

# Benchmarking SHADE algorithm enhanced with model based optimization on the BBOB noiseless testbed

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## ABSTRACT

In this paper we evaluate the SHADE-LM algorithm on the BBOB noiseless testbed. The algorithm hybridizes the SHADE algorithm with a model based optimization. This hybridization is performed in a transparent manner for both optimizers, with SHADE having access to the samples provided by model based optimization, and models of square functions are fitted on the current population. The paper compares this extended version with the performance of the version of SHADE by Tanabe and Fukunaga.

## CCS CONCEPTS

- Computing methodologies → Continuous space search.

## KEYWORDS

SHADE, Model based optimization, Black-box optimization

### ACM Reference Format:

Michał Okulewicz and Mateusz Zaborski. 2021. Benchmarking SHADE algorithm enhanced with model based optimization on the BBOB noiseless testbed. In *2021 Genetic and Evolutionary Computation Conference Companion (GECCO '21 Companion)*, July 10–14, 2021, Lille, France. ACM, New York, NY, USA, 8 pages. <https://doi.org/10.1145/3449726.3463290>

## 1 INTRODUCTION

R-SHADE [9] algorithm has been proposed as one of the more successful modification of a Differential Evolution, following the path of adapting the scale and cross-over probability factors, employing the archive of previous best samples, utilizing the current-to-best position update and restart mechanism based on population locations or values spread.

One of the methods of improving algorithm performance is to hybridize it with another one, preferably one with different search strategy. In our previous work we hybridized basic Particle Swarm Optimization (PSO) and Differential Evolution (DE) algorithms with model based optimizers. This hybridization has improved PSO's and DE's performance [7, 11, 12] and led us to design a Generalized Adaptive Particle Swarm Optimization (GAPSO) framework[7, 10].

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*GECCO '21 Companion, July 10–14, 2021, Lille, France*

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ACM ISBN 978-1-4503-8351-6/21/07...\$15.00  
<https://doi.org/10.1145/3449726.3463290>

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The design concept of the GAPSO framework was a step towards a seamless hybridization of various optimization algorithms. In this paper we utilize the concept of GAPSO framework, to implement within it a version of SHADE [9] and a model based optimizer [12] in order to verify if the model-based optimizer would improve upon a state-of-the-art R-SHADE algorithm, as it did on the basic version of PSO and DE.

## 2 GAPSO FRAMEWORK

The concept of GAPSO framework is to allow for hybridization of optimization algorithms, in a way which will be transparent to the hybridized methods. The framework is named after PSO, as it follows the swarm intelligence design principle of achieving synergy through communicating independent beings. GAPSO approach comes from the observation that methods such as PSO or DE, need only a minimal amount of information about the other individuals (i.e. locations and values of the previously sampled locations) and each individual maintains its own location (Please note that PSO's velocity fits into this, as it is simply a difference between previous and current location). Therefore an algorithm which stores current, previous and best location for each individual (particle) allows to employ sampling of both DE and PSO based algorithms, in a transparent manner from the point of view of an individual (particle).

## 3 SHADE-LM ALGORITHM

SHADE-LM hybridizes the utilization of population based SHADE algorithm, based on [9] and model based optimizer utilizing square functions [12].

### 3.1 SHADE

SHADE is a form of population based Differential Evolution algorithm utilizing:

- archive of samples which have been replaced in the population
- list of adaptable cross-over and scale probabilities
- *current – to – pbest* type of DE mutation operator, shown in Eq. (1)

$$u^{(i)} = x^{(i)} + F_{it} * (x^{(pBest)} - x^{(i)}) + F_{it} * (x^{(rand1)} - x^{(rand2)}) \quad (1)$$

Single iteration of the SHADE pseudocode is given in Algorithm 1.

