Supplementary-Dual-population Evolution-based Collaborative Optimization for Coordinated UAVs Mission Patrol under Mountainous Environments

Yunhe Wang[1], Wenyuan Xiao[1], Dong Wang[2], Yajuan Zhang[1], Qingda Chen[3*], Shengxiang Yang[4,5*]
[1]School of Artificial Intelligence, Hebei University of Technology, Tianjin, China.
[2]Tianjin Aerospace Electromechanical Equipment Research Institute, Tianjin, China.
[3]School of Electronic Information Engineering, Inner Mongolia University, Hohhot, China.
[4]State Key Laboratory of Synthetical Automation for Process Industries, Northeastern University, Shenyang, China
[5]School of Computer Science and Informatics, De Montfort University, Leicester LE1 9BH, U.K.

This is a supplementary material of the paper "Dual-population Evolution-based Collaborative Optimization for Coordinated UAVs Mission Patrol under Mountainous Environments", submitted to IEEE Transactions on Emerging Topics in Computational Intelligence.

I. Simulation experiments

A. Parameter settings

TABLE S1
PARAMETER SETTINGS OF DIFFERENT BENCHMARK ALGORITHMS FOR UAVS TASK ASSIGNMENT AND PATH PLANNING

Algorithm	Parameter
DECOA	$c_1 = 1.5, c_2 = 1.5, \sigma = 0.5$
PSO	$\omega_{max} = 0.9, \omega_{min} = 0.2, C_1 = 2.0,$ $C_2 = 1.5$
ACO	$\alpha = 1.0, \beta = 2.0, \rho = 0.5$
HPSO	$\omega = 0.7, C_1 = 2.0, C_2 = 0$
IPO	-
DGBCO	-
GWO	-
HGWODE	$C_r = 0.5$
AWGPSO	$\omega = 0.9, \alpha_1 = 0.5, \alpha_2 = 0.5, \alpha_3 = 0.5, \alpha_4 = 0.5$
SDPSO	$\omega = 0.9, C_1 = 2.0, C_2 = 2.0$
CDE	$\omega_1 = 0.5, \omega_2 = 0.5$

The evaluation of the proposed DECOA consists of three components: UAV task assignment, UAV path planning, and coordinated UAV mission patrol in mountainous environments. To assess its performance in UAV task assignment, DECOA was compared with three classical evolutionary algorithms: PSO [1], ACO [2], and HPSO [3]. For UAV path planning, DECOA was benchmarked against eight algorithms, including four basic evolutionary algorithms including IPO [4], DGBCO [5], GWO [6], and PSO [1] and four enhanced evolutionary algorithms including HGWODE [7], AWGPSO [8], SDPSO [9], and CDE [10].

The parameters for each algorithm are summarized in Table S1. To ensure a fair comparison, the population size and maximum number of iterations were set uniformly for all algorithms, with $P_n = 100$ and $T_{\max} = 100$, respectively. Each algorithm was executed 20 times per scenario, and the maximum, minimum, and average fitness values were recorded for performance comparison.

B. DECOA for UAVs task assignment

Table S2 summarizes the experimental results across all 15 scenarios. In scenarios with 10 task points, while all algorithms achieve comparable performance in finding the optimal solution, their generated UAV task assignment sequences differ significantly. As illustrated in Fig. S1, the DPSO algorithm, along with other comparison methods, consistently produces optimal task assignment sequences. In contrast, the PSO algorithm demonstrates instability, generating task point sequences

TABLE S2
PERFORMANCE COMPARISON OF DIFFERENT EVOLUTIONARY ALGORITHMS FOR UAVS TASK ASSIGNMENT. $case\_i\_j$ REPRESENTS THE CASE HAS i TASK POINTS AND j UAVS.

