Ranking Results of CEC'13 Special Session & Competition on Real-Parameter Single Objective Optimization

October 15, 2013

1 Ranking procedure

The algorithms presented during the CEC'2013 Special Session & Competition on Real-Parameter Single Objective Optimization were ranked using the procedure described below. The mean ranking values for all algorithms on all problems (28) and dimensions (10D, 30-D, 50-D) are presented in the following figures and tables.

1. For N algorithms (here, $N = 21$ or $= 3$ or $= 2$) the results from K runs (here, K=51) on M benchmark problems (here, 28×3=84) are available.

2. For each problem the best solutions found after a given number of function evaluations in K runs are collected in an array (an array of $K = 51$ values). Such arrays of N algorithms are combined and the best solutions of all algorithms are ranked (with correction for ties) with respect to each others so that each solution found by an algorithm may have some rank value between 1 and $N \times K$.

3. The arrays obtained in the previous step for all M problems are combined, which creates an array of $M \times K \times N$ values, where each value corresponds to some algorithm in some run on some problem.

4. An average or median for each algorithm thus can be computed. For simplicity, the ranking is normalized to the range of [0,1].

Rank	Paper ID/ref	Algorithm Name	Mean Ranking
1	1318 [12]	NBIPOPaCMA	0.27589
2	1566 [11]	icmaesils	0.28289
3	1617 [10]	DRMA-LSCh-CMA	0.30472
4	1652 [17]	SHADE	0.32800
5	1318 [12]	NIPOPaCMA	0.34873
6	1284 [16]	mvmo	0.36127
7	1122 [4]	SMADE	0.45583
8	1732 [1]	TLBSaDE	0.47042
9	1476 [15]	DEcfbLS	0.47222
10	1110 [18]	b6e6rl	0.47687
11	1393 [20]	SPSRDEMMS	0.49421
12	1093 [3]	CMAES-RIS	0.50515
13	1502 [6]	SPSOABC	0.51956
14	1381 [2]	jande	0.52960
15	1148 [8]	DE_APC	0.57617
16	1267 [13]	fk-PSO	0.58058
17	1132 [7]	TPC-GA	0.61008
18	1285 [5]	PVADE	0.63422
19	1238 [9]	CDASA	0.68659
20	1534 [19]	SPSO2011	0.75352
21	1159 [14]	PLES	0.83349

Table 1: The Table gives the mean aggregated rank of **all the 21 algorithms** ($N = 21$) across all problems and all dimensions from the CEC 2013 Special Session & Competition on Real-Parameter Single Objective Optimization after the maximum available number of function evaluations was used.

