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Competition on “numerical optimization considering accuracy and speed”

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Reference:
KV Price, A Kumar, PN Suganthan, “Trial-based dominance for comparing both the speed and accuracy of stochastic optimizers with standard non-parametric tests’’, Swarm and Evolutionary Computation, 78, 101287, 2023.

Contents

- Competition 1-BC-SOPs
- Competition 2-CSOPs
- Competition 3-BC-MOPs
- Competition 4-CMOPs
- Ranking result

Competition 1-BC-SOPs

Bound constrained single objective optimization problems (BC-SOPs)

Test Problems: The 29 real-parameter numerical optimization problems with 30*D* in CEC2017 [1] are adopted as test problems.

Number of Trials/Problem: 25 independent runs.

Maximum Number of Function Evaluations: Max_FEs = 10000**D*, where *D* is the dimensionality of the optimization problems.

Population Size: You are free to have an appropriate population size to suit your algorithm while not exceeding the Max_FEs.

Sampling Points: The best EV (Error Value) every 10**D* evaluations will be recorded for each run. For example, the maximum number of function evaluations Max_FEs is 10000**D*, then 1000 EVs should be saved

Target Error Values: The target error value, TGT_EV for each problem, will be determined after the competition. Hence, all algorithms should be executed until the Maximum number of Function Evaluations (Max_FEs) are consumed.

[1] Awad, N., Ali, M., Liang, J., Qu, B., Suganthan, P., 2016. Problem definitions and evaluation criteria for the cec 2017 special session and competition on single objective bound constrained real-parameter numerical optimization, in: Technical Report. Nanyang Technological University Singapore, pp. 1–34.

Competition 1-BC-SOPs

Bound constrained single objective optimization problems (BC-SOPs)

Presentation of Results: The results can be saved in the form of Table 1, where Min_EV is the best error value of each run at each sampling point. The value should be recorded every 10**D* FEs. Thus, for each algorithm, 29 files should be zipped and sent to the organizers, where 29 represents the total number of test functions.

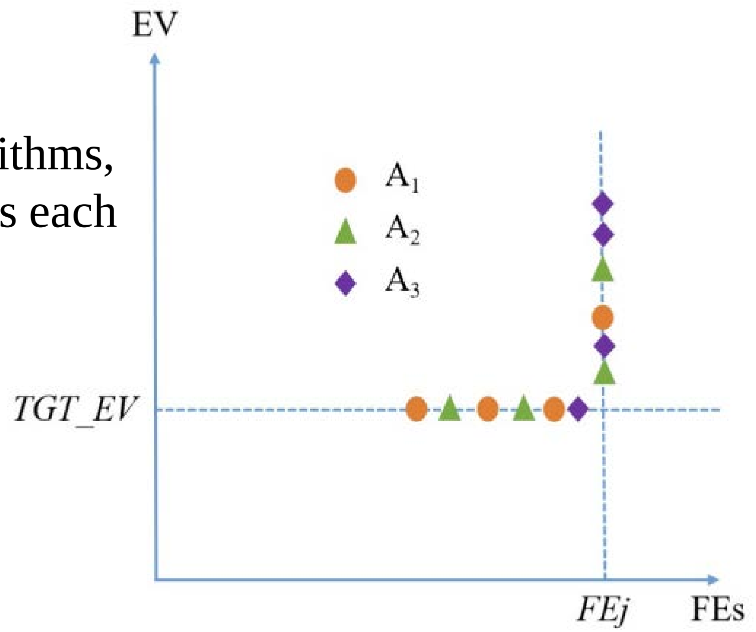
Table 1
Results saved in "PaperID_FJ_Min_EV.mat" where J=1,2,3,...29 problems.

	Run 1	Run 2	Run 3	...	Run 25
Min_EV at Initialisation FEs					
Min_EV at 10*D FEs					
Min_EV at 20*D FEs					
...					
...					
Min_EV at Max_FEs					

Competition 1-BC-SOPs

U-score

Figure 1: Three algorithms, A1–A3, run four trials each on an BC-SOP.



