Results of the 2018 IEEE CEC Competition on Evolutionary Many-Objective Optimization

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Outline

Motivation

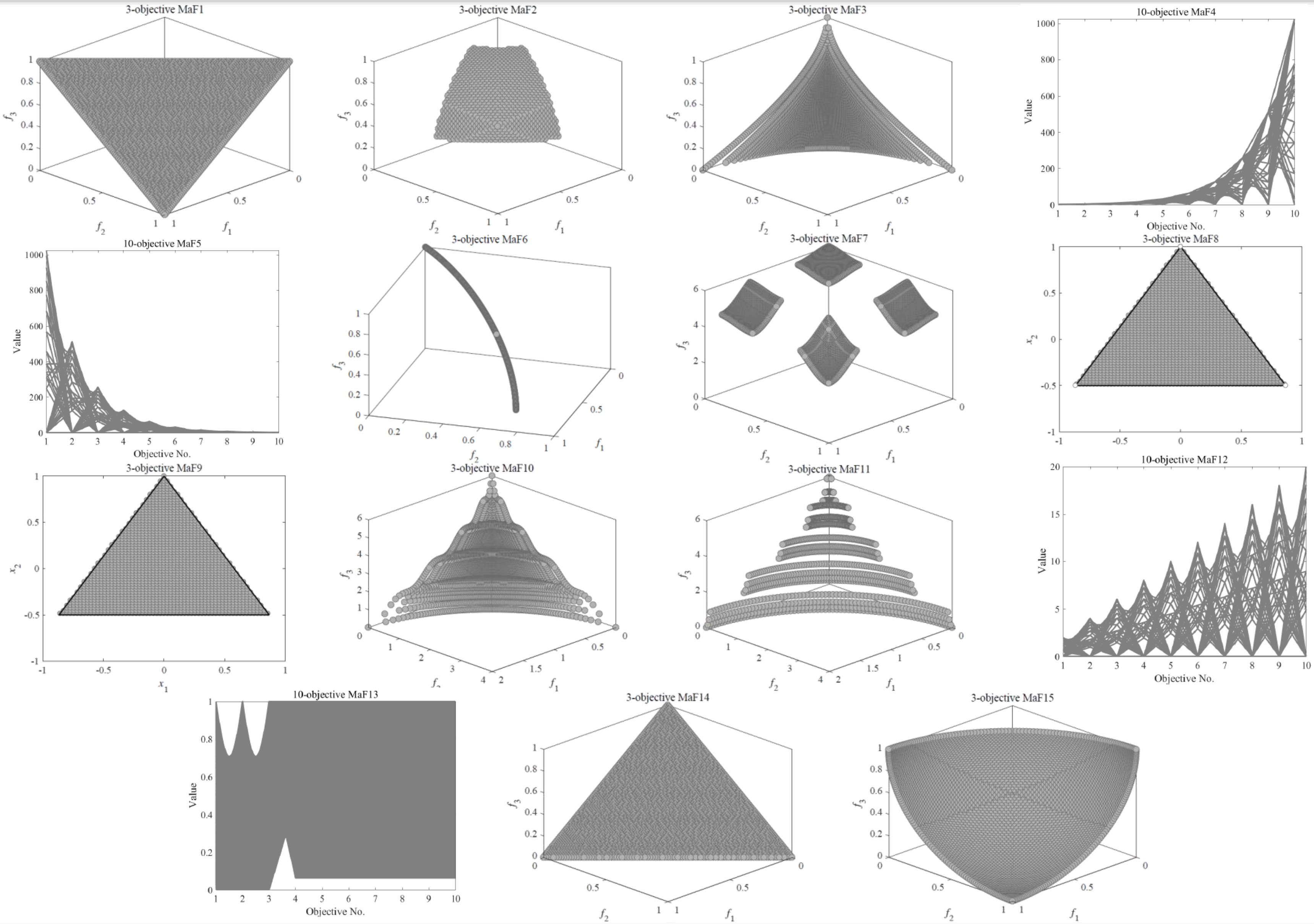
- Optimization problems with more than three objectives (i.e. many-objective) pose great challenge to existing evolutionary algorithms for traditional multi-objective optimization

