Multi-UAV Source Seeking and Optimization Using Particle Swarm Optimization Variants

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***Abstract*—Investigates the performance of various Particle Swarm Optimization (PSO) variants for multi-UAV source seeking and optimization problems. We compare three PSO variants: Standard PSO (SPSO), Acceleration-based PSO (APSO), and Adaptive Random PSO (ARPSO) in both source seeking scenarios and benchmark optimization functions. Our results demonstrate that APSO consistently outperforms other variants in source seeking tasks, particularly in noisy environments, due to its second-order dynamics that provide smoother trajectories and better noise resilience. However, SPSO shows superior performance on most benchmark optimization functions. We also explore four hybrid approaches that combine these PSO variants in different configurations: Particle Hybrid, Sequential Hybrid, Parallel Hybrid, and Adaptive Hybrid. The Particle Hybrid and Parallel Hybrid approaches demonstrate the most promising overall performance, confirming that strategic combinations of PSO variants can enhance optimization capabilities. This provides insights into algorithm selection for UAV applications and suggests directions for further development of hybrid optimization techniques.**

***Index Terms*—particle swarm optimization, unmanned aerial vehicles, source seeking, optimization, hybrid algorithms, swarm intelligence**

I. Introduction

Unmanned Aerial Vehicles (UAVs) have become increasingly important in various applications, including environmental monitoring, search and rescue operations, and surveillance. Multi-UAV systems offer advantages in terms of robustness, efficiency, and coverage compared to single-UAV approaches. However, coordinating multiple UAVs to efficiently locate sources of interest in complex environments remains a challenging problem.

Particle Swarm Optimization (PSO) is a population-based optimization technique inspired by the social behavior of birds flocking or fish schooling. PSO has been widely applied to various optimization problems due to its simplicity, effectiveness, and ease of implementation. In the context of multi-UAV systems, PSO provides a natural framework for coordinating the movement of multiple agents toward an objective.

As per paper [1], we investigates three PSO variants for multi-UAV source seeking and optimization:

- Standard PSO (SPSO): The classic first-order PSO algorithm
- Acceleration-based PSO (APSO): A second-order variant that uses acceleration as the primary update mechanism
- Adaptive Random PSO (ARPSO): A variant that incorporates adaptive parameters and randomness

We evaluate these algorithms in two contexts:

1) Source seeking: Finding the source of a signal in environments with and without noise
2) Optimization: Performance on standard benchmark functions from the CEC 2022 competition

Additionally, we explore four hybrid approaches that combine these PSO variants to leverage their complementary strengths:

- Particle Hybrid: Different particles within the same swarm use different update rules
- Sequential Hybrid: Different algorithms used in sequence
- Parallel Hybrid: Multiple algorithms run simultaneously on separate sub-swarms
- Adaptive Hybrid: Dynamically switches between algorithms based on performance

The remainder of this report is organized as follows: Section II provides background on PSO variants. Section III describes the source seeking problem and presents experimental results. Section IV evaluates the performance of PSO variants on benchmark functions. Section V introduces hybrid approaches and analyzes their performance. Section VI concludes the paper and discusses future work.

II. PSO Variants

A. Standard PSO (SPSO)

Standard PSO is a first-order optimization algorithm that updates particle positions based on their velocity. Each particle's movement is influenced by its own best-known position and the swarm's global best position.

The mathematical formulation of SPSO is as follows:

$$v_i(t+1) = \omega_1 v_i(t) + c_1 r_1 (p_i - x_i) + c_2 r_2 (g - x_i) \quad (1)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (2)$$

where:

- $v_i(t)$ is the velocity of particle i at time t
- $x_i(t)$ is the position of particle i at time t
- p_i is the best position found by particle i so far
- g is the global best position found by any particle
- ω_1 is the inertia weight

- c_1 and c_2 are acceleration coefficients
- r_1 and r_2 are random values in the range [0,1]

SPSO provides a balanced exploration-exploitation trade-off and is widely used as a baseline algorithm in swarm intelligence applications.

B. Acceleration-based PSO (APSO)

APSO is a second-order variant of PSO that uses acceleration as the primary update mechanism. This approach maintains momentum through previous movement history and produces smoother trajectories with more consistent direction.