	case_10_2			case_10_3			case_10_4		
Algorithm	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean
DECOA	**95.0173**	**95.0173**	**95.0173**	**102.6936**	103.1681	102.8851	**94.5360**	**94.8512**	**94.5752**
ACO	**95.0173**	**95.0173**	**95.0173**	**102.6936**	**103.0579**	102.7847	**94.5360**	96.9788	94.7994
PSO	**95.0173**	103.8606	97.9142	**102.6936**	105.8457	103.6679	**94.5360**	101.8009	96.8750
HPSO	**95.0173**	**95.0173**	**95.0173**	**102.6936**	**103.0579**	**102.7118**	**94.5360**	95.8978	94.6842
	case_20_2			case_20_3			case_20_4		
Algorithm	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean
DECOA	**128.1020**	**134.4524**	**130.1941**	121.7251	**140.6820**	**130.9984**	**99.7820**	**108.6281**	**104.1276**
ACO	**128.1020**	138.8783	134.0683	**120.1463**	142.4325	132.1736	103.3672	111.2597	107.0405
PSO	128.3318	144.5638	135.3068	122.1843	154.3297	140.8671	100.1218	111.5065	106.8496
HPSO	**128.1020**	139.4650	132.1258	132.3841	142.2520	136.8965	102.8004	110.0368	106.6998
	case_40_2			case_40_3			case_40_4		
Algorithm	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean
DECOA	**168.0010**	**199.6060**	**182.8683**	**159.7145**	**192.7563**	**177.4713**	**191.6594**	**220.6445**	**203.6119**
ACO	179.6157	207.6421	194.6412	176.0498	196.5447	187.3453	218.4749	234.7648	225.8518
PSO	187.9575	207.4681	196.8069	166.7046	198.9558	184.1511	194.4314	230.3686	214.8135
HPSO	190.9940	204.8178	197.8474	180.3919	197.9806	189.4608	215.4691	236.3192	225.9134
	case_75_2			case_75_3			case_75_4		
Algorithm	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean
DECOA	**289.0116**	**344.6146**	**316.2467**	**276.7202**	**335.0612**	**312.3467**	**267.8907**	**334.5761**	**294.7661**
ACO	330.2769	361.0475	344.7026	316.4366	351.9971	337.5521	311.9582	337.7532	324.7756
PSO	300.0645	367.4517	330.4094	305.2485	361.3840	332.2418	278.5167	323.7019	304.9444
HPSO	309.9940	361.7941	345.0210	326.3265	350.5682	342.0553	301.5252	333.6977	325.0445
	case_200_2			case_200_3			case_200_4		
Algorithm	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean
DECOA	**727.4480**	**879.5441**	**831.5144**	**695.0701**	**786.0734**	**749.1442**	**689.7227**	**804.2446**	**748.7899**
ACO	871.2420	920.2249	901.2771	769.4125	806.8482	793.9523	786.1770	829.5223	808.4702
PSO	794.4697	888.1713	841.5972	712.1557	838.2811	777.1642	732.2872	855.6112	787.2460
HPSO	858.2454	912.2578	892.6909	780.3416	816.6563	800.7627	795.712 9	837.1935	819.1139

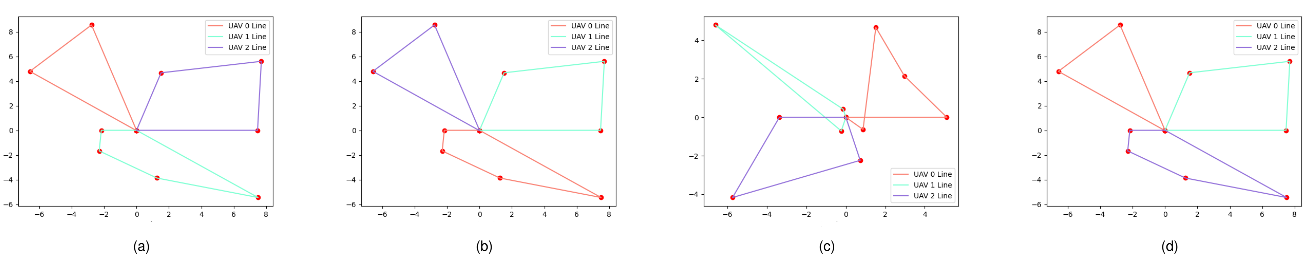


Fig. S1. Experimental results for UAVs task assignment with 10 task points and 2 UAVs. (a) DECOA. (b) ACO. (c) PSO. (d) HPSO.