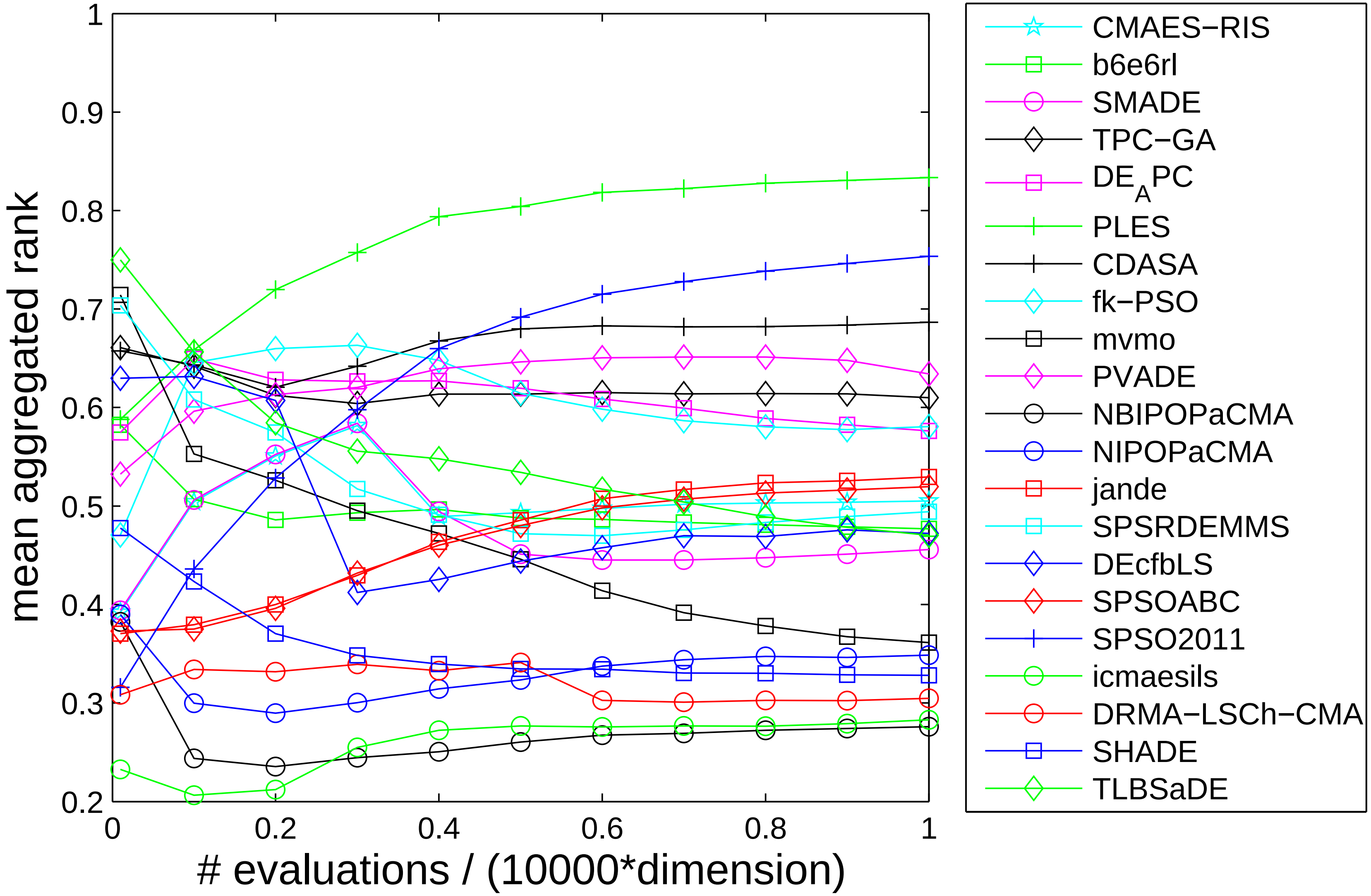

Figure 1: The Figure gives the mean aggregated rank of **all the 21 algorithms** ($N = 21$) across all problems and all dimensions from the CEC 2013 Special Session & Competition on Real-Parameter Single Objective Optimization. The mean aggregated rank is given in dependence of the computational budget as measured by the fraction of the number of function evaluations with respect to the maximum available number of function evaluations.

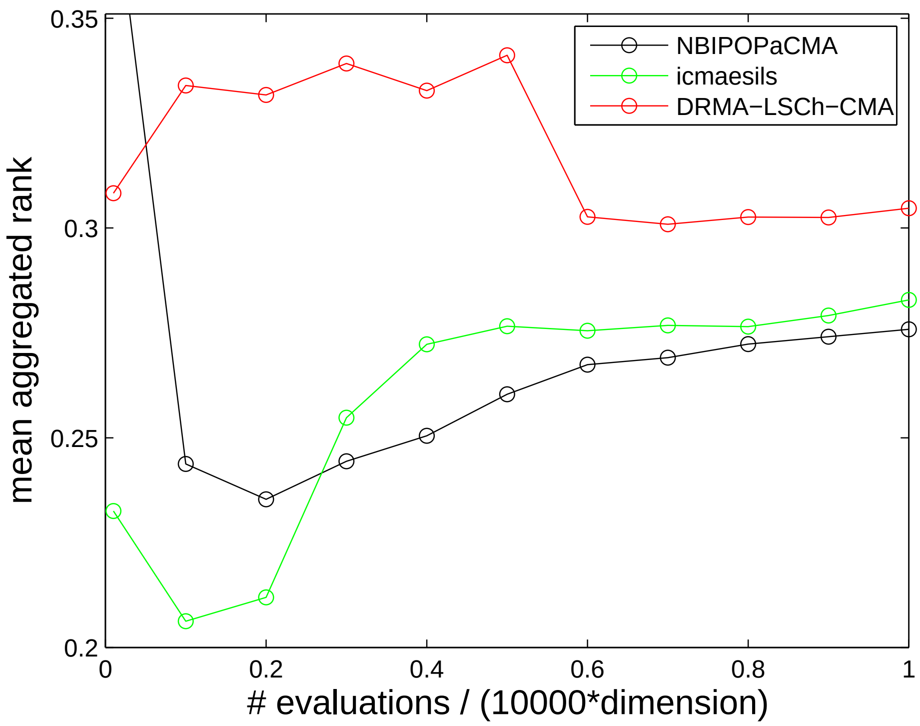

Figure 2: The Figure gives the mean aggregated rank of **the top three performing algorithms** iCMAES-ILS, NBIPOP-ACMA-ES, and DRMA-LSCh-CMA **when all 21 algorithms ($N = 21$) are considered** across all problems and all dimensions from the CEC 2013 Special Session & Competition on Real-Parameter Single Objective Optimization. The mean aggregated rank is given in dependence of the computational budget as measured by the fraction of the number of function evaluations with respect to the maximum available number of function evaluations.