The mathematical formulation of APSO is:

$$a_i(t+1) = \omega_1 a_i(t) + c_1 r_1 (p_i - x_i) + c_2 r_2 (g - x_i) \quad (3)$$

$$v_i(t+1) = \omega_2 v_i(t) + a_i(t+1)T \quad (4)$$

$$x_i(t+1) = x_i(t) + v_i(t+1)T \quad (5)$$

where:

- $a_i(t)$ is the acceleration of particle i at time t
- T is the time step
- ω_2 is the velocity damping coefficient

The second-order dynamics of APSO allow it to maintain momentum, which can be beneficial in noisy environments where consistent movement direction is important.

C. Adaptive Random PSO (ARPSO)

ARPSO incorporates adaptive parameters and randomness to enhance exploration capabilities. It dynamically adjusts the inertia weight based on the swarm's state and includes additional random attractive positions to help particles escape local optima.

The mathematical formulation of ARPSO is:

$$\omega_i(t+1) = f(\text{evolutionary speed}, \text{aggregation degree}) \quad (6)$$

$$v_i(t+1) = \omega_i v_i(t) + c_1 r_1 (p_i - x_i) + c_2 r_2 (g - x_i) + c_3 r_3 (a_i - x_i) \quad (7)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (8)$$

where:

- $\omega_i(t)$ is the adaptive inertia weight for particle i at time t
- a_i is a random attractive position
- c_3 is the coefficient for the random attraction
- r_3 is a random value in the range [0,1]

The adaptive inertia weight is adjusted based on:

- Evolutionary speed: How quickly the swarm's best solution is improving
- Aggregation degree: How clustered the particles are in the search space

When particles cluster too much (high aggregation), the inertia weight increases to push particles to explore more widely. When improvement slows down, the inertia weight is adjusted to help escape potential local optima.

III. Source Seeking

A. Problem Formulation

The source seeking problem involves finding the location of a signal source in an environment. The signal strength typically follows a distribution that decreases with distance from the source. In our experiments, we use a Gaussian distribution centered at the source location:

$$S(x, y) = A \cdot \exp\left(-\frac{(x - x_s)^2 + (y - y_s)^2}{2\sigma^2}\right) \quad (9)$$

where:

- $S(x, y)$ is the signal strength at position (x, y)
- (x_s, y_s) is the source location
- A is the maximum signal strength
- σ is the spread parameter

In noisy environments, the measured signal strength includes additive noise:

$$S_{measured}(x, y) = S(x, y) + \eta \quad (10)$$

where η is Gaussian noise with zero mean and standard deviation proportional to the noise level.

B. Experimental Setup

We conducted experiments to evaluate the performance of SPSO, APSO, and ARPSO in source-seeking tasks with and without noise. The experimental parameters were:

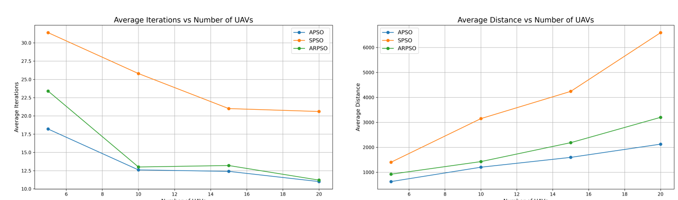
- Search space: 100m × 100m
- Source location: Randomly placed within the search space
- Number of UAVs: 5 to 30
- Noise levels: 0 to 0.15 (as a fraction of maximum signal strength)
- Convergence criterion: Global best position within 2m of the source
- Number of runs: 5 for each configuration

Performance metrics included:

- Number of iterations to convergence
- Total distance traveled by all UAVs

C. Results without Noise

Fig. 1 shows the performance of the three PSO variants in source seeking without noise as the number of UAVs increases.