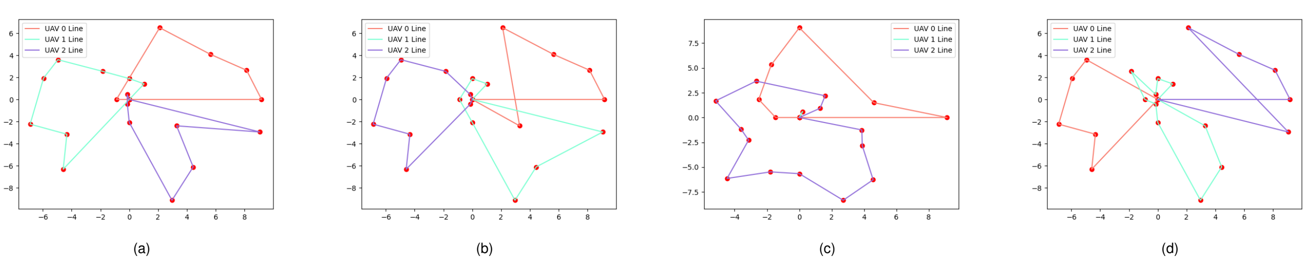
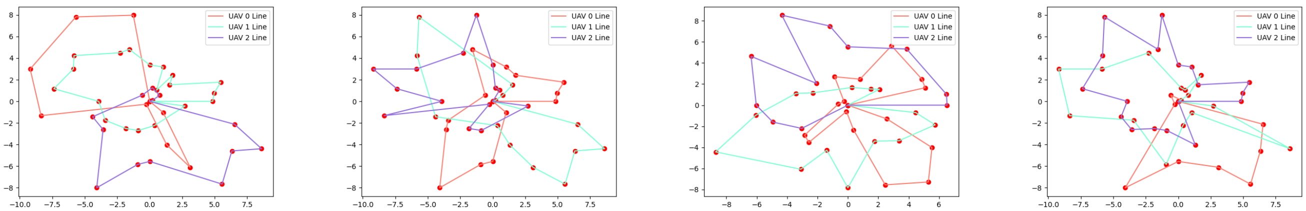


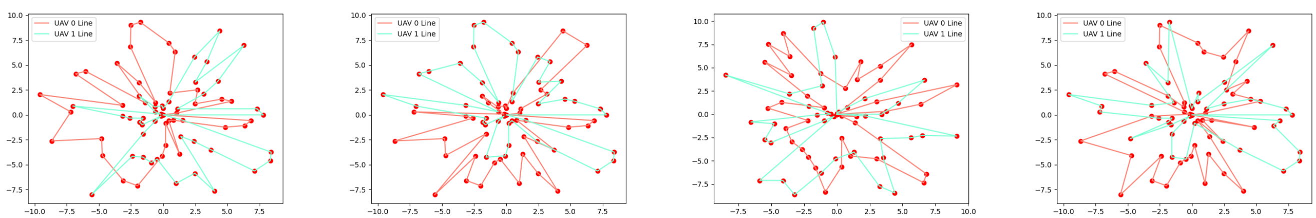
Fig. S2. Experimental results for UAVs task assignment with 20 task points and 2 UAVs. (a) DECOA. (b) ACO. (c) PSO. (d) HPSO.



(a) (b) (c) (d)

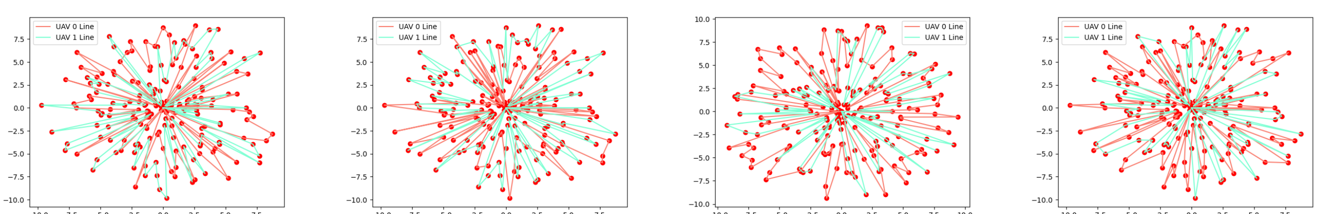
Fig. S3. Experimental results of UAVs task assignment for 40 task points and 2 UAVs. (a) DECOA. (b) ACO. (c) PSO. (d) HPSO.