- This competition aims at proposing 15 many-objective test problems with diverse properties, and investigating the performance of evolutionary algorithms on these problems [1]

Test problems

Test problem	Modified from	Difficulty
MaF1	DTLZ1 [2]	Inverted PF
MaF2	DTLZ2BZ [3]	Concurrent convergence
MaF3	DTLZ3 [2]	Convex PF, multimodal
MaF4	DTLZ3 [2]	Inverted and scaled PF, multimodal
MaF5	DTLZ4 [2]	Scaled PF, highly biased distribution
MaF6	DTLZ5(I,M) [4]	Degenerate PF
MaF7	DTLZ7 [2]	Disconnected PF
MaF8	MP-DMP [5]	Large search space
MaF9	ML-DMP [6]	Large search space
MaF10	WFG1 [7]	Complicated mixed PF
MaF11	WFG2 [7]	Scaled disconnected PF
MaF12	WFG9 [7]	Complicated fitness landscape
MaF13	PF7 [8]	Degenerate PF, complicated variable linkage
MaF14	LSMOP3 [9]	Complicated fitness landscape, large-scale
MaF15	LSMOP8 [9]	Inverted PF, complicated fitness landscape, large-scale

Pareto front of the test problems



Experimental platform

- We provide the benchmark problems respectively embedded in two platforms

- PlatEMO [10]: Open-source MATLAB platform

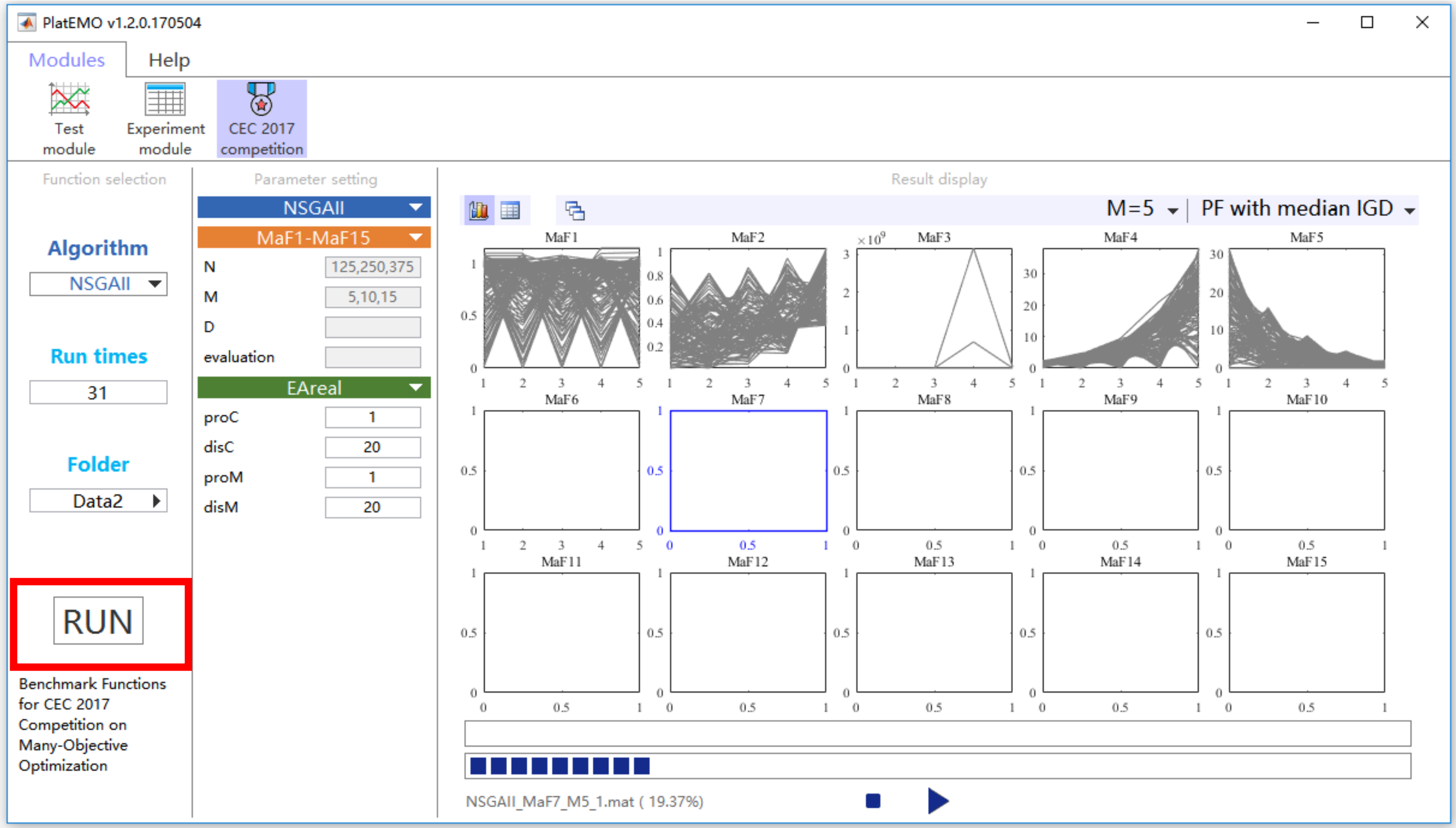
- jMetal [11]: Open-source Java platform