**Algorithm 1** Single iteration of SHADE

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```

1:  $F_{it} \leftarrow SelectScaleFactorFromSlot(slot)$ 
2:  $cp_{it} \leftarrow SelectCrossOverFactor(slot)$ 
3: for  $i \in 1$  to  $pop.size$  do
4:    $F_i \leftarrow SampleFromCauchyDistribution(F_{it}, 0.1)$ 
5:    $cp_i \leftarrow SampleFromNormalDistribution(cp_{it}, 0.1)$ 
6:    $x^{(pBest)} \leftarrow SelectOneOfPBestIndividuals(pBestRatio)$ 
7:    $x^{(rand1)} \leftarrow SelectIndividualFromCurrentPopulation()$ 
8:    $x^{(rand2)} \leftarrow SelectIndividualFromCurrentPopulationOrArchive()$ 
9:    $u^{(i)} \leftarrow GetSample(x^{(pBest)}, x^{(rand1)}, x^{(rand2)}, x^{(i)}, F_i)$ 
10:   $y^{(i)} \leftarrow ApplyCrossOver(x^{(pBest)}, u^{(i)}, cp_i)$ 
11:  if  $f(y^{(i)}) < f(x^{(i)})$  then
12:    PushToArchive( $x^{(i)}$ )
13:     $x^{(i)} \leftarrow y^{(i)}$ 
14:    StoreSuccessfulFactors( $F_i, cp_i$ )
15:  end if
16: end for
17: AdaptScaleAndCrossOverFactors()
18: slot  $\leftarrow slot + 1$ 

```

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### 3.2 Model based optimizers

Model based optimizer fits the linear combination of  $a_i, b_i, c$  coefficients for a simple  $N$ -dimensional square function (2), or if the population size allows it a full  $N$ -dimensional square function (3). Models can be fitted on the samples already gathered during the optimization process, regardless of their source. In the case of SHADE-LM models are fitted on the current population of the algorithm.

$$\hat{f}_{simple}(x) = \sum_{i=1}^N (a_i x_i^2 + b_i x_i) + c \quad (2)$$

$$\hat{f}_{full}(x) = \sum_{i=1}^N \left( b_i x_i + \sum_{j=1}^i (a_{i,j} x_j) \right) + c \quad (3)$$

If the population size is larger than  $min.full.samples$  (Eq. (5)) a full square model is fitted, if the population size is larger than  $min.simple.samples$  (Eq. (4)) the simple one is chosen.

$$min.simple.samples = 2D + 1 \quad (4)$$

$$min.full.samples = \frac{D^2 + 3D}{2} + 1 \quad (5)$$

For simplicity the example for the coefficients of simple square model is given in Eq. (6). The  $a_i, b_i$  and  $c$  coefficients are chosen

$$\text{through the minimization of } MSE = \frac{\sum_{i=1}^{pop.size} (\hat{f}(x_i) - f(x_i))^2}{pop.size}.$$

$$\begin{bmatrix} (x_1^{(1)})^2 & x_1^{(1)} & \dots & 1 \\ \vdots & \vdots & \vdots & \vdots \\ (x_1^{(pop.size)})^2 & x_1^{(pop.size)} & \dots & 1 \end{bmatrix} \begin{bmatrix} a_1 \\ b_1 \\ \vdots \\ a_N \\ b_N \\ c \end{bmatrix} = \begin{bmatrix} \hat{f}(x^{(1)}) \\ \vdots \\ \hat{f}(x^{(pop.size)}) \end{bmatrix} \quad (6)$$

After a model is fitted the optimizer samples the stationary point  $x_\theta$  of the model  $\hat{f}$  function by solving the system of linear equations

for coefficients of first derivatives of  $\hat{f}$  (given for the general case in Eq. (7)).

$$\begin{bmatrix} 2a_{1,1} & \dots & a_{N,1} \\ \vdots & \ddots & \vdots \\ a_{N,1} & \dots & 2a_{N,N} \end{bmatrix} \begin{bmatrix} x_{\theta 1} \\ \vdots \\ x_{\theta N} \end{bmatrix} = \begin{bmatrix} -b_1 \\ \vdots \\ -b_N \end{bmatrix} \quad (7)$$

**3.2.1 Special cases.** If the computed stationary point is outside the bounds defined by sample set, a boundary point closest to the stationary point is selected.

If no model can be fitted due to a too small number of samples or singularity of samples matrix, than a random sample will be selected within the hyperrectangle bounds defined by the samples set.

If the computed simple model is concave along a certain dimension, a boundary point with a minimal model value is selected. For the full model we are currently not detecting convexity, so selecting the model maximum or saddle point simply has the effect of sampling a random point within the samples bounds.

### 3.3 Proposed algorithm

Pseudocode of the proposed algorithm is given in Algorithm 2

**Algorithm 2** SHADE-LM pseudocode

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```

1: InitializePopulation()
2: while OptimizationBudgetIsLeft() do
3:   ModelIndividualsSet  $\leftarrow SelectIndividualsForModelApplication()$ 
4:   SelectSHADEFactors()
5:   for Individual in Population do
6:     if Individual  $\in$  ModelIndividualsSet then
7:        $y \leftarrow GetSampleAsModelFunctionStationaryPoint()$ 
8:     else
9:        $y \leftarrow GetSampleAsInSHADEAndStoreShadeFactors()$ 
10:    end if
11:    if  $f(y) < f(Individual.x)$  then
12:      PushToArchive(Individual.x)
13:      Individual.x  $\leftarrow y^{(i)}$ 
14:    end if
15:  end for
16:  AdaptSHADEScaleAndCrossOverFactors()
17:  if ShouldBeRestarted(Population) then
18:    ReInitializePopulation()
19:    ResetSHADE()
20:  end if
21: end while