Trial	●	▲	●	▲	●	◆	▲	◆	●	▲	◆	◆	*SR*	U-score
Ranks	12	11	10	9	8	7	6	5	4	3	2	1	78	
A1	12		10		8				4				34	24
A2		11		9			6			3			29	19
A3						7		5			2	1	15	5

The "correction factor" (*cf*) is $n(n+1)/2 = 4 * 5/2 = 10$, where n denotes the number of trails. SR denotes the sum of ranks. The scores of algorithms are calculated by the "SR" minus the "*cf*" according to the U-score algorithm.

Figure 2: U-score ranks for algorithms A1, A2 and A3.

Contents

Competition 2-CSOPs

Constrained single objective optimization problems (CSOPs)

Test Problems: The 28 constrained real-parameter optimization problems with 30*D* in CEC2017 [2] are adopted as test problems.

Number of Trials/Problem: 25 independent runs.

Maximum Number of Function Evaluations: Max_FEs = 20000**D*, where *D* is the dimensionality of the optimization problems.

Population Size: You are free to have an appropriate population size to suit your algorithm while not exceeding the Max_FEs.

Sampling Points: Record f_{min} values and *LCV* every 10**D* evaluations. For example, if the maximum number of function evaluations Max_FEs is 20000**D*, then 2000 f_{min} values are recorded for trials with one or more feasible solutions. When the whole population is infeasible, the lowest *LCV* value of the population should be saved at the respective sampling points.

Target Error Values: The target error value will be determined after the competition. Hence, all algorithms should be executed until Maximum number of Function Evaluations (Max_FEs) are consumed.

[2] Wu, G., Mallipeddi, R., Suganthan, P.N., 2017. Problem definitions and evaluation criteria for the cec 2017 competition on constrained real parameter optimization. National University of Defense Technology, Changsha, Hunan, PR China and Kyungpook National University, Daegu, South Korea and Nanyang Technological University, Singapore, Technical Report .

Competition 2-CSOPs

Constrained single objective optimization problems (CSOPs)

Presentation of Results: Save your results as shown in Table 2, in which the first entry is for the evaluation of the initial population. The cumulative FEs at each sampling point should be saved in the first column. Meanwhile, the corresponding $fmin$ and LCV results should be saved in the second and third columns, respectively. So, for a function, one run requires one file in mat format. Please note that if no feasible solution exists at one sampling point, the $fmin$ result should be expressed by "NaN".

$$LCV = \min : CV(P_i),\ i = 1, \ldots, NP$$

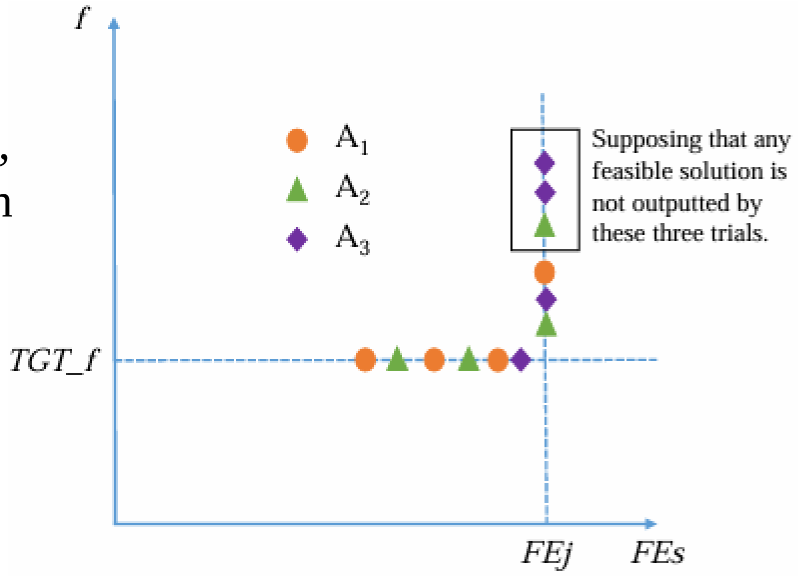
Table 2
Results saved in "PaperID_CPJ.mat" where J=1,2,...,28 problems

FEs	Run1		Run2		. . .	Run25	
	f_{min}	LCV	f_{min}	LCV		f_{min}	LCV
at Initialisation FEs							
Sampling Point 1, FEs=1*10D							
Sampling Point 2, FEs=2*10D							
. . .							
Last Sampling Point, Max_FEs							

Competition 2-CSOPs

U-score

Figure 1: Three algorithms, A1–A3, run four trials each on a CSOP.