About PlatEMO

- PlatEMO includes more than 70 algorithms and 120 multi-objective test problems, which are all open-source and fully commented
- PlatEMO provides friendly GUI for users to perform experiments and obtain experimental results in the format of $\LaTeX$, without writing any code

About PlatEMO

- Specially tailored GUI for this competition – One click to obtain all the results.



Competition entries

- Ten entries from four different countries
- Four new algorithms
- Six existing algorithms

Algorithm	Author	Description
AGE-II [12]	Markus Wagner	Approximation-guided evolution II
AMPDEA	Huangke Chen	Multi-population-driven evolutionary algorithm
BCE-IBEA [13]	Miqing Li	Bi-criterion evolution based IBEA
CVEA3	Jiawei Yuan	Cost value based evolutionary algorithm 3
fastCAR	Mingde Zhao	Fast clustering based algorithm with reference point redistribution
HHcMOEA	Gian Fritsche	Hyper-heuristic collaborative MOEA
KnEA [14]	Xingyi Zhang	Knee point driven evolutionary algorithm
RPEA [15]	Yiping Liu	Reference points-based evolutionary algorithm
RSEA [16]	Cheng He	Radial space division based evolutionary algorithm
RVEA [17]	Ran Cheng	Reference vector guided evolutionary algorithm

Performance indicators

- Inverted generational distance (IGD) [18]

  10,000 uniformly distributed reference points sampled on the Pareto front

$$IGD(P, P^*) = \frac{\sum_{x \in P^*} \min_{y \in P} dis(x, y)}{|P^*|}$$

- Hypervolume (HV) [19]

  Normalize the population by the nadir point of the Pareto front

  Monte Carlo estimation method with 1,000,000 points is adopted

$$HV(P, R) = \lambda(H(P, R))$$

$$H(P, R) = \{z \in Z | \exists x \in P, \exists r \in R : f(x) \leq z \leq r\}$$