```

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The algorithm works in the following way: *InitializePopulation*, generates a uniform random locations within predefined function bounds. The exceptions are samples indexed:  $D + 1, 2D + 2$  and  $\frac{D^2 + 3D}{2} + 2$ , as they are the samples that are taken from linear, simple square and full square model optima (within function bounds).

Within each iteration a subset of individuals is selected by *SelectIndividualsForModelApplication*, which randomizes which individuals are being sampled as model optima instead of SHADE algorithm<sup>1</sup>.

Subsequently an algorithm takes a function sample on the basis of model stationary point (in most cases a model function minimum

<sup>1</sup>In a full version of GAPSO framework there can be an arbitrary number of algorithms, so this function is generalized to generate a sequence of algorithms to be applied for a given generation

within bounds) or on the basis of SHADE sampling (corresponding to the lines 4 – 10 and line 14 in Algorithm 1), denoted as *GetSampleAsModelFunctionStationaryPoint* and *GetSampleAsInSHADEAndStoreShadeFactors*, respectively. There are three possibilities which may trigger the restart of the population (as applied in SHADE):

- (1) There has been no improvement of the global best optimum estimation in a given number of function evaluations
- (2) All the values of the current population are within a given threshold:

$$\max_{i=1,2,\dots,pop.size} f(x_i) - \min_{i=1,2,\dots,pop.size} f(x_i) < \Theta_{values}$$

- (3) The population has converged in at least one dimension:

$$\exists_{d \in \{1,2,\dots,D\}} \max_{i=1,2,\dots,pop.size} x[d]_i - \min_{i=1,2,\dots,pop.size} x[d]_i < \Theta_{locations}$$

## 4 EXPERIMENTAL PROCEDURE

We have run 2 configurations of our proposed approach, with the settings as given in Table 1. Both configuration utilize the same restart procedure, relying on population values or location convergence below a certain threshold or no improvements in the global best value for a certain amount of evaluations. Both configurations rely on the SHADE algorithm, configured roughly like its original version [9], with the exception of omitting population size decrease during a single run of the algorithm. Both configurations utilize the same proportion of samples taken from square function model optimum. The difference between SHADE-LM (SL-10) and SHADE-LM-POP4-to-10 (SL-4-10), is within the management of population size. SHADE-LM employs a large population of  $10 \times$  function dimensionality ( $D$ ), while SHADE-LM-POP4-to-10 gradually increases its population from  $4D$  to  $10D$  after each algorithm restart by 1.2 factor. Baseline for our experiments was the R-SHADE-10e5 configuration of the original R-SHADE[9].

**Table 1: Settings of the SHADE-LM algorithm**

<b>General settings</b>	
Optimization budget	$10^6 \times D$
<b>Specific SHADE-LM settings</b>	
Population size	$10D$
<b>Specific SHADE-LM-POP4-to-10 settings</b>	
Population size	$4D - 10D$
Population size increase after restart	1.2
<b>Model based optimizer parameters</b>	
Model based optimizer use count	$0.05 \times \text{pop. size}$
<b>Restart parameters</b>	
No improvement evaluations	5000D
Values convergence	$10^{-12}$
Locations convergence	$10^{-12}$
<b>SHADE parameters</b>	
Initial cross-over probability	0.9
Initial mutation scaling factor	0.38
Parameters slots	11
pBest count	$0.11 \times \text{pop. size}$
Archive size	$0.12 \times \text{pop. size}$

## 5 CPU TIMING

In order to evaluate the CPU timing of the algorithm, we have run the SHADE-LM on the bbob test suite [5] with restarts for a maximum budget equal to  $10^6 D$  function evaluations according to [6]. The Java code was run on single core of a Windows Intel(R) Core(TM) i7-9750H CPU @ 2.60GHz. The time per function evaluation for dimensions 2, 3, 5, 10, 20 equals  $1.70 \times 10^{-5}$ ,  $1.08 \times 10^{-5}$ ,  $1.49 \times 10^{-5}$ ,  $2.42 \times 10^{-5}$ , and  $5.20 \times 10^{-5}$  seconds respectively.

