

Black-Box Optimization Benchmarking for Noiseless Function Testbed using Artificial Bee Colony Algorithm

Draft version *

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ABSTRACT

This paper benchmarks the artificial bee colony (ABC) algorithm using the noise-free BBOB 2010 testbed.

Categories and Subject Descriptors

G.1.6 [Numerical Analysis]: Optimization—*global optimization, unconstrained optimization*; F.2.1 [Analysis of Algorithms and Problem Complexity]: Numerical Algorithms and Problems

General Terms

Algorithms

Keywords

Benchmarking, Black-box optimization

1. ARTIFICIAL BEE COLONY

The ABC algorithm was first proposed in [7]. The algorithms was inspired by the method adopted by a swarm of honey bees to locate food sources. There are two different honey bee groups that share knowledge in order to successfully locate such sources. First, there are the *employed bees* that are currently exploiting a food source. Second, there are the *onlookers* that wait at the nest and establish communication with the employed bees.

This algorithm was applied to multidimensional and multimodal function optimization in [7, 2, 11]. The swarm is divided into employed bees, scouts and onlookers. S_n solutions to the problem are randomly initialized in the function domain and referred to as food sources. A number of employed bees, set as the number of the food sources (half the colony size), are used to find new food sources using the following equation:

$$v_{ij} = x_{ij} + \phi_{ij} \times (x_{ij} - x_{kj}), \quad (1)$$

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for $j \in \{1 \dots d\}$ where d is the number of dimensions, ϕ_{ij} is a random number uniformly distributed in the range $[-1, 1]$, k is the index of a randomly chosen solution, \mathbf{x}_i is the current food source exploited by employed bee i , and \mathbf{v}_i is the new food source to be exploited. Both \mathbf{v}_i and \mathbf{x}_i are then compared against each other and the employed bee exploits the better food source.

Next, each onlooker bee randomly selects a food source to exploit according to the probability given in equation 2. Then, each onlooker bee tries to find a better food source around the selected one using equation 1.

$$p_i = \frac{fit_i}{\sum_{j=1}^{S_n} fit_j}, \quad (2)$$

where fit_i is the fitness of the i^{th} food source.

If a food source cannot be improved for a predetermined number of cycles, referred to as *limit*, this food source is abandoned. The employed bee that was exploiting this food source becomes a scout and randomly selects another food source in the domain according to:

$$x_{ij} = x_j^{min} + rand \times (x_j^{max} - x_j^{min}), \quad (3)$$

where x_j^{min} and x_j^{max} are the minimum and maximum domain bounds.

The ABC algorithm is shown in Algorithm 1.

Algorithm 1 The ABC algorithm

Require: Max_Cycles, ColonySize, *limit*.

```
1: Initialize the food sources
2: Evaluate the food sources
3: Cycle=1
4: while Cycle ≤ Max_Cycles do
5:   for each employed bee  $i$  do
6:     Produce a new solution
7:     Evaluate the new solution
8:     Apply Greedy selection choosing the better solution
9:   end for
10:  for each onlooker bee  $i$  do
11:    Probabilistically choose a solution according to  $p_i$ 
12:    Evaluate the new solution
13:    Apply Greedy selection choosing the better solution
14:  end for
15:  Re-initialize solutions not improved for limit cycles
16:  Memorize the best solution
17:  Cycle = Cycle + 1
18: end while
19: return best solution
```

Previous studies performed to assess the performance ABC

included the work in [12] showing that the ABC algorithm performs better than PSO, an evolutionary algorithm (EA) and DE on a small suite of classical benchmark functions. Another study was carried in [10] that compared ABC against PSO, a Genetic Algorithm (GA), DE and an Evolutionary Strategy (ES) algorithm on a larger number of functions. It was shown that the performance of ABC is better than or at least similar to those algorithms while having a smaller number of parameters to tune. The work in [9] compared ABC to HS and the Bees Algorithm (BA) proposed in [13]. The comparison was based on a small set of classical functions and the ABC showed superior performance over both algorithms while producing reasonable results for higher dimensions.

2. PARAMETER TUNING

For ABC, the work in [1] indicated that there is no need to have a huge colony size in order to provide good results. We use 40 bees as our previous experiments conducted on the CEC05 benchmarks [14] and repeated using populations of 20, 40 and 100 bees for different problem sizes showed that this setting provided the best results on average. The recommendations in [10] were followed by setting the *limit* parameters to $S_n \times D$, although recent research [1] indicated that lower values might be needed for more difficult functions.