with substantial crossovers that result in significantly suboptimal task assignments. With 20 task points, the performance of the algorithms varies significantly. DECOA achieves optimal minimum, maximum, and average fitness values for scenarios with 2 and 4 UAVs. In the 3-UAV scenario, while DECOA's minimum fitness exceeds only ACO, it outperforms all algorithms in other metrics. As shown in Fig. S2, despite not finding the optimal solution with the best fitness in the 3-UAV scenario compared to ACO, DECOA generates more efficient paths compared with other algorithms. A notable issue identified in competing algorithms is the path intersections within single UAV routes. For 40 task points, DECOA demonstrates consistent superiority across all fitness metrics, indicating its strong global optimization capability and stable robustness. Fig. S3 confirms DECOA's advantage in UAV task assignment with 40 tasks, exhibiting smoother trajectories and reduced path intersections compared to alternative approaches. Fig. S4 demonstrates DECOA's advantages in fitness values and path quality, generating smoother trajectories with fewer deviations than competing algorithms. This performance pattern extends to 200-task scenarios, as illustrated in Fig. S5, where DECOA achieves optimal results across all metrics. In conclusion, DECOA demonstrates superior performance during the task assignment stage within the UAV mission patrol model.



(a) (b) (c) (d)

Fig. S4. Experimental results of UAVs task assignment for 75 task points and 2 UAVs. (a) DECOA. (b) ACO. (c) PSO. (d) HPSO.



(a) (b) (c) (d)

Fig. S5. Experimental results of UAVs task assignment for 200 task points and 2 UAVs. (a) DECOA. (b) ACO. (c) PSO. (d) HPSO.

C. DECOA for UAV path planning

The path planning experiments were conducted across four distinct scenarios, each featuring an increasing number of infeasible regions: 3, 4, 5, and 6. Each algorithm was executed 20 times within these varying environments to determine the minimum, maximum, and average fitness values. The results of these experiments are presented in Table S3. Notably, DECOA consistently achieved the best performance in scenarios denoted as $case\_3$, cas_4, $case\_5$, and $case\_6$ across all fitness metrics.

Fig. S6 illustrates that the path obtained by DECOA outperformed other evolutionary algorithms in those $case\_3$-$case\_6$ scenarios. Specifically, Fig. S6(a) shows that the DECOA's path is shorter compared to the basic evolutionary algorithm. Fig. S6(b) demonstrates that the DECOA's path effectively avoids infeasible regions and maintains a relatively smooth trajectory.

Compared to other algorithms, the DECOA exhibits fewer twists and turns when navigating around infeasible regions, suggesting higher efficiency in path planning. This trend is consistent across Fig. S6(c) and S6(d). The performance of the DECOA in Fig. S6(d) validates its strengths in UAV path planning, as it maintains the shortest path distance while avoiding infeasible regions, a critical factor in the real-world environment. Fig. S7 illustrates that the path obtained by DECOA outperformed other evolutionary algorithms in those $case\_3$-$case\_6$ scenarios. Specifically, Fig. S7(a) indicates that its path is smoother when compared to other enhanced evolutionary algorithms. Fig. S7(b), S7(c), and S7(d) demonstrate that the DECOA's path effectively avoids infeasible regions and maintains a relatively smooth trajectory. Compared to other algorithms, the DECOA exhibits fewer twists and turns when navigating around infeasible regions, suggesting higher efficiency in path planning.

In summary, the DECOA has demonstrated superior path planning capabilities, excelling in path smoothness, infeasible region avoidance, and optimization across all scenarios. These attributes render the DECOA a potential tool for effective path planning in complex environments.

D. Convergence speed analysis

To verify the robustness performance of the DECOA, we conducted the convergence speed analysis in this section. The convergence rate test is conducted on the DECOA for UAV task assignment and path planning. The scenarios of UAV task assignment involving two UAVs across varying task points (20, 40, 75, and 200) are employed on DCPO and other benchmark

TABLE S3
PERFORMANCE COMPARISON OF DIFFERENT ALGORITHMS FOR UAV PATH PLANNING. $case\_i$ REPRESENTS THE CASE HAS i OBSTACLES.