## 6 RESULTS

Results from SHADE-LM (denoted SL-10) and SHADE-LM-POP4-to-10 (denoted SL-4-10) experiments performed according to [6] and [2] on the benchmark functions given in [1, 5] are presented in Figures 1, 2 and 3 and in Tables 2 and 3. The experiments were performed with COCO [4], version 2.3, the plots were produced with version 2.4.

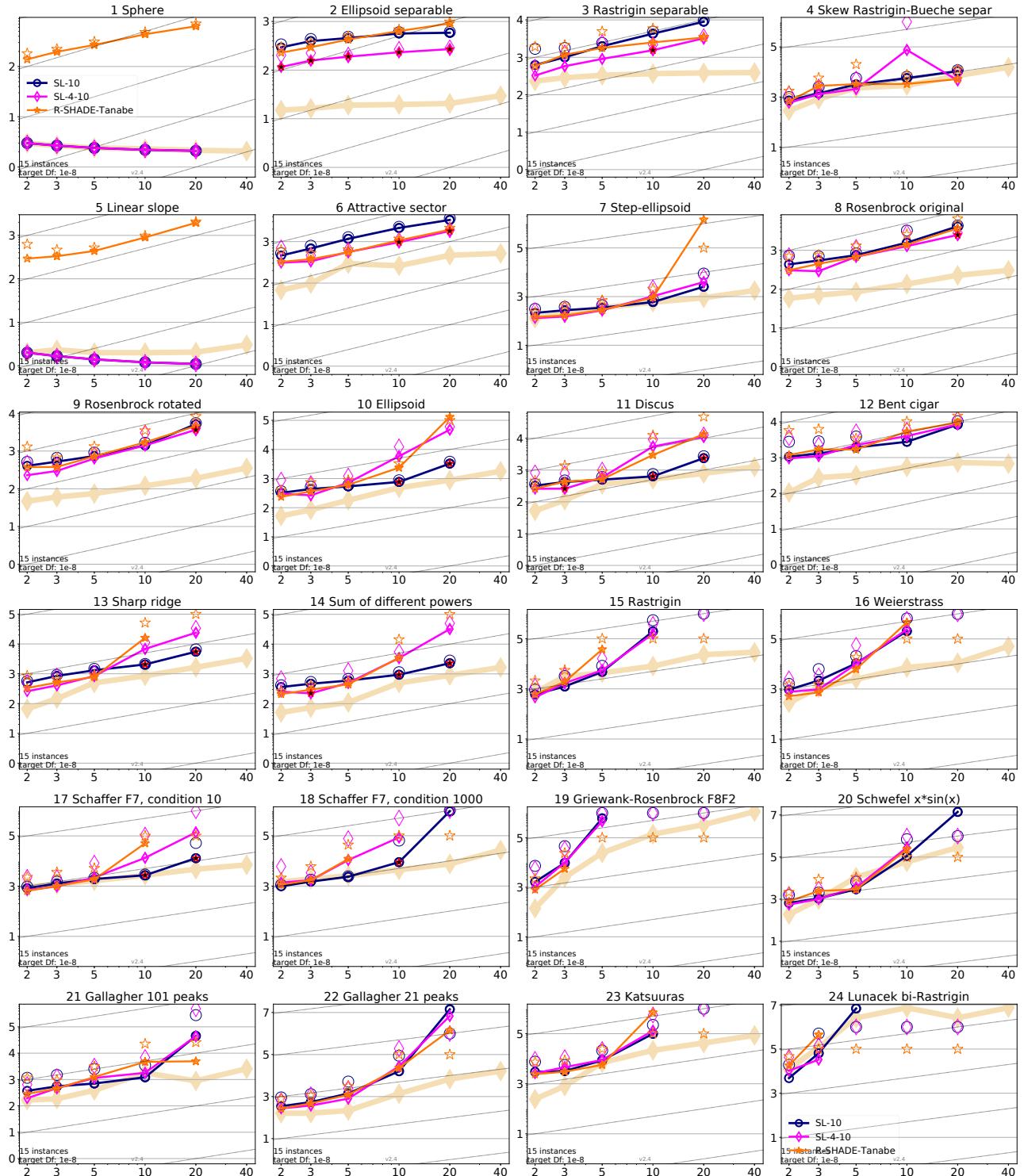
The **expected runtime (ERT)**, used in the figures and tables, depends on a given target function value,  $f_t = f_{opt} + \Delta f$ , and is computed over all relevant trials as the number of function evaluations executed during each trial while the best function value did not reach  $f_t$ , summed over all trials and divided by the number of trials that actually reached  $f_t$  [3, 8]. **Statistical significance** is tested with the rank-sum test for a given target  $\Delta f_t$  using, for each trial, either the number of needed function evaluations to reach  $\Delta f_t$  (inverted and multiplied by  $-1$ ), or, if the target was not reached, the best  $\Delta f$ -value achieved, measured only up to the smallest number of overall function evaluations for any unsuccessful trial under consideration.