3. RESULTS

Results from experiments according to [4] on the benchmark functions given in [3, 6] are presented in Figures 1, 2 and 3 and in Tables 1 and 2.

Experiments use the ABC code available at [8]. The ABC algorithm is allowed to perform a maximum of $10^5 \times D$ function evaluations for all test functions and no restart mechanism was used.

4. CPU TIMING EXPERIMENT

For the timing experiment, ABC was run on f8 and restarted until at least 30 seconds had passed (according to Figure 2 in [5]). The experiments have been conducted with an Intel Core 2 Quad 2.4 GHz under Windows Vista using the MATLAB-code provided. The results were 2.0×10^{-4} seconds per function evaluation in dimensions 2 up to 20. A dependency of CPU time on the search space dimensionality is not visible.

5. REFERENCES

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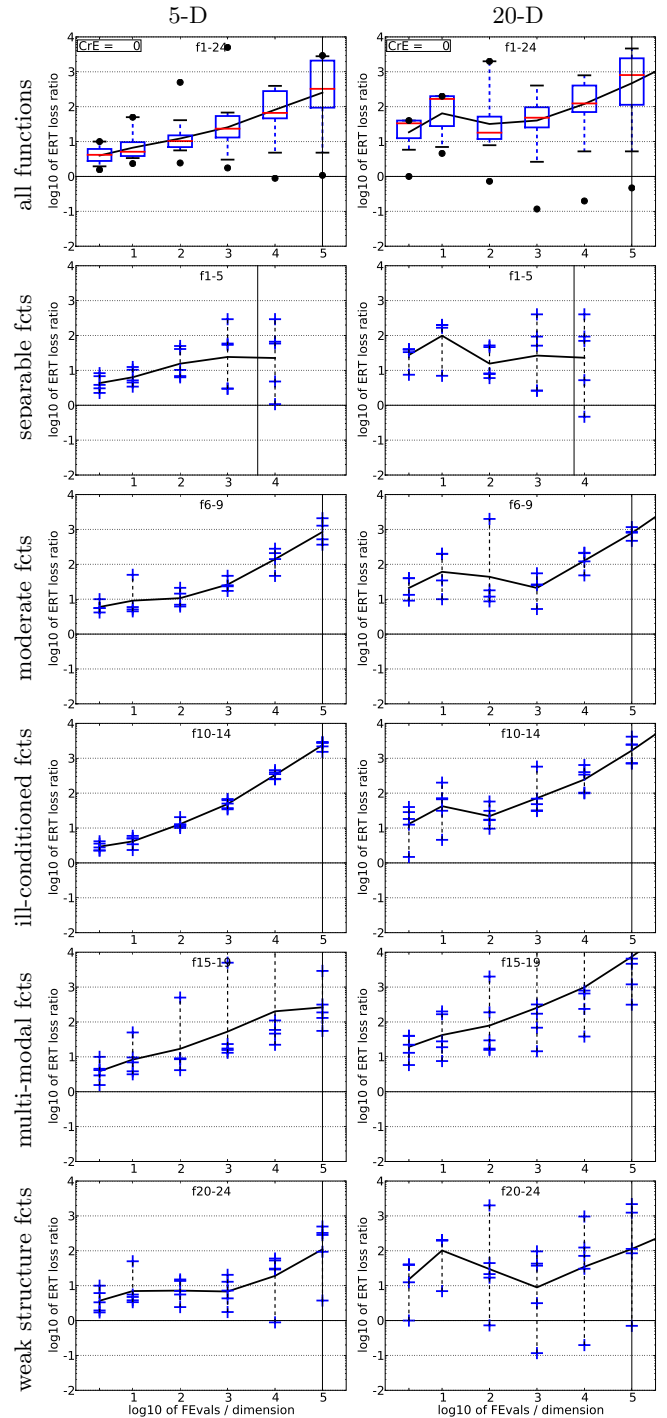


Figure 3: ERT loss ratio versus given budget FEvals. The target value f_t for ERT (see Figure 1) is the smallest (best) recorded function value such that $ERT(f_t) \leq \text{FEvals}$ for the presented algorithm. Shown is FEvals divided by the respective best $ERT(f_t)$ from BBOB-2009 for functions f_1 – f_{24} in 5-D and 20-D. Each ERT is multiplied by $\exp(\text{CrE})$ correcting for the parameter crafting effort. Line: geometric mean. Box-Whisker error bar: 25-75%-ile with median (box), 10-90%-ile (caps), and minimum and maximum ERT loss ratio (points). The vertical line gives the maximal number of function evaluations in this function subset.