		DECOA	IPO	DGBCO	GWO	PSO	HGWODE	AWGPSO	SDPSO	CDE
case_3	Min	**16.8773**	31.0816	29.8786	17.6802	24.2309	17.7657	27.1048	18.5240	17.5186
	Max	**21.4870**	46.4888	46.4121	30.6925	53.0989	23.3996	35.2683	29.2181	27.1021
	Mean	**20.2693**	41.8192	36.4573	24.8508	36.3390	20.8973	31.9708	24.1834	21.8639
case_4	Min	**18.0764**	36.2560	28.5746	19.6580	24.7000	18.7204	25.0731	21.1757	19.3380
	Max	**22.5525**	45.7794	42.4832	28.2912	52.4693	24.0656	36.8574	28.0113	26.6118
	Mean	**20.0866**	42.8099	37.1168	24.9432	38.0265	20.9923	31.9600	24.4690	22.4231
case_5	Min	**16.7661**	41.7986	32.2063	20.8946	22.7157	18.5275	25.9044	21.1156	17.7214
	Max	**22.8117**	49.2379	42.8564	31.7273	50.1551	23.8694	39.0735	30.1889	25.8396
	Mean	**20.2556**	45.2636	37.4453	25.9061	37.6960	20.9406	32.9739	25.7920	21.5836
case_6	Min	**17.5728**	39.8884	32.0571	19.2573	24.7954	18.6248	27.2108	21.1119	20.0002
	Max	**22.9570**	48.2502	44.8757	34.3202	52.3869	26.3454	40.1556	31.3030	27.5513
	Mean	**20.4060**	45.6015	37.6271	26.1875	38.8331	22.0462	34.7341	25.2397	24.4608

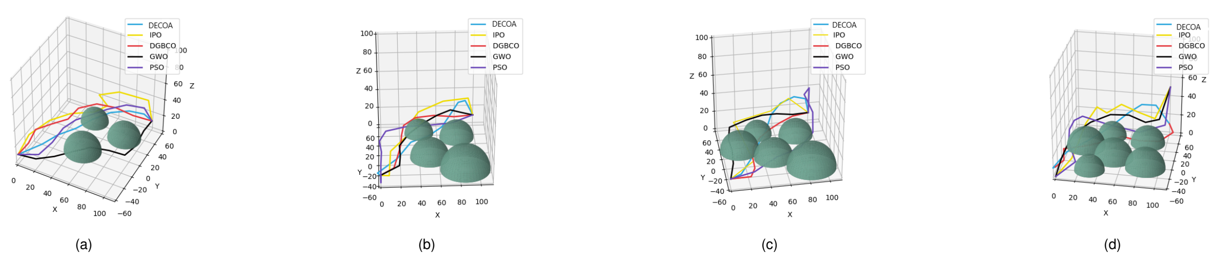


Fig. S6. The UAV paths planned by basic evolutionary algorithms in different scenarios. $case\_i$ is the environment has i obstacles. (a) case_3. (b) case_4. (c) case_5. (d) case_6