Trial	●	▲	●	▲	●	◆	▲	◆	●	▲	◆	◆	*SR*	U-score
Ranks	12	11	10	9	8	7	6	5	4	3	2	1	78	
A1	12		10		8				4				34	24
A2		11		9			6			3			29	19
A3						7		5			2	1	15	5

The "correction factor" (*cf*) is $n(n+1)/2 = 4 * 5/2 = 10$, where n denotes the number of trails. SR denotes the sum of ranks. The scores of algorithms are calculated by the "SR" minus the "*cf*" according to the U-score algorithm.

Figure 2: U-score ranks for CSOPs.

Contents

- Competition 1-BC-SOPs
- Competition 2-CSOPs
- Competition 3-BC-MOPs
- Competition 4-CMOPs
- Ranking result

Competition 3-BC-MOPs

Bound constrained multi-objective optimization problems (BC-MOPs)

Test Problems: We adopt the benchmark of [3] including 10 multi-objective problems to rank the optimizers of MOPs without constraints.

Number of Trials/Problem: 30 independent runs.

Maximum Number of Function Evaluations: 100000 for each function.

Population Size: 100.

Sampling Points: The *IGD* values will be recorded once every 200 function evaluations. For example, if the maximum number of evaluations Max_FEs is 100000, then 500 *IGD* values are saved.

Target Error Values: The target *IGD* value will be determined after the competition. Hence, all algorithms should be executed until Maximum number of Function Evaluations (Max_FEs) are consumed.

[3] Li, H., Deb, K., Zhang, Q., Suganthan, P.N., Chen, L., 2019. Comparison between moea/d and nsga-iii on a set of novel many and multi-objective benchmark problems with challenging difficulties. Swarm and Evolutionary Computation 46, 104–117.

Competition 3-BC-MOPs

Bound constrained multi-objective optimization problems (BC-MOPs)

Presentation of Results: To compare and evaluate the algorithms participating in the competition, it is necessary that the authors email the results as shown in Table 4 to the organizers after submitting the final version of the accepted paper.

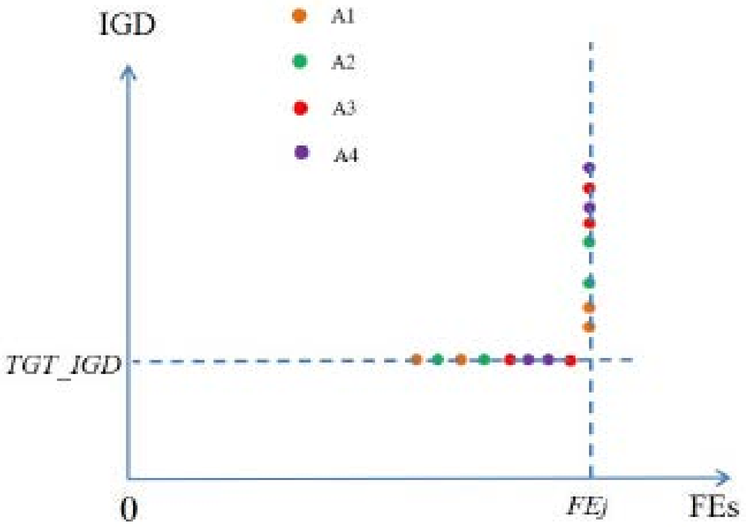
Table 4
Results saved in"PaperID RCMJ IGD.txt" where J=1,2,...,10 problems

	Run 1	Run 2	Run 3	...	Run 30
IGD at Initialisation FEs					
IGD at Sampling Point 1					
IGD at Sampling Point 2					
...					
...					
IGD at Sampling Point 500, 100K FEs					

Competition 3-BC-MOPs

U-score

Figure 5: Four algorithms, A1–A4, run four trials each on an BC-MOP.



