adaptability of the improved HHO, two categories of experimental scenarios were designed.

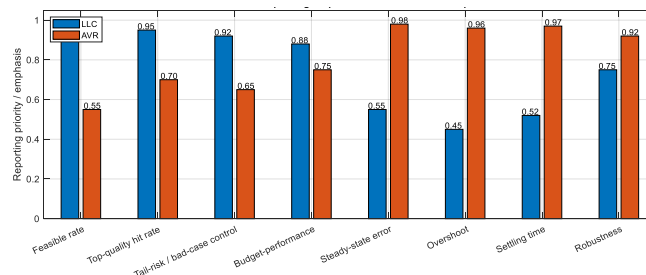


Figure 2 Recommended reporting emphasis for LLC and AVR experiments

The first category consists of LLC and AVR control tuning scenarios, in which the baseline HHO, hybrid-initialized HHO, improved HHO, PSO, and GWO are systematically compared [7-9]. This part focuses on evaluating the effect of the proposed improvements on problems with narrow feasible regions, strong boundary sensitivity, and demanding dynamic performance tuning requirements [10].

The second category consists of supplementary THIRD and MMS scenarios, where the improved HHO is compared with PSO_refine and GWO_refine. This part is intended to examine the overall competitiveness and task specificity of the

proposed method under more complex objective landscapes.

5.3 Parameter Settings

In the experiments, the maximum number of iterations was set to 40, the population size was set to 28, and the number of independent runs was set to 24. The hybrid initialization ratios were set as 0.35 for globally random samples, 0.40 for prior-guided samples, and 0.25 for opposition-based samples. The proportion of the global search stage was set to 45%, the continuous stagnation window was set to 4 generations, the diversity threshold was set to 0.08, and the number of elite individuals retained was set to 4. The numbers of rounds and step-size ratios for lightweight refinement, heavy refinement, and random polishing in the late stage were determined according to unified rules to ensure fairness across different algorithms^[11-13].

5.4 Results on LLC and AVR Scenarios

From the AVR results, it can be observed that the advantage of the improved HHO is mainly reflected in typical performance and stability. Although the best values of all algorithms are close to 1, the improved HHO achieves a median value of only 1.0013, a worst-case value of only 1.0213, and a standard deviation of only 0.0050, which are significantly better than those of the baseline HHO, PSO, and GWO. Compared with the baseline HHO, the improved HHO reduces the median value by approximately 60.9% and the worst-case value by approximately 98.8%. This indicates that the proposed stagnation-awareness and elite-guided refinement mechanisms can effectively alleviate premature convergence on AVR-type problems with many local extrema.

In the LLC scenario, the advantage of the improved HHO is mainly reflected in tail-risk compression. Compared with PSO, both methods reach a median value of 1.0000, but the worst-case value of the improved HHO decreases from 1.0658 to 1.0207, and the standard deviation decreases from 0.0068 to 0.0040. This indicates that its additional benefit lies not in occasionally finding a better solution, but in more consistently avoiding failure samples. This observation is consistent with the structural characteristics of the LLC problem, namely a narrow feasible region and boundary-adjacent high-quality solutions, and further confirms the strong suitability of the hybrid initialization and stagnation recovery mechanisms for this type of task.

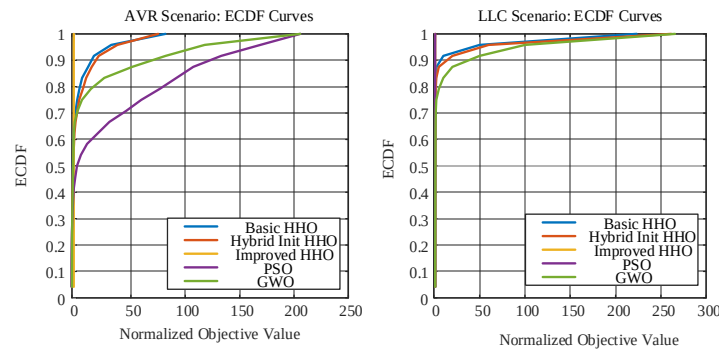


Figure 3 ECDF Summary for AVR and LLC Scenarios

Overall, for both LLC and AVR control tuning problems, the advantage of the improved HHO is not limited to single-run best values. More importantly, it yields better median performance, lower tail risk, and more stable results across repeated runs. Such behavior is more consistent with the practical requirements of engineering control tuning in terms of robustness and repeatability.