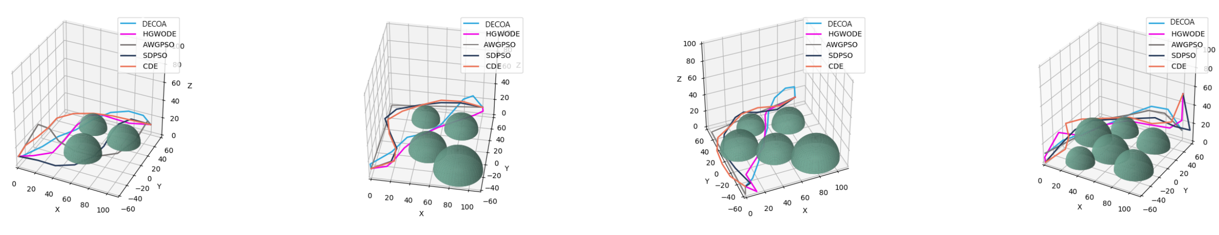
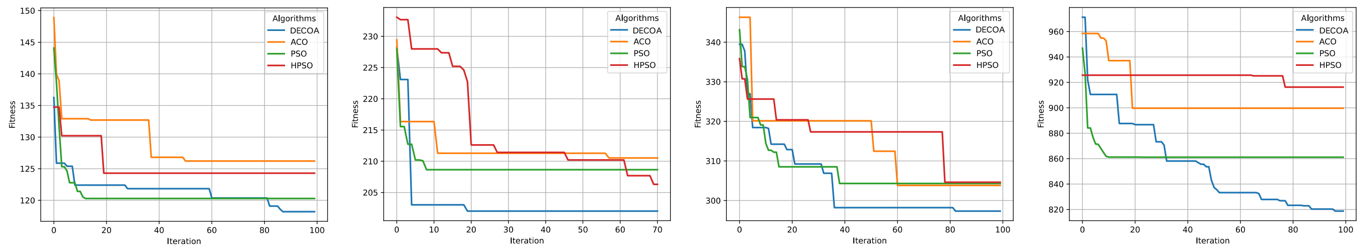
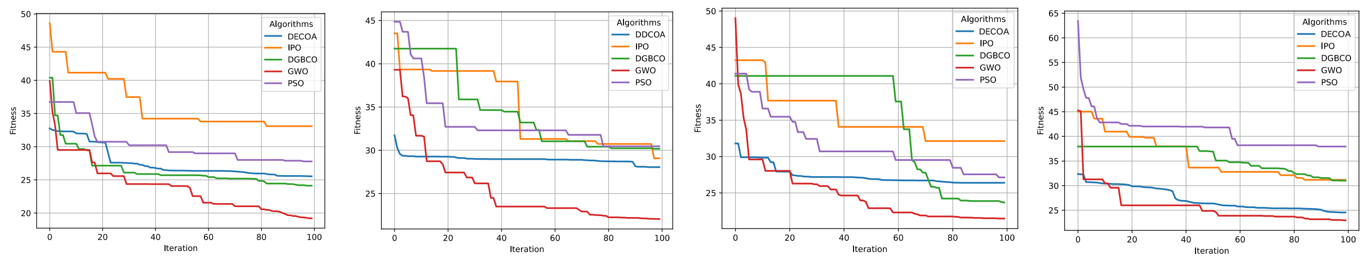


Fig. S7. The UAV paths planned by enhanced evolutionary algorithms in different scenarios. $case\_i$ is the environment has i obstacles. (a) case_3. (b) case_4. (c) case_5. (d) case_6



(a) (b) (c) (d)

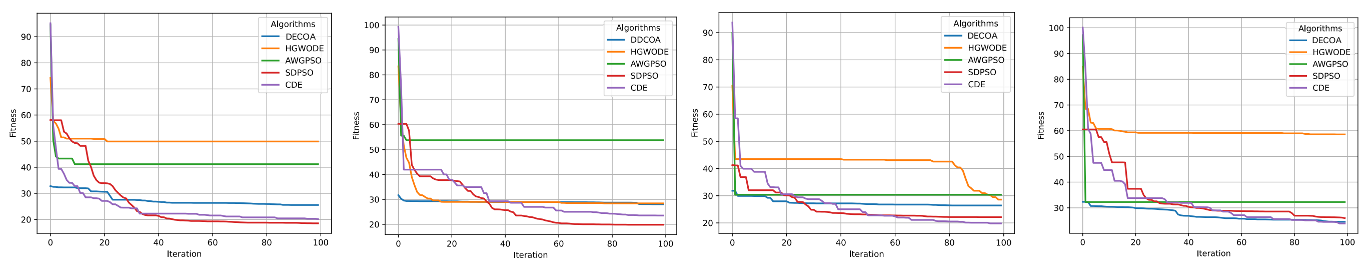
Fig. S8. Experimental results on convergence speed in UAV task assignment. $case\_i\_j$ represents the case has i task points and j UAVs. (a) case_20_2. (b) case_40_2. (c) case_75_2. (d) case_200_2.



(a) (b) (c) (d)

Fig. S9. Experimental results on convergence speed based on basic evolutionary algorithms in UAV path planning. $case\_i$ represents the case has i infeasible regions. (a) case_3. (b) case_4. (c) case_5. (d) case_6.

evolutionary algorithms. The convergence rate test on UAV path planning is conducted across four distinct scenarios, each featuring an increasing number of infeasible regions: 3, 4, 5, and 6.