(a) Iterations vs. Number of UAVs (b) Distance vs. Number of UAVs

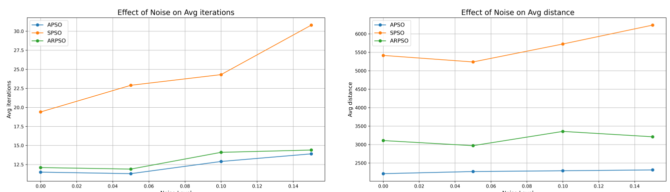
Fig. 1: Source seeking performance without noise

Key observations:

- APSO consistently outperforms both SPSO and ARPSO in terms of iterations and distance traveled
- APSO shows the best scaling as UAV count increases, with iterations actually decreasing as more UAVs are added
- SPSO shows the worst scaling in terms of distance traveled

D. Results with Noise

Fig. 2 shows the performance of the three PSO variants in source seeking with varying noise levels for 30 UAVs.



(a) Iterations vs. Noise Level (b) Distance vs. Noise Level

Fig. 2: Source seeking performance with noise (30 UAVs)

Key observations:

- All algorithms show degraded performance as noise increases
- APSO maintains the best performance across all noise levels
- APSO shows the best robustness to noise, with a less steep performance degradation
- Even at 0.15 noise level, APSO maintains good performance

E. Discussion

APSO's superior performance in source seeking can be attributed to its second-order dynamics, which provide several advantages:

- Momentum: APSO maintains momentum through previous movement history, making it less susceptible to being misled by noisy measurements
- Smooth trajectories: The acceleration-based approach produces smoother trajectories that are more energy-efficient for UAVs
- Noise filtering: The second-order dynamics naturally filter out noise through momentum
- Consistent direction: APSO maintains more consistent movement direction, which is beneficial when navigating toward a source

The decreasing number of iterations with increasing UAV count for APSO is particularly interesting. This suggests that APSO effectively leverages the parallel exploration capability of multiple UAVs, with more UAVs providing better sampling of the environment and faster convergence.

IV. Benchmark Function Optimization

A. CEC 2022 Benchmark Functions

To evaluate the optimization performance of the PSO variants, we used five functions from the CEC 2022 benchmark suite [2]:

- F1 (Zakharov): Continuous unimodal function with interdependent variables
- F2 (Rosenbrock): Continuous function with narrow curved valley
- F3 (Schaffer): Highly multimodal function with many local optima
- F4 (Step Rastrigin): Discontinuous multimodal function with plateaus
- F5 (Levy): Multimodal function with many local minima

These functions represent diverse optimization challenges:

- F1-F2: Test convergence precision and speed
- F3-F5: Test ability to escape local optima

B. Experimental Setup

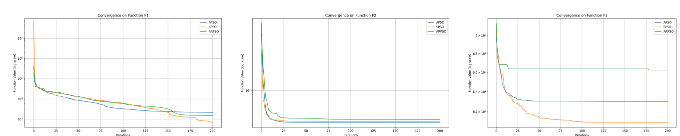
We conducted experiments with the following parameters:

- Dimension: 10
- Number of particles: 30
- Maximum iterations: 200
- Number of runs: 5 for each function and algorithm

Performance was measured by the final function value achieved (lower is better).

C. Results

Fig. 3 shows the convergence behavior of the three PSO variants on the five benchmark functions.



(a) F1 (Zakharov) (b) F2 (Rosenbrock) (c) F3 (Schaffer)

(d) F4 (Step Rastrigin) (e) F5 (Levy)

Fig. 3: Convergence plots for PSO variants on CEC 2022 benchmark functions

Table I summarizes the mean and standard deviation of the final function values achieved by each algorithm across the five benchmark functions.

Fig. 4 shows a radar chart comparing the relative performance of the three PSO variants across the five benchmark functions.