Trial	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	*SR*	U-score[1]
Ranks	16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	136	
A1	16		14						8	7							45	**35**
A2		15		13							6	5					39	**29**
A3					12			9					4		2		27	**17**
A4						11	10							3		1	25	**15**

[1] The "correction factor" *cf* is $n(n+1)/2 = 4 * 5/2 = 10$, where n denotes the number of trials. *SR* denotes the sum of ranks. The scores of algorithms are calculated by the "*SR*" minus the "*cf*" according to the U-score algorithm.

Figure 6: U-score ranks for BC-MOEAs.

Contents

Competition 4-CMOPs

Constrained multi-objective optimization problems (CMOPs)

Test Problems: The latest constrained multiobjective optimization problems with scalable decision space constraints (SDC problems) [4] are adopted as test problems. SDC benchmark contains 15 problems.

Number of Trials/Problem: 30 independent runs.

Maximum Number of Function Evaluations: 200000 for each function.

Population Size: 100. **Dimension:** 30 for each SDC function.

Sampling Points: The IGD values will be recorded once every 200 function evaluations. For example, if the maximum number of evaluations Max_FEs is 200000, then 1000 IGD values are saved.

Target Error Values: The target IGD value will be determined after the competition. Hence, all algorithms should be executed until the Maximum number of Function Evaluations (Max_FEs) are consumed. Please note that the minimal IGD value is unknown for multiobjective optimization problems. So, the mean or median IGD value of all trials from all algorithms participating in the competition will be set as the target IGD value

[4] Qiao, K., Liang, J., Yu, K., Yue, C., Lin, H., Zhang, D., Qu, B., 2023. Evolutionary constrained multiobjective optimization: Scalable highdimensional constraint benchmarks and algorithm. IEEE Transactions on Evolutionary Computation , 1–1doi:10.1109/TEVC.2023.3281666..

Competition 4-CMOPs

Constrained multi-objective optimization problems (CMOPs)

Presentation of Results: To compare and evaluate the algorithms participating in the competition, it is necessary that the authors email the results in the format as shown in Table 5 to the organizers, after submitting the final version of the accepted papers.

$$MCV = \frac{\sum_{i=1}^{PF} CV(P_i)}{PF}$$

Table 5

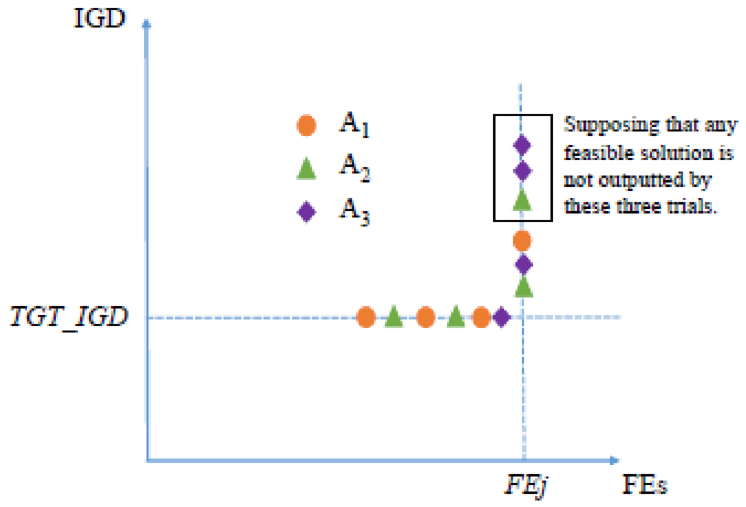
Results saved in "PaperID_SDCJ.mat" where J=1,2,...,15 problems.

	Run1		Run2		...	Run 30	
	IGD	MCV	IGD	MCV		IGD	MCV
at initialization FEs							
Sampling point 1							
Sampling point 2							
...							
...							
Sampling point 1000							

Competition 4-CMOPs

U-score

Figure 7: Four algorithms, A1–A3, run four trials each on a CMOP.



Trial	●	▲	●	▲	●	◆	▲	◆	●	▲	◆	◆	*SR*	U-score
Ranks	12	11	10	9	8	7	6	5	4	3	2	1	78	
A1	12		10		8				4				34	24
A2		11		9			6			3			29	19
A3						7		5			2	1	15	5

The "correction factor" (*cf*) is $n(n+1)/2 = 4 * 5/2 = 10$, where n denotes the number of trails. SR denotes the sum of ranks. The scores of algorithms are calculated by the "SR" minus the "*cf*" according to the U-score algorithm.