(a) (b) (c) (d)

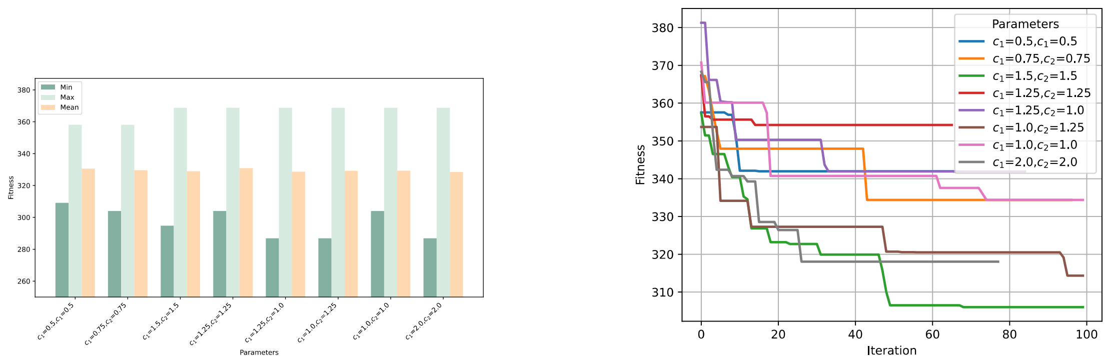
Fig. S10. Experimental results on convergence speed based on enhanced evolutionary algorithms in UAV path planning. $case\_i$ represents the case has i infeasible regions. (a) case_3. (b) case_4. (c) case_5. (d) case_6.

In addition, each algorithm executes 100 iterations. The result is shown in Fig. S8, Fig. S9, and Fig. S10 where the horizontal axis represents the number of iterations and the vertical axis is the fitness. As shown in Fig. S8(b) and Fig. S8(c), DECOA achieves optimal convergence rates for scenarios with 40 and 75 task points, identifying global optima with rapid convergence. For scenarios with 20 and 200 task points (Fig. S8(a) and Fig. S8(d)), DECOA maintains competitive performance, achieving near-optimal convergence rates with minimal deviation from the best-performing algorithm. As shown in Fig. S8(b) and Fig. S8(c), DECOA achieves optimal convergence rates for scenarios with 40 and 75 task points, identifying global optima with rapid convergence. For scenarios with 20 and 200 task points (Fig. S8(a) and Fig. S8(d), DECOA maintains competitive performance, achieving near-optimal convergence rates with minimal deviation from the best-performing algorithm. In the experiments on the UAV path planning convergence speed, DECOA shows a clear advantage over the other algorithms in the scenarios with 4 and 5 infeasible regions, as shown in Fig. S10(b) and Fig. S10(c). Fig. S10(a) and Fig. S10(d) show that DECOA is not optimal in the scenarios with 3 and 6 infeasible regions, but its convergence rate is still among the highest. The dual-subpopulation architecture in DECOA enables efficient escape from local optima while maintaining rapid convergence. This dynamic dual-population search strategy contributes to enhanced convergence speed and superior solution quality compared to alternative approaches.

E. Parameter sensitivity discussion

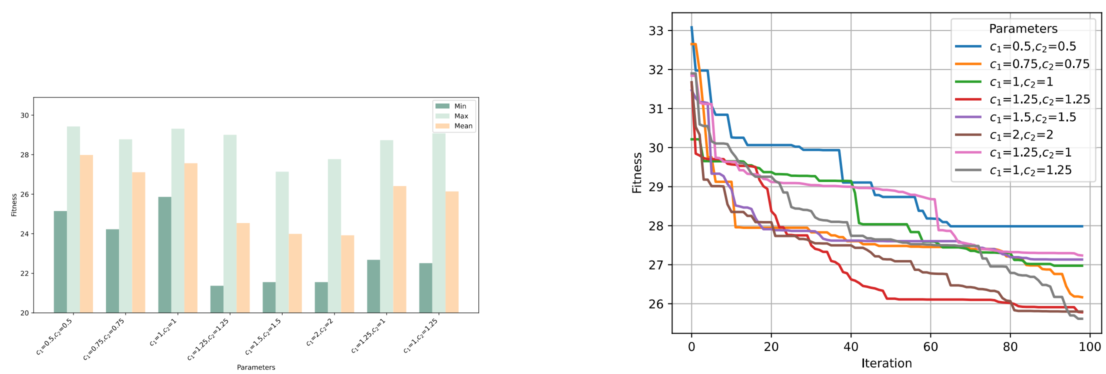
In this section, a parameter sensitivity analysis is performed through two scenarios. One is a task assignment of 75 task points with two UAVs, and the other considers path planning for UAVs with three infeasible regions. Fig. S11 and and Fig.