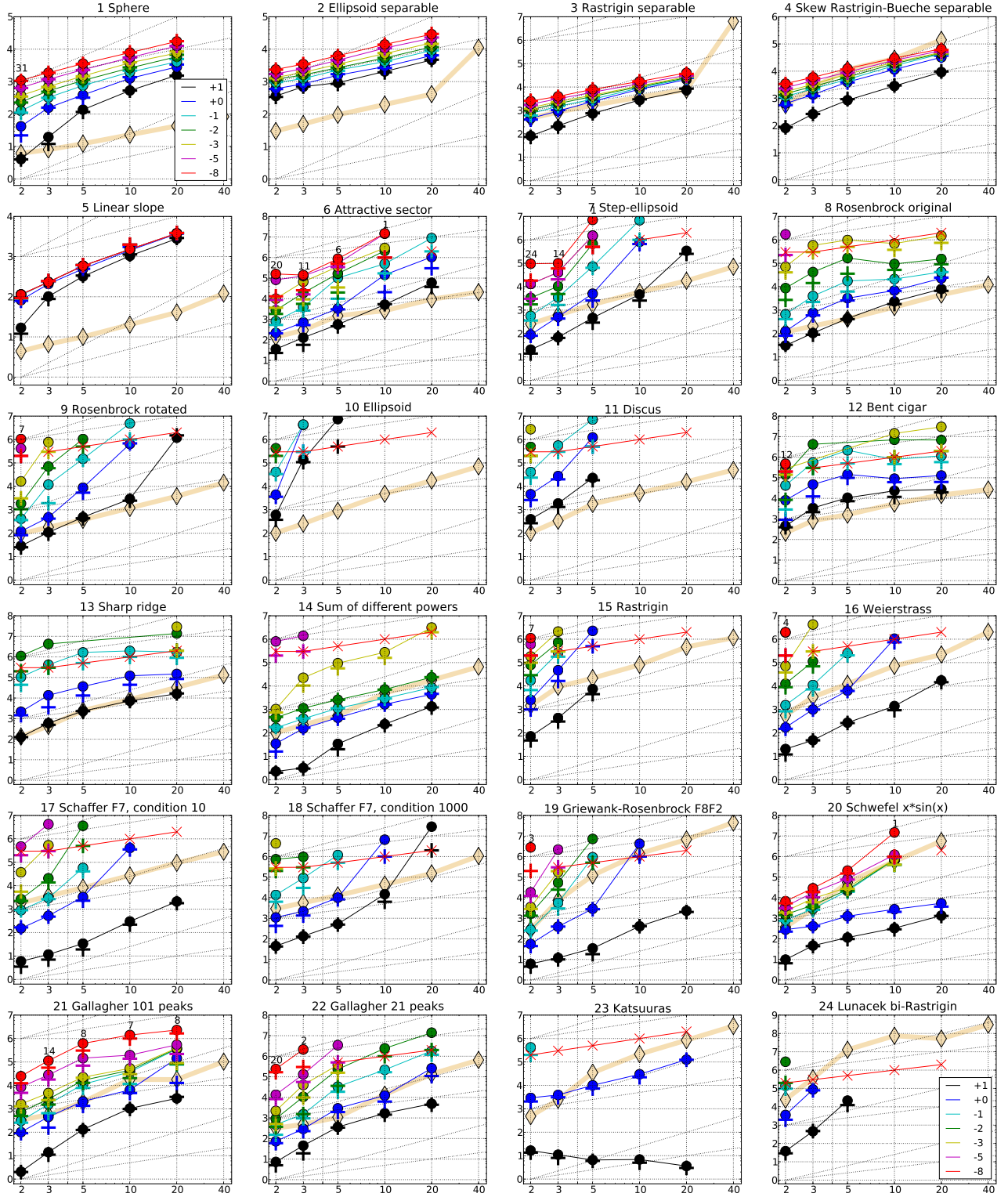


Figure 1: Expected Running Time (ERT, ●) to reach $f_{\text{opt}} + \Delta f$ and median number of f -evaluations from successful trials (+), for $\Delta f = 10^{\{+1, 0, -1, -2, -3, -5, -8\}}$ (the exponent is given in the legend of f_1 and f_{24}) versus dimension in log-log presentation. For each function and dimension, $\text{ERT}(\Delta f)$ equals to $\#FEs(\Delta f)$ divided by the number of successful trials, where a trial is successful if $f_{\text{opt}} + \Delta f$ was surpassed. The $\#FEs(\Delta f)$ are the total number (sum) of f -evaluations while $f_{\text{opt}} + \Delta f$ was not surpassed in the trial, from all (successful and unsuccessful) trials, and f_{opt} is the optimal function value. Crosses (×) indicate the total number of f -evaluations, $\#FEs(-\infty)$, divided by the number of trials. Numbers above ERT-symbols indicate the number of successful trials. Y-axis annotations are decimal logarithms. The thick light line with diamonds shows the single best results from BBOB-2009 for $\Delta f = 10^{-8}$. Additional grid lines show linear and quadratic scaling.