Proposed SHADE-LM and SHADE-LM-POP4-to-10 configurations, improved the overall performance of the original R-SHADE algorithm. The improved results for  $f_1$  and  $f_5$  come directly from fitting the model, as those are spherical and linear functions. Additionally, we have observed that starting with a smaller population size of  $4D$  improves the performance for low optimization budget, up to  $10^3 \times D$ . Setting population size to its final value of  $10D$  proves beneficial in the long run for the optimization budgets higher than  $10^4 \times D$ , especially for dimensions 10 and 20. The original R-SHADE was found to be definitely better only for  $f_{21}$  and  $f_{22}$  function on  $20D$ , as the functions in  $f_{21} - f_{24}$  weakly structured functions group do not have a general trend factor to be exploited by fitting a single model.

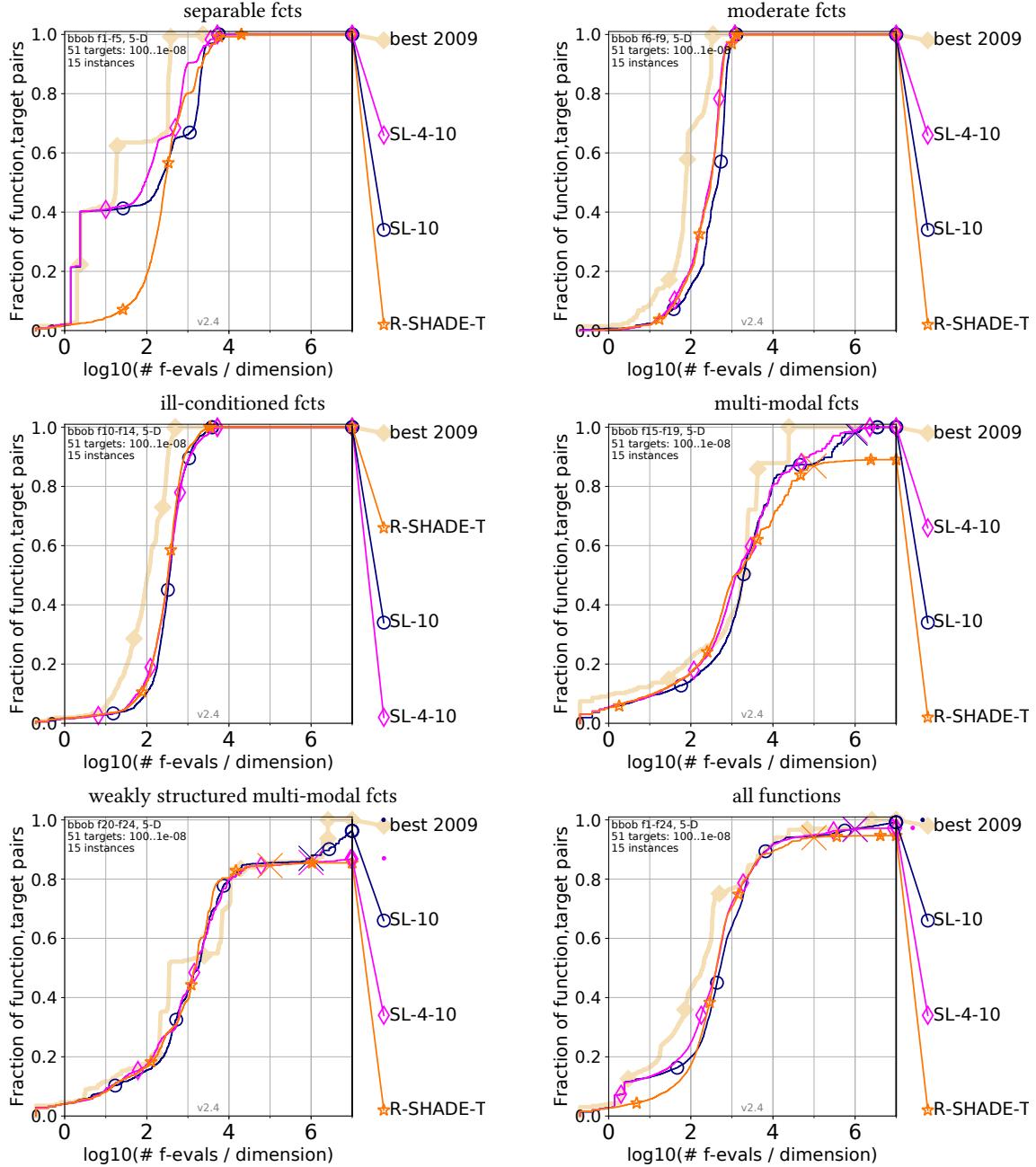
For future work we plan to include within this hybrid also the CMA-ES optimizer which poses an additional challenge of adapting CMA-ES' covariance matrix and  $\sigma$  on the basis of other algorithms samples. Initial experiments proved it to be non-trivial as CMA-ES is easily destabilized after recalculating those parameters on the basis of external samples.