S12 illustrate the impact of varying parameters on the performance of DECOA on task assignment. Results demonstrate that DECOA with the setting $c_1 = 1.5$ and $c_2 = 1.5$ yields optimal performance across minimum, maximum, and average fitness metrics. Under these parameters, the algorithm DECOA achieves best average fitness when minimum and maximum fitness values are equal, and best maximum fitness when minimum and average fitness values are equal.



(a) (b)

Fig. S11. Experimental results of algorithm parameters on UAV task assignment. (a) Fitness. (b) Convergence rate.



(a) (b)

Fig. S12. Experimental results of algorithm parameters on UAV path planning. (a) Fitness. (b) Convergence rate.

Moreover, Fig. S11(b) and Fig. S12(b) indicate that parameter values $c_1 = 1.5$ and $c_2 = 1.5$ facilitate rapid convergence toward global optima. While DECOA with this parameter setting may not yield the absolute fastest convergence rate, it consistently achieves superior convergence stability and solution quality. Based on these results, $c_1 = 1.5$ and $c_2 = 1.5$ were selected as the optimal parameters for the proposed algorithm DECOA.

References

[1] R. Eberhart and J. Kennedy, "A new optimizer using particle swarm theory," in *MHS'95. Proceedings of the sixth international symposium on micro machine and human science*. Ieee, Aug. 1995, pp. 39–43.

[2] M. Dorigo, M. Birattari, and T. Stutzle, "Ant colony optimization," *IEEE Comput Intell Mag.*, vol. 1, no. 4, pp. 28–39, Mar. 2006.

[3] N. Higashi and H. Iba, "Particle swarm optimization with gaussian mutation," in *Proceedings of the 2003 IEEE Swarm Intelligence Symposium. SIS'03 (Cat. No. 03EX706)*. IEEE, Jun. 2003, pp. 72–79.

[4] S. Aslan and T. Erkin, "A multi-population immune plasma algorithm for path planning of unmanned combat aerial vehicle," *Prog Adv Comput Intell Eng.*, vol. 55, pp. 101 829–101 843, Jan. 2023.

[5] Z. Qadir, M. H. Zafar, S. K. R. Moosavi, K. N. Le, and M. P. Mahmud, "Autonomous uav path-planning optimization using metaheuristic approach for predisaster assessment," *IEEE Internet Things J.*, vol. 9, no. 14, pp. 12 505–12 514, Jul. 2021.

[6] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey wolf optimizer," *Adv Eng Softw.*, vol. 69, pp. 46–61, Mar. 2014.

[7] X. Yu, N. Jiang, X. Wang, and M. Li, "A hybrid algorithm based on grey wolf optimizer and differential evolution for uav path planning," *Expert Syst Appl.*, vol. 215, pp. 119 327–119 341, Apr. 2023.

[8] G. M. Nayeem, M. Fan, G. M. Daiyan, and K. S. Fahad, "Uav path planning with an adaptive hybrid pso," in *2023 International Conference on Information and Communication Technology for Sustainable Development (ICICT4SD)*. IEEE, Sep. 2023, pp. 139–143.

[9] Z. Yu, Z. Si, X. Li, D. Wang, and H. Song, "A novel hybrid particle swarm optimization algorithm for path planning of uavs," *IEEE Internet Things J.*, vol. 9, no. 22, pp. 22 547–22 558, Nov. 2022.

[10] X. Yu, C. Li, and J. Zhou, "A constrained differential evolution algorithm to solve uav path planning in disaster scenarios," *Knowl Based Syst.*, vol. 204, pp. 106 209–106 223, Sep. 2020.