Figure 8: U-score ranks for CMOPs.

Contents

Competition 1-BC-SOPs

Algorithm	Ranking	Authors	Paper title/link
RDEx	**1**	Sichen Tao	https://github.com/SichenTao/IEEE-CEC-2025-Competition-RDEx/tree/main
L-SRTDE	**2**	Vladimir Stanovov Eugene Semenkin	Success Rate-based Adaptive Differential Evolution L-SRTDE for CEC 2024 Competition
RDE	**3**	Sichen Tao, Ruihan Zhao, Kaiyu Wang, Shangce Gao	An Efficient Reconstructed Differential Evolution Variant by Some of the Current State-of-the-art Strategies for Solving Single Objective Bound Constrained Problems
mLSHADE_LR	**4**	Dikshit Chauhan, Anupam Trivedi, Shivani	https://arxiv.org/abs/2409.15994

Competition 1-BC-SOPs

Algorithm	Ranking	Authors	Paper title/link
BlockEA	**5**	Xuhong Qi	https://github.com/QiXuhong520/Algorithm-report
jSOa	**6**	Petr Bujok	https://github.com/PetBuj/jSOa/blob/main/jSOaGitHub.pdf
IEACOP	**7**	Andrea Tangherloni Vasco Coelho Francesca M. Buffa Paolo Cazzaniga	A modified EACOP implementation for Real-Parameter Single Objective Optimization Problems

Competition 1-BC-SOPs

RDEx	◆ **Sichen Tao. https://github.com/SichenTao/IEEE-CEC-2025-Competition-RDEx/tree/main, 2025.**
L-SRTDE	◆ Vladimir Stanovov, Eugene Semenkin. Success Rate-based Adaptive Differential Evolution L-SRTDE for CEC 2024 Competition, https://github.com/VladimirStanovov/L-SRTDE_CEC-2024, 2024.
RDE	◆ Sichen Tao, Ruihan Zhao, Kaiyu Wang, Shangce Gao. An Efficient Reconstructed Differential Evolution Variant by Some of the Current State-of-the-art Strategies for Solving Single Objective Bound Constrained Problems, 2024.
mLSHADE_LR	◆ Dikshit Chauhan, Anupam Trivedi, Shivani. A Multi-operator Ensemble LSHADE with Restart and Local Search Mechanisms for Single-objective Optimization, https://arxiv.org/abs/2409.15994, 2024.
BlockEA	◆ Xuhong Qi. Algorithm report for Block Evolutionary Algorithm, https://github.com/QiXuhong520/Algorithm-report, 2024.
jSO	◆ Petr Bujok. Progressive Archive in Adaptive jSO Algorithm, https://github.com/PetBuj/jSOa/blob/main/jSOaGitHub.pdf, 20224.
iEACOP	◆ Andrea Tangherloni, Vasco Coelho, Francesca M. Buffa, Paolo Cazzaniga. A modified EACOP implementation for Real-Parameter Single Objective Optimization Problems, 2024.

Competition 1-BC-SOPs

Prob\Algo	BlockEA	IEACOP	RDE	mLSHADE_LR	L-SRTDE	jSOa	RDEx
F1	594/6	77/7	3750/1	1280/5	2478/3	1821/4	3125/2
F2	0/7	3141/2	3325/1	625/6	2059/4	1275/5	2700/3
F3	1500/5	3634/1	1625/4	3238/2	0/7	625/6	2503/3
F4	992/6	114/7	1761/4	2347/3	3113/2	1286/5	3512/1
F5	3750/1	1024/6	3110/2	0/7	1760/4	1092/5	2389/3
F6	3750/1	42/7	1305/5	3125/2	1863/4	888/6	2152/3
F7	1846/4	752/6	2154/3	47/7	3043/2	1800/5	3483/1
F8	2739/2	977/6	3350/1	26/7	2174/4	1375/5	2484/3
F9	3750/1	38/7	913/6	3125/2	1984/4	924/5	2391/3
F10	538/6	3672/1	2520/3	87/7	1905/4	1253/5	3150/2
F11	3557/1	0/7	1966/3	3318/2	1361/5	1016/6	1907/4
F12	1369/6	1664/4	2209/3	167/7	2766/2	1500/5	3450/1
F13	640/6	0/7	2334/3	1457/5	3277/2	1819/4	3598/1
F14	315/7	553/6	3097/2	1123/5	2633/3	1828/4	3576/1
F15	1016/6	47/7	1663/4	3695/1	3061/2	1030/5	2613/3