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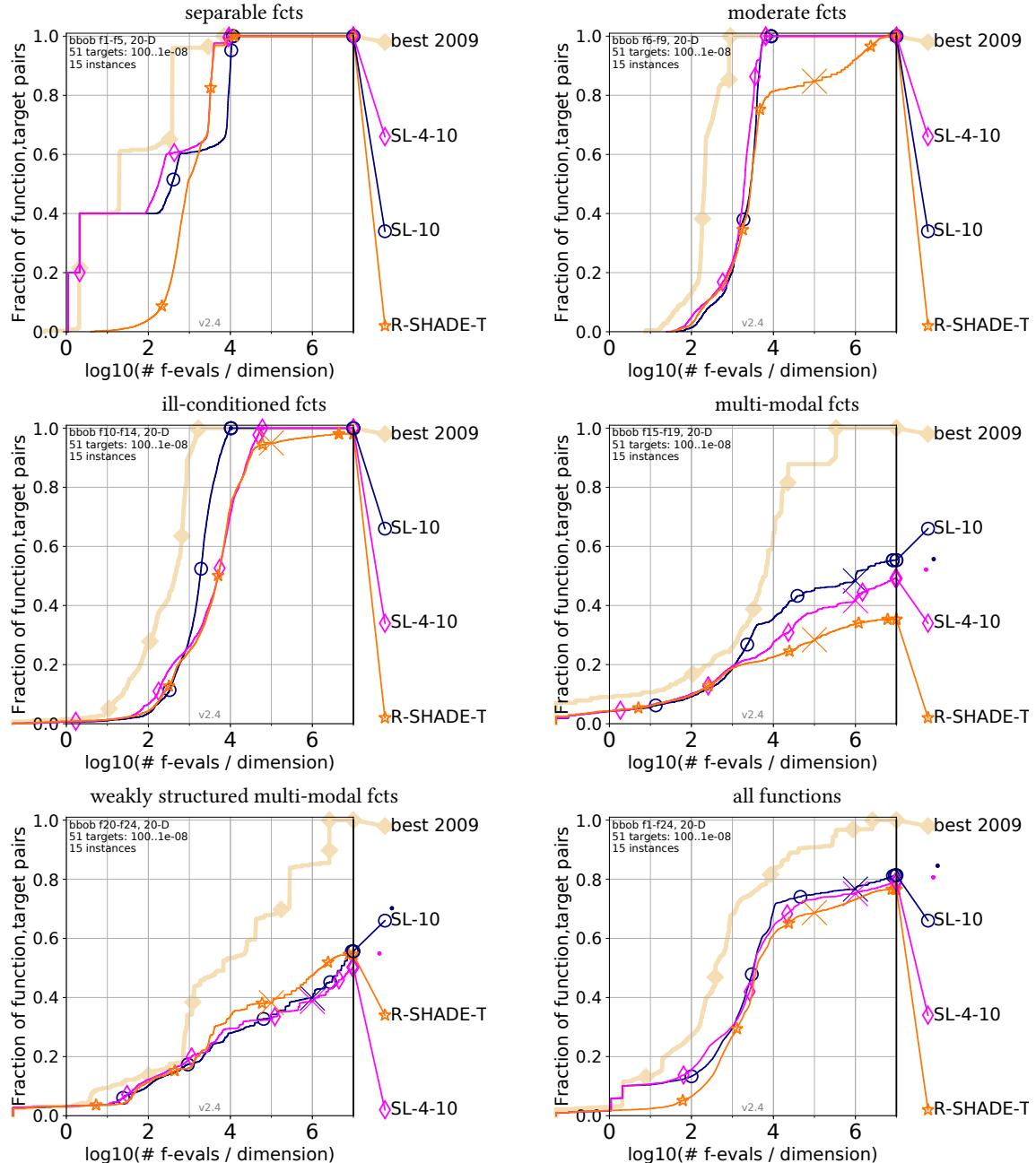