$$\lambda(H(P, R)) = \int_{\mathbb{R}^n} 1_{H(P,R)}(z) dz$$

Ranking strategy

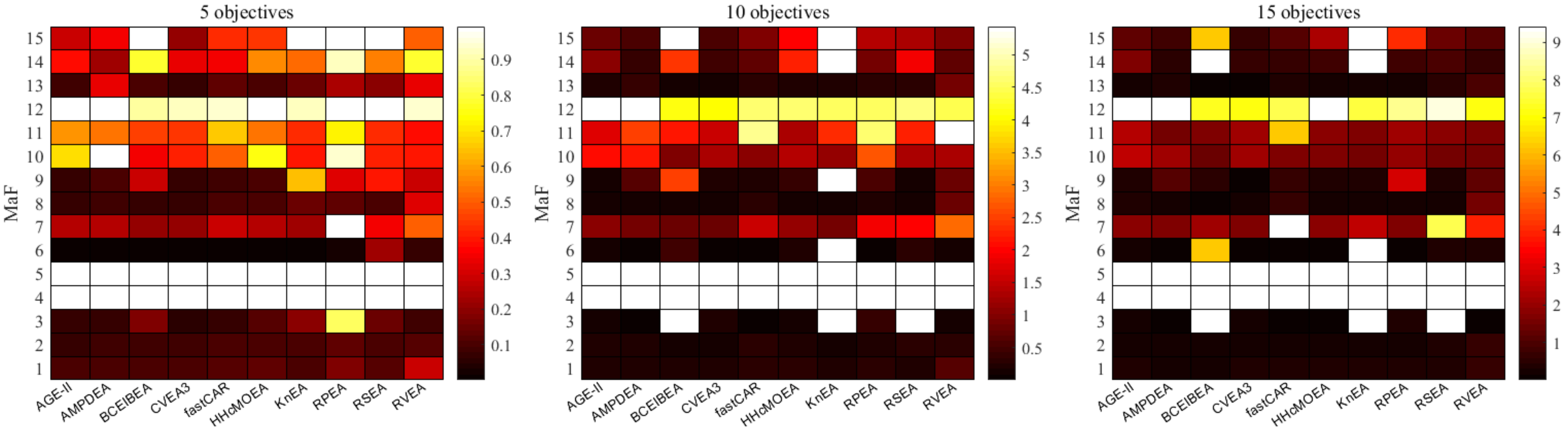
- Each algorithm executes on each problem with 5, 10 and 15 objectives for 20 runs, respectively (i.e., 900 results)

- Sort the means of each indicator value on each problem with each number of objectives (i.e., 90 ranks)

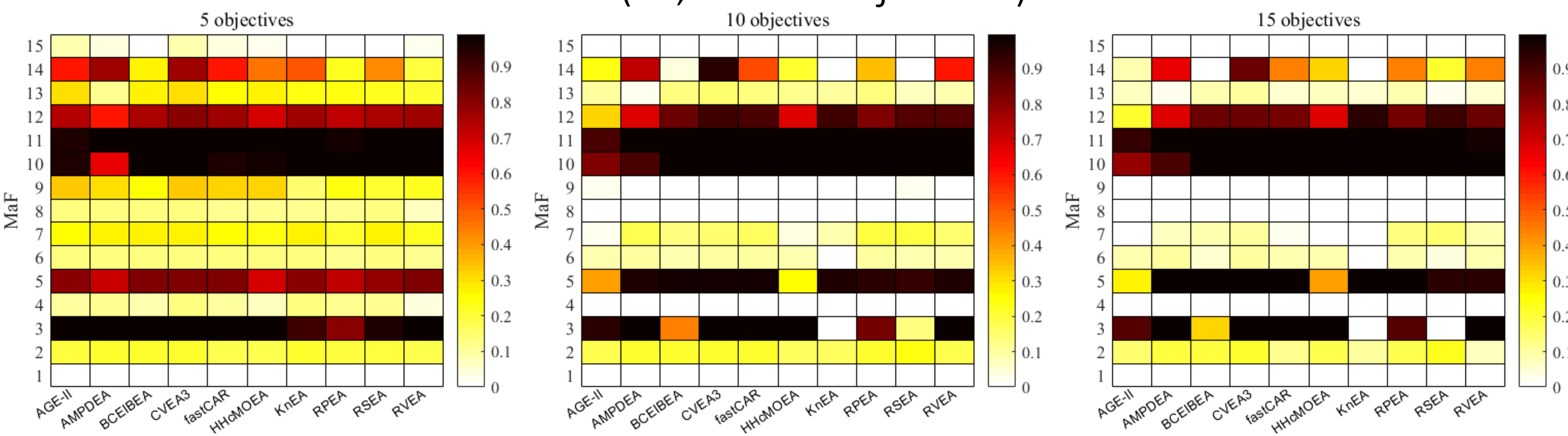
- The SCORE achieved by each algorithm is the sum of the reciprocal values of the ranks.