f_1 in 5-D, N=15, mFE=3980					f_1 in 20-D, N=15, mFE=18380					f_2 in 5-D, N=15, mFE=7022					f_2 in 20-D, N=15, mFE=30621										
Δf	#	ERT	10%	90%	RT _{succ}	#	ERT	10%	90%	RT _{succ}	Δf	#	ERT	10%	90%	RT _{succ}	#	ERT	10%	90%	RT _{succ}				
	10	15	1.4e2	1.2e1	3.1e2	1.4e2	15	1.6e3	6.5e2	2.7e3	1.6e3	10	15	9.3e2	5.7e2	1.5e3	9.3e2	15	4.6e3	2.8e3	5.5e3	4.6e3			
	1	15	3.9e2	1.7e2	6.9e2	3.9e2	15	2.8e3	8.8e2	4.6e3	2.8e3	1	15	1.6e3	7.4e2	2.6e3	1.6e3	15	6.4e3	4.9e3	7.8e3	6.4e3			
1e-1	15	7.6e2	3.8e2	1.0e3	7.6e2	15	4.1e3	1.4e3	6.2e3	4.1e3	1e-1	15	2.3e3	1.6e3	3.4e3	2.3e3	15	9.1e3	7.0e3	1.2e4	9.1e3				
1e-3	15	1.5e3	1.2e3	1.8e3	1.5e3	15	7.6e3	3.5e3	9.7e3	7.6e3	1e-3	15	3.4e3	2.0e3	3.9e3	3.4e3	15	1.6e4	1.3e4	1.8e4	1.6e4				
1e-5	15	2.3e3	2.2e3	2.7e3	2.3e3	15	1.3e4	1.2e4	1.3e4	1.3e4	1e-5	15	4.6e3	3.7e3	5.5e3	4.6e3	15	2.2e4	2.0e4	2.4e4	2.2e4				
1e-8	15	3.6e3	3.4e3	3.9e3	3.6e3	15	1.7e4	1.7e4	1.8e4	1.7e4	1e-8	15	6.3e3	5.8e3	6.8e3	6.3e3	15	2.9e4	2.7e4	3.1e4	2.9e4				
f_3 in 5-D, N=15, mFE=9620					f_3 in 20-D, N=15, mFE=73315					f_4 in 5-D, N=15, mFE=21552					f_4 in 20-D, N=15, mFE=121198										
Δf	#	ERT	10%	90%	RT _{succ}	#	ERT	10%	90%	RT _{succ}	Δf	#	ERT	10%	90%	RT _{succ}	#	ERT	10%	90%	RT _{succ}				
	10	15	7.4e2	4.1e2	1.2e3	7.4e2	15	7.4e3	2.9e3	1.1e4	7.4e3	10	15	8.6e2	3.0e2	1.1e3	8.6e2	15	9.3e3	3.8e3	1.5e4	9.3e3			
	1	15	2.4e3	1.5e3	3.3e3	2.4e3	15	2.1e4	8.6e3	2.8e4	2.1e4	1	15	4.0e3	2.2e3	5.2e3	4.0e3	15	3.2e4	2.0e4	4.3e4	3.2e4			
1e-1	15	3.0e3	2.1e3	4.0e3	3.0e3	15	2.3e4	8.5e3	3.6e4	2.3e4	1e-1	15	5.0e3	3.2e3	7.3e3	5.0e3	15	4.3e4	1.5e4	6.5e4	4.3e4				
1e-3	15	4.5e3	3.7e3	5.0e3	4.5e3	15	2.7e4	1.3e4	3.7e4	2.7e4	1e-3	15	7.8e3	5.8e3	1.3e4	7.8e3	15	4.9e4	2.9e4	8.4e4	4.9e4				
1e-5	15	6.0e3	4.7e3	6.9e3	6.0e3	15	3.2e4	2.3e4	3.9e4	3.2e4	1e-5	15	9.2e3	7.2e3	1.2e4	9.2e3	15	5.7e4	4.5e4	1.0e5	5.7e4				
1e-8	15	8.0e3	7.1e3	9.4e3	8.0e3	15	4.0e4	3.5e4	4.5e4	4.0e4	1e-8	15	1.2e4	9.5e3	1.6e4	1.2e4	15	6.6e4	5.4e4	8.8e4	6.6e4				
f_5 in 5-D, N=15, mFE=980					f_5 in 20-D, N=15, mFE=5940					f_6 in 5-D, N=15, mFE=500058					f_6 in 20-D, N=15, mFE=2.00e6										
Δf	#	ERT	10%	90%	RT _{succ}	#	ERT	10%	90%	RT _{succ}	Δf	#	ERT	10%	90%	RT _{succ}	#	ERT	10%	90%	RT _{succ}				
	10	15	3.2e2	5.4e1	4.5e2	3.2e2	15	2.8e3	1.9e3	4.2e3	2.8e3	10	15	5.6e2	2.1e2	9.4e2	5.6e2	15	6.0e4	9.7e3	1.4e5	6.0e4			