**Figure 1:** Expected running time (ERT in number of  $f$ -evaluations as  $\log_{10}$  value), divided by dimension for target function value  $10^{-8}$  versus dimension. Slanted grid lines indicate quadratic scaling with the dimension. Different symbols correspond to different algorithms given in the legend of  $f_1$  and  $f_{24}$ . Light symbols give the maximum number of function evaluations from the longest trial divided by dimension. Black stars indicate a statistically better result compared to all other algorithms with  $p < 0.01$  and Bonferroni correction number of dimensions (six). Legend:  $\circ$ : SHADE-LM (SL-10),  $\diamond$ : SHADE-LM-POP4-to-10 (SL-4-10),  $*$ : R-SHADE-10e5 (R-SHADE-Tanabe)



**Figure 2: Bootstrapped empirical cumulative distribution of the number of objective function evaluations divided by dimension (FEvals/DIM) for 51 targets with target precision in  $10^{[-8..2]}$  for all functions and subgroups in 5-D. As reference algorithm, the best algorithm from BBOB 2009 is shown as light thick line with diamond markers.**

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**Figure 3: Bootstrapped empirical cumulative distribution of the number of objective function evaluations divided by dimension (FEvals/DIM) for 51 targets with target precision in  $10^{-8..2}$  for all functions and subgroups in 20-D. As reference algorithm, the best algorithm from BBOB 2009 is shown as light thick line with diamond markers.**