Overview of the Results

- IGD values of the results (5-, 10- 15-ojective)



- HV values of the results (5-, 10- 15-ojective)



Overview of the Ranks

- Ranks according to IGD values

	AGE-II	AMPDEA	BCE-IBEA	CVEA3	fastCAR	HHcMOEA	KnEA	RPEA	RSEA	RVEA
MaF1	1	4	3	5	6	8	2	9	7	10
MaF2	1	2	3	4	7	5	6	10	8	9
MaF3	4	3	8	1	2	6	9	10	7	5
MaF4	9	2	3	1	4	7	6	5	8	10
MaF5	4	9	1	2	5	8	3	10	7	6
MaF6	5	4	1	2	7	6	3	8	10	9
MaF7	6	4	2	1	7	5	3	10	8	9
MaF8	1	4	2	3	6	5	9	8	7	10
MaF9	1	5	6	2	3	4	10	8	9	7
MaF10	7	10	1	5	6	8	3	9	4	2
MaF11	8	6	5	4	9	7	3	10	2	1
MaF12	6	10	1	2	4	9	3	8	7	5
MaF13	2	9	4	1	5	3	6	8	7	10
MaF14	4	1	8	2	3	7	5	10	6	9
MaF15	2	3	8	1	4	5	10	9	7	6
Total	3	4	2	1	5	7	6	10	8	9

	AGE-II	AMPDEA	BCE-IBEA	CVEA3	fastCAR	HHcMOEA	KnEA	RPEA	RSEA	RVEA
MaF1	6	1	2	4	8	7	3	9	5	10
MaF2	7	5	3	2	8	4	1	6	10	9
MaF3	5	2	10	6	1	4	9	7	8	3
MaF4	9	1	6	2	4	8	5	3	7	10
MaF5	9	4	1	2	7	10	5	3	6	8
MaF6	5	2	9	1	4	7	10	3	8	6
MaF7	5	4	1	2	7	6	3	8	9	10
MaF8	2	6	1	3	9	4	5	8	7	10
MaF9	1	7	9	3	4	5	10	6	2	8
MaF10	8	9	1	6	2	7	3	10	5	4
MaF11	3	7	4	2	9	1	6	8	5	10
MaF12	10	9	2	1	6	7	5	4	8	3
MaF13	5	9	2	1	8	3	4	6	7	10
MaF14	6	1	9	2	4	8	10	5	7	3
MaF15	3	2	9	1	5	8	10	7	6	4
Total	4	2	3	1	5	6	7	8	9	10

	AGE-II	AMPDEA	BCE-IBEA	CVEA3	fastCAR	HHcMOEA	KnEA	RPEA	RSEA	RVEA
MaF1	9	1	2	5	6	8	3	7	4	10
MaF2	6	1	8	2	7	5	3	4	9	10
MaF3	6	2	10	5	1	4	9	7	8	3
MaF4	8	1	5	3	6	10	4	2	7	9
MaF5	9	4	1	3	7	8	5	2	6	10
MaF6	6	2	9	1	4	3	10	5	8	7
MaF7	5	3	6	1	10	4	7	2	9	8
MaF8	8	3	1	2	9	4	5	6	7	10
MaF9	4	8	6	1	7	3	2	10	5	9
MaF10	10	9	1	8	5	6	3	7	4	2
MaF11	9	1	2	7	10	6	3	8	5	4
MaF12	9	10	3	1	5	8	4	6	7	2
MaF13	5	7	2	1	8	3	4	6	9	10
MaF14	8	1	9	2	4	5	10	6	7	3
MaF15	5	2	9	1	3	7	10	8	6	4
Total	10	2	3	1	7	5	4	6	8	9