	1	15	4.9e2	2.3e2	7.6e2	4.9e2	15	3.7e3	2.0e3	5.0e3	3.7e3	1	15	3.3e3	1.7e3	5.5e3	3.3e3	11	1.1e6	1.1e5	3.0e6	3.3e5			
1e-1	15	5.8e2	2.1e2	8.9e2	5.8e2	15	3.8e3	2.3e3	4.7e3	3.8e3	1e-1	13	1.0e5	5.6e3	5.1e5	2.6e4	3	8.8e6	8.7e5	1.7e7	8.3e5				
1e-3	15	5.9e2	2.1e2	9.1e2	5.9e2	15	3.8e3	2.3e3	5.2e3	3.8e3	1e-3	9	3.6e5	1.3e4	1.0e6	2.6e4	0	54e-2	76e-3	14e-1	1.1e6				
1e-5	15	5.9e2	2.1e2	9.1e2	5.9e2	15	3.8e3	2.3e3	5.2e3	3.8e3	1e-5	8	5.2e5	2.1e4	1.9e6	7.9e4									
1e-8	15	5.9e2	2.1e2	9.1e2	5.9e2	15	3.8e3	2.0e3	4.7e3	3.8e3	1e-8	6	8.8e5	4.2e4	2.1e6	1.3e5									
f_7 in 5-D, N=15, mFE=500055					f_7 in 20-D, N=15, mFE=2.00e6					f_8 in 5-D, N=15, mFE=500057					f_8 in 20-D, N=15, mFE=2.00e6										
Δf	#	ERT	10%	90%	RT _{succ}	#	ERT	10%	90%	RT _{succ}	Δf	#	ERT	10%	90%	RT _{succ}	#	ERT	10%	90%	RT _{succ}				
	10	15	4.7e2	6.1e1	1.4e3	4.7e2	15	3.4e5	5.3e4	9.4e5	3.4e5	10	15	4.4e2	1.8e2	7.3e2	4.4e2	15	8.0e3	4.6e3	1.4e4	8.0e3			
	1	15	5.0e3	1.1e3	1.0e4	5.0e3	0	60e-1	37e-1	89e-1	5.8e5	1	15	3.2e3	9.7e2	6.6e3	3.2e3	15	2.3e4	1.3e4	3.1e4	2.3e4			
1e-1	15	7.3e4	1.5e4	1.5e5	7.3e4						1e-1	15	1.8e4	3.6e3	1.5e4	1.8e4	15	4.2e4	3.3e4	7.9e4	4.2e4				
1e-3	4	1.5e6	2.0e4	3.5e6	1.3e5						1e-3	6	9.8e5	5.9e4	2.4e6	2.3e5	11	1.5e6	5.3e5	3.5e6	7.6e5				
1e-5	4	1.5e6	2.5e4	3.2e6	1.3e5						1e-5	0	10e-4	25e-5	18e-3	1.2e5	0	24e-5	47e-6	29e-4	8.0e5				
1e-8	1	7.1e6	5.9e5	1.7e7	9.0e4						1e-8														
f_9 in 5-D, N=15, mFE=500056					f_9 in 20-D, N=15, mFE=2.00e6					f_{10} in 5-D, N=15, mFE=500059					f_{10} in 20-D, N=15, mFE=2.00e6										
Δf	#	ERT	10%	90%	RT _{succ}	#	ERT	10%	90%	RT _{succ}	Δf	#	ERT	10%	90%	RT _{succ}	#	ERT	10%	90%	RT _{succ}				
	10	15	4.8e2	2.1e2	8.1e2	4.8e2	13	1.2e6	9.5e4	1.8e6	8.9e5	10	1	7.4e6	9.2e5	1.6e7	4.2e5	0	50e+2	34e+2	79e+2	1.3e6			
	1	15	8.8e3	2.0e3	3.1e4	8.8e3	0	92e-1	67e-1	10e+0	2.0e6	1	0	55e+0	15e+0	17e+1	2.6e5								
1e-1	15	1.5e5	8.0e3	3.5e5	1.5e5						1e-1														
1e-3	0	13e-3	18e-4	49e-3	3.1e5						1e-3														
1e-5											1e-5														
1e-8											1e-8														
f_{11} in 5-D, N=15, mFE=500059					f_{11} in 20-D, N=15, mFE=2.00e6					f_{12} in 5-D, N=15, mFE=500059					f_{12} in 20-D, N=15, mFE=2.00e6										