TABLE I: Mean Function Values Across Benchmark Functions

Algorithm	**F1**	**F2**	**F3**	**F4**	**F5**
APSO	2.14e+03	4.45e+02	6.30e+02	8.32e+02	1.30e+03
SPSO	6.86e+02	4.55e+02	6.09e+02	8.22e+02	9.17e+02
ARPSO	1.49e+03	**4.17e+02**	6.62e+02	8.92e+02	9.34e+02

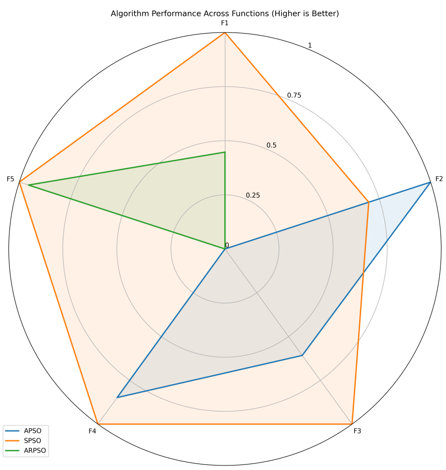


Fig. 4: Radar chart of PSO performance across benchmark functions

D. Discussion

The benchmark results reveal a different performance pattern compared to the source seeking experiments:

- SPSO performs best overall, winning on 4 out of 5 functions (F1, F3, F4, F5)
- ARPSO shows mixed performance, winning on F2 (Rosenbrock) but struggling with other functions
- APSO consistently underperforms on most benchmark functions compared to SPSO, though it shows competitive performance on F2

These results can be explained by the characteristics of the algorithms and the nature of the benchmark functions:

- SPSO's balanced exploration-exploitation approach works well for diverse optimization challenges
- APSO's momentum can be advantageous for functions with narrow valleys (like Rosenbrock) but may cause overshooting in other cases
- ARPSO's focus on exploration through randomness can make precise convergence difficult

The convergence plots provide additional insights:

- APSO shows faster initial convergence on some functions (F2, F4) but plateaus earlier
- SPSO demonstrates steady, consistent improvement and achieves the best final solutions on most functions
- ARPSO plateaus early on several functions but occasionally shows late improvements

These observations suggest that each PSO variant has complementary strengths that could potentially be combined in hybrid approaches.

V. Hybrid PSO Approaches

A. Hybrid Strategies

Based on the complementary strengths observed in the PSO variants, we developed four hybrid approaches:

1) Particle Hybrid: In this approach, different particles within the same swarm use different update rules:

- The swarm is divided into 3 groups of 10 particles each
- Group 1: APSO update rules
- Group 2: SPSO update rules
- Group 3: ARPSO update rules
- All particles share information about the global best position

2) Sequential Hybrid: This approach uses different algorithms in sequence:

- Phase 1: APSO runs for 40% of total iterations
- Phase 2: SPSO is initialized around APSO's final solution and runs for 60% of iterations
- The best solution from APSO is used as a starting point for SPSO

3) Parallel Hybrid: In this approach, multiple algorithms run simultaneously on separate sub-swarms:

- Three separate swarms run in parallel (10 particles each)
- Swarm 1: APSO
- Swarm 2: SPSO
- Swarm 3: ARPSO
- After each iteration, the best solution across all swarms is shared with all algorithms

4) Adaptive Hybrid: This approach dynamically switches between algorithms based on their recent performance:

- Maintains three algorithm instances (APSO, SPSO, ARPSO)
- Starts with APSO
- Every 10 iterations, evaluates which algorithm has made the most improvement
- Switches to the best-performing algorithm for the next 10 iterations
- All algorithms share the same global best information

B. Experimental Setup

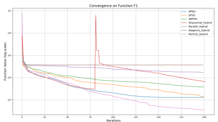
We evaluated the hybrid approaches on the same five CEC 2022 benchmark functions used in Section IV. The experimental parameters were:

- Dimension: 10
- Total number of particles: 30 (distributed as described for each hybrid approach)
- Maximum iterations: 200
- Number of runs: 5 for each function and algorithm

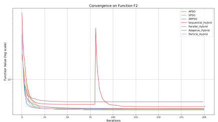
C. Results

Fig. 5 shows the convergence behavior of the hybrid approaches compared to the original PSO variants on the five benchmark functions.

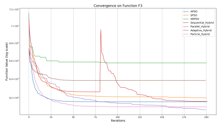
Table II summarizes the performance ranking of all algorithms across the five benchmark functions, with 1 indicating the best performance and 7 the worst.