Competition 1-BC-SOPs

Prob\Algo	BlockEA	IEACOP	RDE	mLSHADE_LR	L-SRTDE	jSOa	RDEx
F16	1719/3	491/7	1630/4	1375/5	3144/2	1366/6	3400/1
F17	1021/5	27/7	2964/2	875/6	2661/3	1827/4	3750/1
F18	937/5	329/7	2597/3	635/6	3034/2	1850/4	3743/1
F19	575/6	50/7	1847/4	3750/1	2613/3	1278/5	3012/2
F20	3395/1	26/7	1284/5	3225/2	2257/3	698/6	2240/4
F21	20/7	3750/1	3125/2	605/6	1878/4	1250/5	2497/3
F22	1429/5	3105/2	824/6	3341/1	1689/4	551/7	2186/3
F23	3748/1	0/7	1236/5	3025/2	2239/3	661/6	2216/4
F24	12/7	3639/1	3217/2	613/6	1818/4	1307/5	2519/3
F25	3750/1	631/6	984/5	3125/2	1867/4	559/7	2209/3
F26	3064/2	3388/1	2429/3	0/7	681/6	1722/5	1841/4
F27	184/7	3351/1	1803/4	441/6	2735/3	1538/5	3073/2
F28	1881/4	2/7	1839/5	3063/2	3743/1	692/6	1905/3
F29	3710/1	0/7	1485/5	2803/3	2862/2	625/6	1640/4
sum/RS	51801/120	34524/149	62346/100	50536/123	66698/96	35456/152	79264/72

Competition 2-CSOPs

Algorithm	Ranking	Authors	Paper title/link
RDEx	**1**	Sichen Tao	https://github.com/SichenTao/IEEE-CEC-2025-Competition-RDEx/tree/main
UDE-III	**2**	Anupam Trivedi Dikshit Chauhan	https://arxiv.org/abs/2410.03992
UDE_IV	**3**	Anupam Trivedi	UDE-IV: An Enhanced Unified Differential Evolution Algorithm for CEC 2025 Constrained Optimization Problems
CL-SRDE	**4**	Vladimir Stanovov Eugene Semenkin	Differential Evolution with Success Rate-based adaptation CL-SRDE for Constrained Optimization

Competition 2-CSOPs

RDEx	◆ Anupam Trivedi, Dikshit Chauhan. https://github.com/SichenTao/IEEE-CEC-2025-Competition-RDEx/tree/main, 2025.
UDE-III	◆ Anupam Trivedi, Dikshit Chauhan. UDE-III: An Enhanced Unified Differential Evolution Algorithm for Constrained Optimization Problems. https://arxiv.org/abs/2410.03992, 2024.
UDE_IV	◆ Dikshit Chauhan, Anupam Trivedi. UDE-IV: An Enhanced Unified Differential Evolution Algorithm for CEC 2025 Constrained Optimization Problems, 2025.
CL-SRDE	◆ Vladimir Stanovov, Eugene Semenkin. Differential Evolution with Success Rate-based adaptation CL-SRDE for Constrained Optimization, https://github.com/VladimirStanovov/CL-SRDE_CEC-2024, 2024.

Competition 2-CSOPs

Pro\Algo	UDE-III	CL-SRDE	RDEx	UDE_IV
C01	95.5/4	1350/2	1743/1	561.5/3
C02	144.5/4	1288.5/1	1745/2	572/3
C03	1257.5/2	4/4	638/3	1850.5/1
C04	1825/1	0/4	625/3	1300/2
C05	844.5/2	766/3	1855/1	284.5/4
C06	1008/2	175/4	1875/1	692/3
C07	712.5/3	854/2	1719.5/1	464/4
C08	610/3	1250/2	1875/1	15/4
C09	1526/2	0/4	1599/1	625/3
C10	1250/2	625/3	1875/1	0/4
C11	527/3	1207/2	1780/1	236/4
C12	1551/1	767/3	75/4	1357/2
C13	685/3	934/2	1751/1	380/4
C14	1875/1	275/4	350/3	1250/2