Δf	#	ERT	10%	90%	RT _{succ}	#	ERT	10%	90%	RT _{succ}	Δf	#	ERT	10%	90%	RT _{succ}	#	ERT	10%	90%	RT _{succ}				
	10	15	2.3e4	2.3e3	8.4e4	2.3e4	0	92e+0	65e+0	10e+1	5.2e5	10	15	1.1e4	1.4e3	1.9e4	1.1e4	15	2.8e4	1.5e4	2.6e4	2.8e4			
	1	15	1.2e6	1.5e5	2.3e6	2.3e5						1	14	1.5e5	2.1e4	2.8e5	1.1e5	15	1.3e5	2.6e4	1.9e5	1.3e5			
1e-1	1	7.1e6	6.2e5	1.7e7	1.2e5						1e-1	3	2.2e6	1.7e5	5.2e6	1.7e5	12	1.2e6	2.3e5	2.5e6	6.8e5				
1e-3	0	15e-1	18e-2	28e-1	1.8e5						1e-3	0	29e-2	54e-3	49e-2	2.8e5	1	3.0e7	4.0e6	6.5e7	2.0e6				
1e-5											1e-5														
1e-8											1e-8														
f_{13} in 5-D, N=15, mFE=500059					f_{13} in 20-D, N=15, mFE=2.00e6					f_{14} in 5-D, N=15, mFE=500057					f_{14} in 20-D, N=15, mFE=2.00e6										
Δf	#	ERT	10%	90%	RT _{succ}	#	ERT	10%	90%	RT _{succ}	Δf	#	ERT	10%	90%	RT _{succ}	#	ERT	10%	90%	RT _{succ}				
	10	15	2.3e3	4.1e2	4.5e3	2.3e3	15	1.6e4	8.6e3	2.3e4	1.6e4	10	15	3.4e1	1.1e1	7.3e1	3.4e1	15	1.3e3	5.5e2	2.8e3	1.3e3			
	1	15	3.6e4	5.7e3	6.8e4	3.6e4	15	1.5e5	4.0e4	6.8e5	1.5e5	1	15	4.5e2	1.7e2	7.6e2	4.5e2	15	4.4e3	1.5e3	6.8e3	4.4e3			
1e-1	4	1.7e6	2.2e5	3.5e6	2.8e5	10	1.7e6	3.3e5	3.0e6	7.2e5	1e-1	15	1.1e3	7.1e2	1.5e3	1.1e3	15	8.6e3	6.4e3	1.1e4	8.6e3				
1e-3	0	15e-2	71e-3	62e-2	1.7e5	1	2.9e7	3.2e6	6.8e7	1.2e6	1e-3	15	9.4e4	8.0e3	2.3e5	9.4e4	8	3.1e6	1.0e6	8.0e6	1.4e6				
1e-5						0	60e-3	93e-4	15e-2	1.3e6	1e-5	0	27e-5	11e-5	89e-5	1.8e5	0	10e-4	82e-5	13e-4	1.8e6				
1e-8											1e-8														
f_{15} in 5-D, N=15, mFE=500055					f_{15} in 20-D, N=15, mFE=2.00e6					f_{16} in 5-D, N=15, mFE=500057					f_{16} in 20-D, N=15, mFE=2.00e6										
Δf	#	ERT	10%	90%	RT _{succ}	#	ERT	10%	90%	RT _{succ}	Δf	#	ERT	10%	90%	RT _{succ}	#	ERT	10%	90%	RT _{succ}				
	10	15	7.5e3	1.4e3	8.3e3	7.5e3	0	84e+0	69e+0	99e+0	1.1e6	10	15	2.7e2	1.3e2	4.1e2	2.7e2	15	1.7e4	2.5e3	4.1e4	1.7e4			
	1	3	2.3e6	2.7e5	5.3e6	2.6e5						1	15	6.4e3	2.7e3	1.0e4	6.4e3	0	39e-1	28e-1	45e-1	1.2e6			
1e-1	0	11e-1	15e-2	20e-1	2.7e5						1e-1	13	2.5e5	4.3e4	6.9e5	1.8e5									
1e-3											1e-3	0	48e-3	17e-3	11e-2	2.9e5									
1e-5											1e-5														
1e-8											1e-8														
f_{17} in 5-D, N=15, mFE=500053					f_{17} in 20-D, N=15, mFE=2.00e6					f_{18} in 5-D, N=15, mFE=500059					f_{18} in 20-D,										