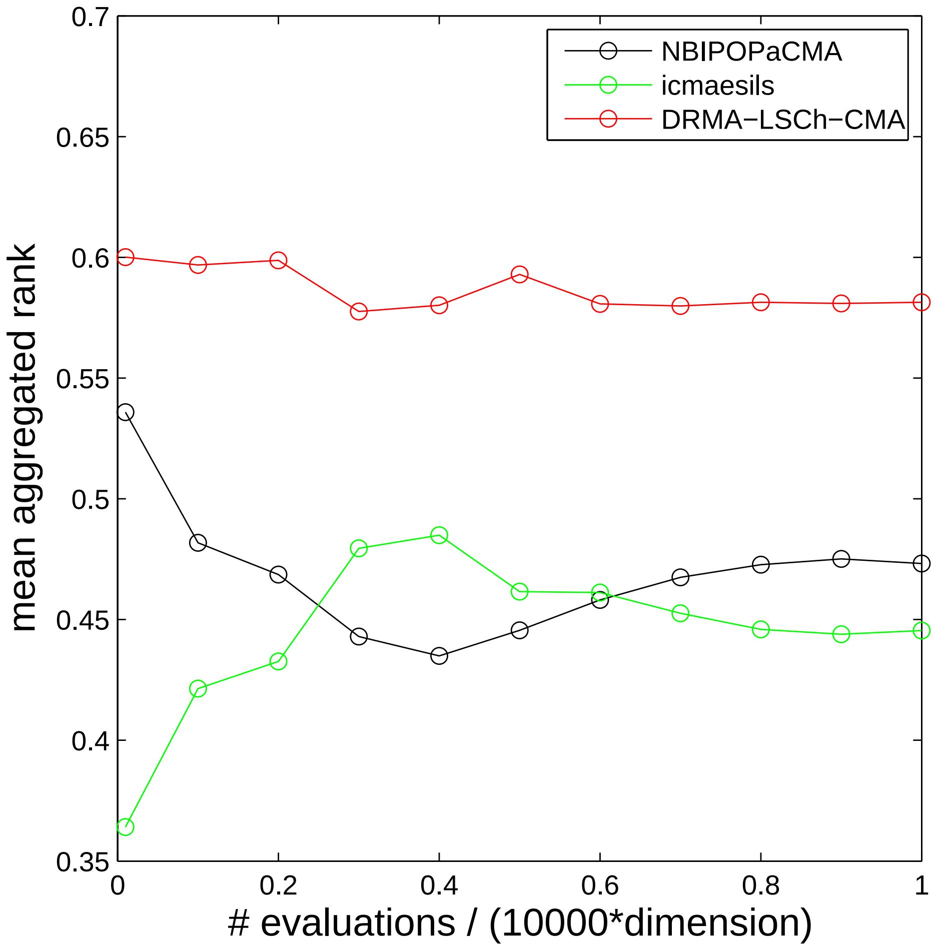

Figure 3: The Figure gives the mean aggregated rank of **the top three performing algorithms** iCMAES-ILS, NBIPOP-ACMA-ES, and DRMA-LSCh-CMA **when these 3 algorithms** $(N = 3)$ **are considered** across all problems and all dimensions from the CEC 2013 Special Session & Competition on Real-Parameter Single Objective Optimization. The mean aggregated rank is given in dependence of the computational budget as measured by the fraction of the number of function evaluations with respect to the maximum available number of function evaluations.

Table 2: Given is for each of **the top three performing algorithms** iCMAES-ILS, NBIPOP-ACMA-ES, and DRMA-LSCh-CMA the sum of the ranks with respect to the average error values that are measured for each of the 28 CEC 2013 benchmark functions. The average error values correspond to the errors measured at the maximum number of function evaluations. Given are also the results of a Friedman test at the significance level $\alpha = 0.05$. ΔR_α are the minimum significant difference 22.07 for all dimensions, Inf for dimension 10, 12.64 for dimension 30 and 12.96 for dimension 50, respectively. The numbers in parenthesis are the difference of the sum of ranks relative to the best algorithm. Algorithms that are significantly different from the best algorithm are highlighted.