Competition 2-CSOPs

Prob\Algo	UDE-III	CL-SRDE	RDEx	UDE_IV
C15	1020.5/2	0/4	1875/1	854.5/3
C16	1301.5/2	116/4	509/3	1823.5/1
C17	1387.5/2	362.5/3	362.5/3	1637.5/1
C18	0/4	1217/2	1791/1	742/3
C19	937.5/2	0/3	1875/1	937.5/2
C20	837/3	149/4	1852/1	912/2
C21	1350.5/1	232/4	927/3	1240.5/2
C22	442/3	1250/2	1875/1	183/4
C23	530/3	1875/1	450/4	895/2
C24	742/3	0/4	1875/1	1133/2
C25	1453.5/1	136/4	746.5/3	1414/2
C26	1123.5/1	825/3	825/3	976.5/2
C27	0/4	1733.5/1	1270.5/2	746/3
C28	517/3	1725/1	1400/2	108/4
sum/RS	25554/67	19116.5/80	37139/53	23190.5/76

Competition 3-BC-MOPs

Algorithm	Ranking	Authors	Paper title/link
RDE	**1**	Sichen Tao Yifei Yang Ruihan Zhao Chenxi Wang Kaiyu Wang Sicheng Liu Shangce Gao	Efficient Reconstructed Differenticial Evolution for IEEE CEC 2025 Numerical Optimization Competitions
TFBCEIBEA	**2**	Peng Chen Jing Liang Kangjia Qia Ponnuthurai Nagaratnam Suganthan Xuanxuan Ban	A Two-stage Evolutionary Framework For Multi-objective Optimization
TGFMMOEA	**3**	Peng Chen	A Two-stage Evolutionary Framework For Multi-objective Optimization

Competition 3-BC-MOPs

RDE	◆ Efficient Reconstructed Differenticial Evolution for IEEE CEC 2025 Numerical Optimization Competitions

Prob\Algo	RED	TFBCEIBEA	TGFMMOEA
MaOP1	1800/1	789/2	111/3
MaOP2	1800/1	824/2	106/3
MaOP3	1800/1	509/2	391/3
MaOP4	1800/1	128/3	772/2
MaOP5	1800/1	637/2	263/3
MaOP6	1800/1	883/2	17/3
MaOP7	1800/1	419/3	481/2
MaOP8	1800/1	458/2	442/3
MaOP9	1800/1	329/3	571/2
MaOP10	1800/1	399/3	501/2
sum/RS	17970/10	5375/24	3655/26

Competition 4-CMOPs

Algorithm	Ranking	Authors	Paper title/link
RDE	1	Sichen Tao	https://github.com/SichenTao/IEEE-CEC-2025-Competition-RDEx/tree/main
DESDE	2	Kangjia Qiao	A Dynamic Exemplars Selection-based Differential Evolution Algorithm for Constrained Multi-objective Optimization
CCEMT	3	Xiaoyu Zhong	https://github.com/wcq1536113693/zxyCCEMT
IMTCMO	4	Dezheng Zhang	https://github.com/DezhengZ/Algorithm-Description-IMTCMO
CCPTEA	5	Lianhe Duan	https://github.com/LianheDuan/Algorithm-Description.git
MTCMMO	6	Wenhao Wu	https://github.com/zaishuiyifang1507/A-noverl-genetic-algorithm-forCEC2024
CMOEA-DPMS	7	Rammohan Mallipeddi	https://github.com/mssraju/CMOEA-DPMS-PlatEMO-4.12/blob/main/CMOEA-DPMS.pdf
cISDE	8	Oladayo S. Ajani, Sri Srinivasa Raju M, Rammohan Mallipeddi	https://github.com/oladayosolomon/cISDE-DE/blob/main/cISDE%2BDE.pdf