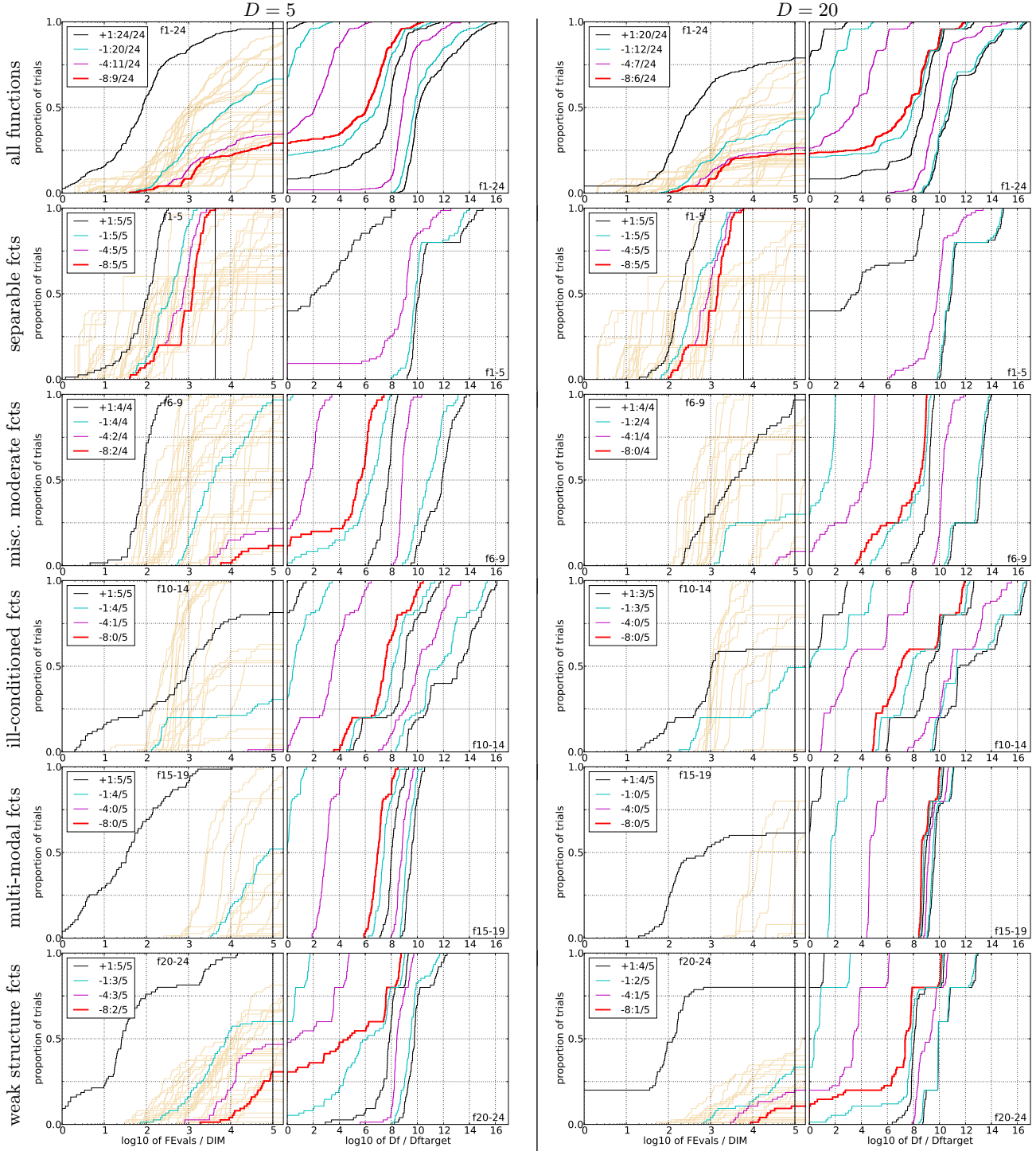


Figure 2: Empirical cumulative distribution functions (ECDFs), plotting the fraction of trials versus running time (left subplots) or versus Δf (right subplots). The thick red line represents the best achieved results. Left subplots: ECDF of the running time (number of function evaluations), divided by search space dimension D , to fall below $f_{\text{opt}} + \Delta f$ with $\Delta f = 10^k$, where k is the first value in the legend. Right subplots: ECDF of the best achieved Δf divided by 10^k (upper left lines in continuation of the left subplot), and best achieved Δf divided by 10^{-8} for running times of $D, 10D, 100D \dots$ function evaluations (from right to left cycling black-cyan-magenta). The legends indicate the number of functions that were solved in at least one trial. FEvals denotes number of function evaluations, D and DIM denote search space dimension, and Δf and Df denote the difference to the optimal function value. Light brown lines in the background show ECDFs for target value 10^{-8} of all algorithms benchmarked during BBOB-2009.