All Dims	Algorithms	Sum Rank	(ΔR)
	iCMAES-ILS	148.0	(0)
	NBIPOP-ACMA-ES	160.5	(12.5)
	DRMA-LSCh-CMA	195.5	(47.5)
Dim=10	**Algorithms**	**Sum Rank**	**(ΔR)**
	NBIPOP-ACMA-ES	51.5	(0)
	iCMAES-ILS	54.0	(2.5)
	DRMA-LSCh-CMA	62.5	(11.0)
Dim=30	**Algorithms**	**Sum Rank**	**(ΔR)**
	iCMAES-ILS	46.5	(0)
	NBIPOP-ACMA-ES	56.5	(10.0)
	DRMA-LSCh-CMA	65.0	(18.5)
Dim=50	**Algorithms**	**Sum Rank**	**(ΔR)**
	iCMAES-ILS	47.5	(0)
	NBIPOP-ACMA-ES	52.5	(5.0)
	DRMA-LSCh-CMA	68.0	(20.5)

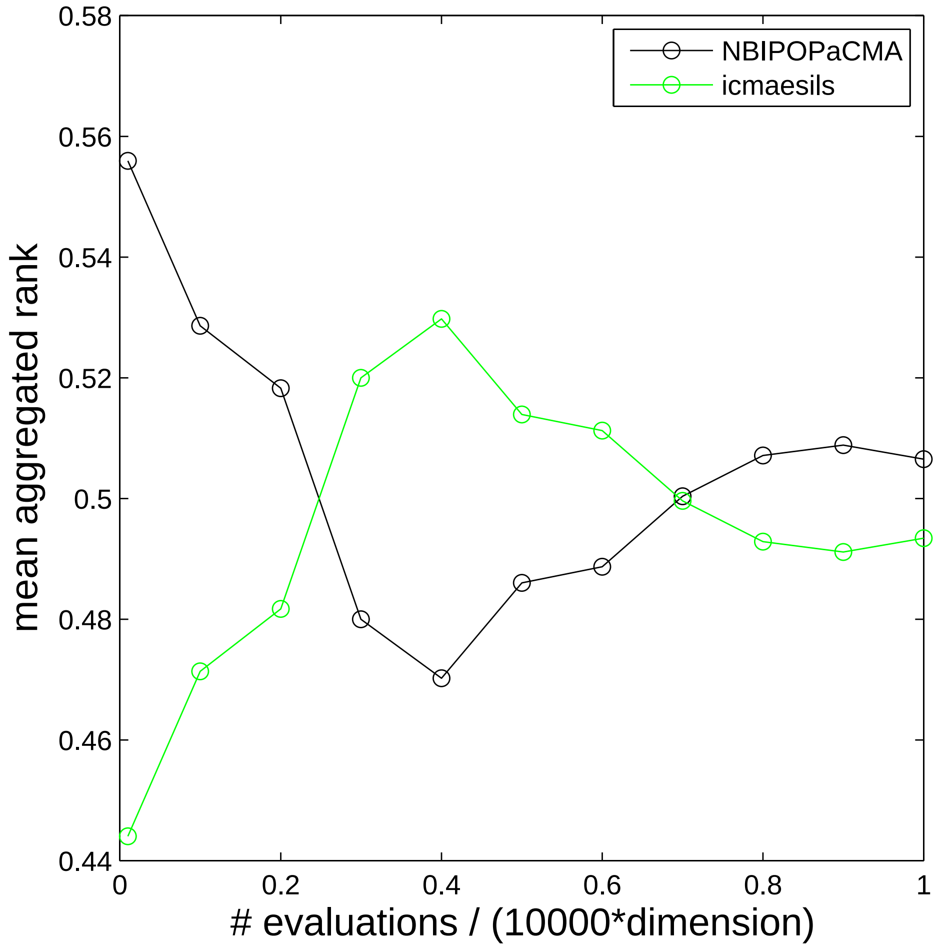

Figure 4: The Figure gives the mean aggregated rank of **the top two performing algorithms** iCMAES-ILS, NBIPOP-ACMA-ES **when these 2 algorithms** $(N = 2)$ **are considered** on all problems and all dimensions, from the CEC 2013 Special Session & Competition on Real-Parameter Single Objective Optimization, in dependence of the computational budget as measured by the fraction of the number of function evaluations with respect to the maximum available number of function evaluations.