5.5 Results on Supplementary Scenarios

To further evaluate the generalization capability of the proposed method, the improved HHO was compared with PSO_refine and GWO_refine on the THIRD and MMS scenarios.

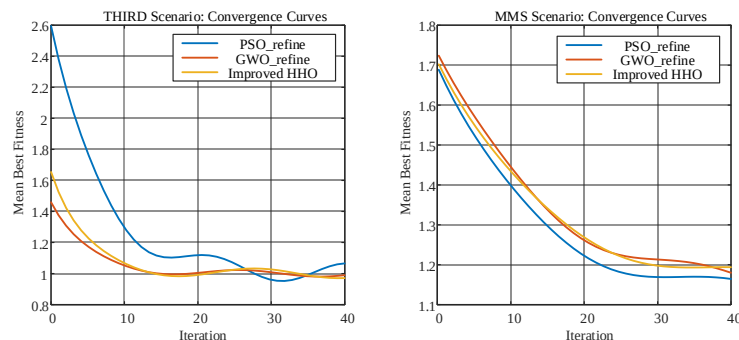


Figure 2 Fitness Convergence in THIRD and MMS Scenarios

In the THIRD scenario, all three algorithms achieve a best value of 1, and the difference mainly lies in stability. Both GWO_refine and the improved HHO exhibit good typical performance, and the median value of the improved HHO also reaches 1.0000. This indicates that the proposed method remains competitive in general engineering scenarios, although its advantage is weaker than that observed on typical control tuning problems such as LLC and AVR.

In the MMS scenario, the improved HHO does not show absolute superiority. PSO_refine performs slightly better than the improved HHO in terms of both best and median values, and GWO_refine is also close to it, while the differences in worst-case values among the three methods are not significant. This suggests that the improvements proposed in this paper are not intended as a universal enhancement for all general multimodal complex landscapes, but rather are more specifically designed to improve performance on control tuning problems characterized by narrow feasible regions, strong boundary sensitivity, and stringent terminal refinement requirements.

Therefore, the supplementary experiments further verify the task specificity of the improved HHO: the method exhibits significant advantages on control tuning scenarios such as LLC and AVR, while maintaining good overall competitiveness on general complex optimization problems without necessarily aiming for absolute dominance in all cases.

6 Conclusion

To address the limitations of standard HHO in control parameter tuning problems, including insufficient initialization coverage, a tendency to stagnate in the middle stage, and limited late-stage refinement capability, this paper proposes an improved Harris Hawks Optimization algorithm for engineering-oriented tuning tasks. The proposed method improves the proportion of effective initial samples through hybrid initialization, enhances mid-stage search recovery through stagnation awareness and directed escape, and improves late-stage exploitation accuracy and result stability through elite-guided local refinement.

Experimental results show that the improved HHO demonstrates clear advantages on two representative control tuning scenarios, namely LLC and AVR. Its improvement is reflected not only in the best solution obtained in a single run, but more importantly in better median performance, lower tail risk, and more stable results across repeated runs, indicating that the method is more consistent with the practical requirements of engineering control tuning in terms of robustness and repeatability. Supplementary experiments further show that the improved HHO exhibits clear task specificity and is particularly suitable for control tuning problems with narrow feasible regions, pronounced boundary high-quality regions, and strong late-stage refinement requirements.

Future work may proceed in two directions. The first is to introduce adaptive parameter adjustment mechanisms, allowing the algorithm to automatically modify stagnation detection and refinement intensity according to the search stage. The second is to extend the method to multi-objective control parameter tuning and high-cost simulation-based optimization problems, thereby further enhancing its practical applicability and scope of use.

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