Table 2: ERT loss ratio (see Figure 3) compared to the respective best result from BBOB-2009 for budgets given in the first column. The last row RL_{US}/D gives the number of function evaluations in unsuccessful runs divided by dimension. Shown are the smallest, 10%-ile, 25%-ile, 50%-ile, 75%-ile and 90%-ile value (smaller values are better).

$f1-f24$ in 5-D, maxFE/D=100011						
#FEs/D	best	10%	25%	med	75%	90%
2	1.6	1.9	2.5	4.0	5.8	10
10	2.3	3.3	3.8	5.1	8.3	50
100	2.4	5.4	6.9	10	15	42
1e3	1.8	3.0	13	23	52	90
1e4	0.89	4.4	39	63	2.7e2	4.0e2
1e5	1.1	4.7	80	3.2e2	1.8e3	2.8e3
RL_{US}/D	1e5	1e5	1e5	1e5	1e5	1e5
$f1-f24$ in 20-D, maxFE/D=100002						
#FEs/D	best	10%	25%	med	75%	90%
2	1.0	5.4	13	31	40	40
10	4.6	7.0	23	1.7e2	2.0e2	2.0e2
100	0.73	7.7	11	18	49	2.0e3
1e3	0.12	2.6	20	46	95	4.2e2
1e4	0.20	4.8	59	1.2e2	4.0e2	8.1e2
1e5	0.47	4.8	1.0e2	7.7e2	2.3e3	4.8e3
1e6	0.47	9.0	2.7e2	5.3e3	1.6e4	4.3e4
RL_{US}/D	1e5	1e5	1e5	1e5	1e5	1e5

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