- Ranks according to HV values

	AGE-II	AMPDEA	BCE-IBEA	CVEA3	fastCAR	HHcMOEA	KnEA	RPEA	RSEA	RVEA
MaF1	1	2	4	5	6	8	3	9	7	10
MaF2	7	4	3	1	8	10	2	6	5	9
MaF3	7	3	6	1	2	4	9	10	8	5
MaF4	6	5	8	1	7	9	2	3	4	10
MaF5	6	9	4	3	1	10	5	8	7	2
MaF6	2	4	1	3	6	7	5	9	8	10
MaF7	6	4	1	2	7	8	5	10	3	9
MaF8	1	4	3	2	6	7	8	9	5	10
MaF9	2	5	6	1	3	4	10	7	9	8
MaF10	8	10	3	1	9	7	4	5	2	6
MaF11	10	8	3	1	4	5	7	9	2	6
MaF12	7	10	5	1	3	9	2	8	6	4
MaF13	1	10	4	2	5	3	7	6	8	9
MaF14	4	2	8	1	3	6	5	9	7	10
MaF15	2	3	9	1	4	6	10	8	7	5
Total	3	5	2	1	4	8	6	10	7	9

	AGE-II	AMPDEA	BCE-IBEA	CVEA3	fastCAR	HHcMOEA	KnEA	RPEA	RSEA	RVEA
MaF1	6	4	2	7	3	9	5	8	1	10
MaF2	8	4	6	3	5	9	10	2	1	7
MaF3	6	1	8	2	4	3	10	7	9	5
MaF4	8	3	9	2	7	6	4	5	1	10
MaF5	9	4	2	3	1	10	5	7	8	6
MaF6	6	1	9	2	3	5	10	4	7	8
MaF7	10	3	7	5	4	9	8	2	1	6
MaF8	4	5	3	2	9	7	6	8	1	10
MaF9	1	6	9	3	4	5	10	7	2	8
MaF10	10	9	6	1	3	7	5	4	2	8
MaF11	10	1	4	2	6	5	7	9	3	8
MaF12	10	9	6	1	3	8	2	7	4	5
MaF13	7	10	4	1	3	5	6	2	9	8
MaF14	6	2	8	1	4	7	10	5	9	3
MaF15	5	1	7	2	4	6	9	10	8	3
Total	9	2	6	1	3	7	10	5	4	8

	AGE-II	AMPDEA	BCE-IBEA	CVEA3	fastCAR	HHcMOEA	KnEA	RPEA	RSEA	RVEA
MaF1	4	6	3	7	2	8	9	10	1	5
MaF2	7	4	3	2	8	6	9	5	1	10
MaF3	6	4	8	5	2	1	9	7	10	3
MaF4	5	9	8	2	6	3	4	10	1	7
MaF5	10	5	2	1	4	9	3	6	7	8
MaF6	7	1	8	2	4	5	10	3	9	6
MaF7	10	6	5	3	7	9	8	2	1	4
MaF8	8	2	5	3	10	6	4	7	1	9
MaF9	5	9	6	1	8	4	2	7	3	10
MaF10	10	9	7	1	6	3	8	4	2	5
MaF11	10	1	5	4	6	2	7	8	3	9
MaF12	10	9	5	4	7	8	1	6	2	3
MaF13	5	10	3	1	8	4	6	2	9	7
MaF14	8	2	9	1	4	6	10	5	7	3
MaF15	8	5	7	1	2	4	9	10	6	3
Total	10	4	5	1	6	3	9	7	2	8

Winner Algorithms

CVEA3 NEW

Cost value based evolutionary algorithm 3
Jiawei Yuan, Hai-Lin Liu, and Fangqing Gu
Guangdong University of Technology, China

AMPDEA NEW

Multi-population-driven evolutionary algorithm
Huangke Chen and Guohua Wu
National University of Defense Technology, China

BCE-IBEA

Bi-criterion evolution based IBEA
Miqing Li, Shengxiang Yang, and Xiaohui Liu
Brunel University, U. K.

Conclusion

- 15 many-objective test problems were proposed for this competition
- 10 many-objective evolutionary algorithms joined the competition
- According to the final ranking based on IGD and HV metrics, the winner is CVEA3 (Cost value based evolutionary algorithm 3)

Future work

- Re-organize this competition with further enhancements (C code, better computational efficiency, etc.)

- Attract more effective algorithms to join the competition

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Competition Homepage:
http://www.cs.bham.ac.uk/~chengr/CEC_Comp_on_MaOO/2018/webpage.html

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