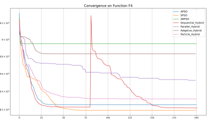
(a) F1 (Zakharov)



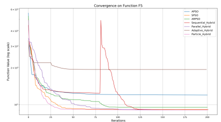
(b) F2 (Rosenbrock)



(c) F3 (Schaffer)



(d) F4 (Step Rastrigin)



(e) F5 (Levy)

Fig. 5: Convergence plots for hybrid approaches on CEC 2022 benchmark functions

TABLE II: Performance Ranking of Algorithms (1=Best, 7=Worst)

Algorithm	F1	F2	F3	F4	F5	Wins	Avg Rank
Particle_Hybrid	1	4	3	5	3	1	2.20
Parallel_Hybrid	6	3	1	4	1	2	3.20
APSO	2	2	2	2	7	0	3.60
SPSO	3	5	4	1	5	1	3.60
Sequential_Hybrid	5	6	5	3	2	0	4.00
ARPSO	4	1	6	6	6	1	4.80
Adaptive_Hybrid	7	7	7	7	4	0	6.60

D. Discussion

The hybrid approaches show interesting performance patterns:

- Particle Hybrid performs well overall (average rank 2.2)
- Sequential Hybrid shows mixed performance (average rank 4.0), with a notable spike in the convergence plot at the transition point between APSO and SPSO phases
- Parallel Hybrid performs well overall (average rank 3.20), coming in second to Particle Hybrid (average rank 2.20)
- Adaptive Hybrid performs poorly (average rank 6.6), suggesting that frequent algorithm switching disrupts the optimization process

The strong performance of the Particle Hybrid approach suggests that combining different PSO variants within a single swarm allows the algorithm to leverage the complementary strengths of each variant. The particles using APSO dynamics can provide quick initial progress, while those using SPSO can refine solutions more precisely.

The poor performance of the Adaptive Hybrid approach is somewhat surprising but can be explained by several factors:

- The 10-iteration evaluation window may be too short to accurately assess algorithm performance
- Frequent switching between algorithms disrupts the momentum and learning history of each method
- The performance metric (improvement in best solution) may not capture long-term potential

The spike in the Sequential Hybrid's convergence plot occurs at the transition point (around iteration 80) when the algorithm switches from APSO to SPSO. This happens because SPSO is initialized around APSO's final solution but with some random perturbation to maintain diversity. This perturbation temporarily worsens the fitness before SPSO begins to improve it. Reducing this perturbation could potentially eliminate this spike and improve overall performance.

VI. Conclusion and Future Work

A. Conclusion

This report has investigated the performance of three PSO variants (SPSO, APSO, and ARPSO) in multi-UAV source seeking and optimization tasks, as well as four hybrid approaches that combine these variants.

Key findings include:

- APSO consistently outperforms other variants in source seeking tasks, particularly in noisy environments, due to its second-order dynamics that provide smoother trajectories and better noise resilience
- SPSO shows superior performance on most benchmark optimization functions, demonstrating a better balance between exploration and exploitation for diverse optimization challenges
- ARPSO generally underperforms in both source seeking and benchmark optimization, though it occasionally excels on specific functions
- Among the hybrid approaches, Particle Hybrid shows the most promising overall performance, suggesting that combining different PSO variants within a single swarm can leverage their complementary strengths
- The performance of each PSO variant is strongly influenced by how well its movement dynamics match the characteristics of the problem landscape

These results provide valuable insights for algorithm selection in multi-UAV applications and suggest that hybrid approaches can offer performance improvements over individual PSO variants.

B. Future Work

Several directions for future work have been identified:

- Conduct more extensive experiments (10-30 runs) to ensure statistical significance of the results
- Refine the Sequential Hybrid approach by reducing or removing random perturbation during the transition between algorithms

By addressing these areas, we aim to develop more robust and efficient algorithms for multi-UAV coordination in complex environments.

References

[1] A. Shankar, Himanshu, H. Kandath, and J. Senthilnath, "Acceleration-Based PSO for Multi-UAV Source-Seeking," in IECON 2023- 49th Annual Conference of the IEEE Industrial Electronics Society, pp. 1-6, 2023, doi: 10.1109/IECON51785.2023.10312321.

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