Competition 4-CMOPs

RDE	◆ Sichen Tao. https://github.com/SichenTao/IEEE-CEC-2025-Competition-RDEx/tree/main, 2025.
DESDE	◆ Kangjia Qiao. A Dynamic Exemplars Selection-based Differential Evolution Algorithm for Constrained Multi-objective Optimization, https://github.com/xxuanban/DESDE/blob/main/DESDE.pdf, 2024.
CCEMT	◆ Xiaoyu Zhong. Constrained Multi-Objective Optimization via Competitive and Cooperative Evolutionary Multitasking (CCEMT), https://github.com/wcq1536113693/zxyCCEMT, 2024.
IMTCMO	◆ Dezheng Zhang. Evolutionary Constrained Multiobjective Optimization: Scalable High-Dimensional Constraint Benchmarks and Algorithm, https://github.com/DezhengZ/Algorithm-Description-IMTCMO, 2024.
CCPTEA	◆ Lianhe Duan. A Cooperation and Competition-Based Tri-Population Evolutionary Algorithm for Constrained Multi-objective Optimization Problems, https://github.com/LianheDuan/Algorithm-Description.git, 2024.
MTCMMO	◆ Wenhao Wu. A Novel Genetic Algorithm for CEC2024, https://github.com/zaishuiyifang1507/A-noverl-genetic-algorithm-forCEC2024, 2024.
CMOEA-DPMS	◆ Sri Srinivasa Raju M, Saykat Dutta, Rammohan Mallipeddi, Kedar Nath Das. A Dual-Population and Multi-Stage based Constrained Multi-Objective Evolutionary Algorithm, https://github.com/mssraju/CMOEA-DPMS-PlatEMO-4.12/blob/main/CMOEA-DPMS.pdf,2025.
cISDE	◆ Oladayo S. Ajani, Sri Srinivasa Raju M, Rammohan Mallipeddi. IEEE CEC Competition Report: A Fitness-assignment Method for Evolutionary Constrained Multi-objective Optimization, https://github.com/oladayosolomon/cISDE-DE/blob/main/cISDE%2BDE.pdf, 2025

Competition 4-CMOPs

Prob\Algo	RDE	DESDE	CCEMT	IMTCMO	CCPTEA	MTCMMO	CMOEA-DPMS	cISDE
SDC1	4161/4	5049/1	5001/2	4220/3	4069/5	1647/6	604/7	449/8
SDC2	5372/1	4976/2	4238/3	3983/4	3931/5	1357/6	94/8	1249/7
SDC3	5825/1	5049/2	3979/3	3563/4	3168/5	2716/6	566/7	334/8
SDC4	5432/1	4652/2	3805/5	4337/3	4274/4	1800/6	900/7	0/8
SDC5	5678/1	5050/2	3895/3	3492/5	3777/4	2044/6	1161/7	103/8
SDC6	5476/1	4386/2	4174/3	4017/4	3869/5	2378/6	900/7	0/8
SDC7	5277/1	3185/6	4400/2	4347/3	3689/4	0/8	1113/7	3189/5
SDC8	1833/6	4074/5	4564/2	4432/4	4442/3	661/7	4759/1	435/8

Competition 4-CMOPs

Prob\Algo	RDE	DESDE	CCEMT	IMTCMO	CCPTEA	MTCMMO	CMOEA-DPMS	cISDE
SDC9	6072/1	5628/2	3042/5	3538/3	3413/4	1943/6	1564/7	0/8
SDC10	5249/1	4515/2	4214/3	3762/5	3975/4	2585/6	900/7	0/8
SDC11	5696/1	4929/2	3921/3	3904/4	3843/5	8/8	1142/7	1757/6
SDC12	3898/4	3885/5	5098/1	4952/2	4667/3	1800/6	900/7	0/8
SDC13	6130/1	5545/2	3073/5	3240/4	3396/3	2831/6	870/7	115/8
SDC14	5777/1	5167/2	2645/6	2922/4	3389/3	2824/5	2157/7	319/8
SDC15	6296/1	4677/2	4421/3	3393/5	3539/4	1974/6	0/8	900/7
sum/RS	78172/26	70767/39	60470/49	58102/57	57441/61	26568/94	17630/102	8850/107

Verification

Ranking related codes and data are made available online.

Codes of top performing algorithms are available online.

We verified the codes and results.

Thanks for your attention!

Questions?