Table 3: Given are the mean error values obtained by **the top two performing algorithms** iCMAES-ILS and NBIPOP-ACMA-ES at the CEC 2013 competition. The average error values correspond to the errors measured at the maximum number of function evaluations. NBIACMA is used as the abbreviation of NBIPOP-ACMA-ES in the table. At the bottom is indicated the number of times iCMAES-ILS gives lower, same or worse mean values (win, draw, loss) than NBIACMA. The lower mean errors values are highlighted. The sum of ranks with respect to the mean error values are given, the smaller the better.

func	Dim=10		Dim=30		Dim=50	
	iCMAES-ILS	NBIACMA	iCMAES-ILS	NBIACMA	iCMAES-ILS	NBIACMA
f_1	1.00E−08	1.00E−08	1.00E−08	1.00E−08	1.00E−08	1.00E−08
f_2	1.00E−08	1.00E−08	1.00E−08	1.00E−08	1.00E−08	1.00E−08
f_3	1.00E−08	1.00E−08	1.00E−08	1.00E−08	2.01E−02	1.82E+01
f_4	1.00E−08	1.00E−08	1.00E−08	1.00E−08	1.00E−08	1.00E−08
f_5	1.00E−08	1.00E−08	1.00E−08	1.00E−08	1.52E−08	1.00E−08
f_6	3.89E+00	1.00E−08	1.00E−08	1.00E−08	4.19E+01	1.00E−08
f_7	4.91E−06	1.00E−08	7.01E−02	2.31E+00	5.44E−01	4.97E+00
f_8	2.04E+01	2.03E+01	2.09E+01	2.09E+01	2.11E+01	2.11E+01
f_9	2.86E−01	2.32E−01	4.34E+00	3.30E+00	8.18E+00	7.22E+00
f_{10}	1.00E−08	1.00E−08	1.00E−08	1.00E−08	1.00E−08	1.00E−08
f_{11}	4.77E−01	3.64E−01	2.25E+00	3.04E+00	5.94E+00	5.51E+00
f_{12}	2.34E−01	2.38E−01	1.72E+00	2.91E+00	5.77E+00	5.37E+00
f_{13}	3.33E−01	4.84E−01	2.16E+00	2.78E+00	5.73E+00	7.60E+00
f_{14}	5.08E+01	1.15E+02	7.08E+02	8.10E+02	8.59E+02	1.38E+03
f_{15}	4.42E+01	1.58E+02	2.59E+02	7.65E+02	6.42E+02	1.55E+03
f_{16}	3.73E−01	1.20E−01	3.75E−01	4.40E−01	6.28E−01	8.78E−01
f_{17}	1.12E+01	1.13E+01	3.43E+01	3.44E+01	5.75E+01	5.74E+01
f_{18}	1.12E+01	1.13E+01	4.01E+01	6.23E+01	6.43E+01	1.34E+02
f_{19}	6.98E−01	5.25E−01	2.24E+00	2.23E+00	3.62E+00	4.46E+00
f_{20}	2.72E+00	2.73E+00	1.44E+01	1.29E+01	2.44E+01	2.25E+01
f_{21}	2.18E+02	1.53E+02	1.88E+02	1.92E+02	2.00E+02	1.98E+02
f_{22}	1.66E+02	1.75E+02	5.33E+02	8.38E+02	5.87E+02	1.45E+03
f_{23}	4.08E+01	1.74E+02	2.69E+02	6.67E+02	5.57E+02	1.71E+03
f_{24}	1.32E+02	1.20E+02	2.00E+02	1.62E+02	2.00E+02	2.40E+02
f_{25}	1.92E+02	1.77E+02	2.40E+02	2.20E+02	2.74E+02	2.48E+02
f_{26}	1.18E+02	1.11E+02	2.16E+02	1.58E+02	2.41E+02	1.96E+02
f_{27}	3.25E+02	3.17E+02	3.00E+02	4.69E+02	3.02E+02	7.28E+02
f_{28}	2.24E+02	2.49E+02	2.45E+02	2.69E+02	4.00E+02	4.00E+02
Times	(10, 6, 12)		(14, 8, 6)		(12, 6, 10)	
Sum ranks	43	41	38	46	41	43

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