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$\Delta f_{\text{opt}}$	1e1	1e0	1e-1	1e-2	1e-3	1e-5	1e-7	#succ	$\Delta f_{\text{opt}}$	1e1	1e0	1e-1	1e-2	1e-3	1e-5	1e-7	#succ
<b>f1</b>	11	12	12	12	12	12	12	15/15	<b>f13</b>	132	195	250	319	1310	1752	2255	15/15
SL-10	1.1(0)	<b>1(0)</b>	<b>1(0)</b>	1(0)	1(0)	1(0)	1(0)	15/15	SL-10	4.4(4)	5.3(0.8)	6.3(0.7)	6.4(0.5)	2.0(0.1)	2.1(0.1)	2.5(0.2)	15/15
SL-4-10	1.0(0)	1(0)	1(0)	1(0)	1(0)	1(0)	1(0)	15/15	SL-4-10	3.5(0.5)	4.5(1)	5.1(1)	5.4(1)	1.7(0.4)	1.7(0.4)	1.7(0.2)	15/15
R-SHADE	4.1(3)	14(4)	25(4)	36(3)	48(8)	72(7)	97(12)	15/15	R-SHADE	3.6(1)	4.2(1)	4.7(1)	4.9(0.9)	1.5(0.1)	1.5(0.2)	1.5(0.2)	15/15
<b>f2</b>	83	87	88	89	90	92	94	15/15	<b>f14</b>	10	41	58	90	139	251	476	15/15
SL-10	8.8(1)	11(1)	12(1)	13(1)	16(2)	19(1)	23(2)	15/15	SL-10	1.7(1)	5.0(3)	7.2(2)	8.4(2)	7.0(0.9)	6.8(0.9)	5.4(0.5)	15/15
SL-4-10	3.7(0.7) <sup>*4</sup>	<b>4.4(0.6)<sup>*4</sup></b>	5.0(0.8) <sup>*4</sup>	5.6(0.7) <sup>*4</sup>	6.5(0.7) <sup>*4</sup>	8.0(0.3) <sup>*4</sup>	9.3(0.8) <sup>*4</sup>	15/15	SL-4-10	2.0(2)	<b>3.1(0.9)</b>	3.9(0.9) <sup>*2</sup>	<b>4.2(1)<sup>*2</sup></b>	4.4(0.8)	<b>4.8(1)</b>	<b>3.8(1)</b>	15/15
R-SHADE	7.5(1)	8.7(2)	10(2)	12(3)	14(2)	17(3)	21(2)	15/15	R-SHADE	1.3(0.8)	3.4(1)	5.2(1)	5.7(1)	5.4(0.8)	5.3(1)	4.0(0.7)	15/15
<b>f3</b>	716	1622	1637	1642	1646	1650	1654	15/15	<b>f15</b>	511	9310	19369	19743	20073	20769	21359	14/15
SL-10	1.6(0.9)	4.2(0.9)	5.0(1)	5.3(1.0)	5.3(0.9)	5.6(1)	5.8(1)	15/15	SL-10	4.3(3)	<b>1.1(0.3)</b>	<b>1.00(0.5)</b>	<b>1.1(0.7)</b>	<b>1.1(0.6)</b>	<b>1.1(0.6)</b>	<b>1.1(0.6)</b>	15/15
SL-4-10	1.1(0.5)	1.7(0.7)	2.3(0.4)	2.4(2)	2.4(2)	2.7(2)	2.7(2)	15/15	SL-4-10	2.1(0.8)	1.3(1)	1.3(2)	1.3(1)	1.3(2)	1.3(2)	1.3(2)	15/15
R-SHADE	<b>1.1(0.4)</b>	1.7(0.4)	4.5(4)	4.7(3)	4.8(4)	5.1(5)	5.3(5)	15/15	R-SHADE	<b>1.9(1.0)</b>	2.3(4)	6.3(8)	6.2(7)	8.3(11)	9.0(6)	8.7(12)	14/15
<b>f4</b>	809	1633	1688	1758	1817	1886	1903	15/15	<b>f16</b>	120	612	2662	10163	10449	11644	12095	15/15
SL-10	3.1(1)	5.0(1)	7.1(3)	7.4(4)	7.5(2)	7.7(2)	8.1(4)	15/15	SL-10	2.1(3)	10(4)	11(6)	4.8(4)	4.8(4)	4.4(3)	4.3(2)	15/15
SL-4-10	1.3(0.4)	2.2(2)	5.0(6)	5.0(4)	5.1(6)	5.2(6)	5.4(6)	15/15	SL-4-10	2.5(3)	5.3(2)	3.2(3)	2.2(2)	4.0(8)	4.1(9)	4.0(4)	15/15
R-SHADE	1.4(0.5)	4.5(4)	8.7(18)	8.5(4)	8.3(5)	8.3(14)	8.4(16)	15/15	R-SHADE	<b>1.1(0.9)</b>	2.7(0.6) <sup>*3</sup>	2.5(4)	<b>1.4(2)</b>	2.2(2)	2.4(3)	2.3(3)	15/15
<b>f5</b>	10	10	10	10	10	10	10	15/15	<b>f17</b>	5.0	215	899	2861	3669	6351	7934	15/15
SL-10	<b>0.70(0)</b>	<b>0.70(0)</b>	<b>0.70(0)</b>	<b>0.70(0)</b>	<b>0.70(0)</b>	<b>0.70(0)</b>	<b>0.70(0)</b>	15/15	SL-10	3.3(4)	2.7(0.9)	<b>1.7(0.3)</b>	0.94(0.1)	1.1(0.2)	<b>1.0(0.1)</b>	<b>1.1(0.1)</b>	15/15
SL-4-10	<b>0.70(0)</b>	<b>0.70(0)</b>	<b>0.70(0)</b>	<b>0.70(0)</b>	<b>0.70(0)</b>	<b>0.70(0)</b>	<b>0.70(0)</b>	15/15	SL-4-10	2.4(3)	<b>1.4(0.8)</b>	3.7(10)	1.4(0.4)	1.3(0.4)	1.2(0.6)	1.3(2)	15/15
R-SHADE	21(8)	43(11)	62(16)	84(12)	106(22)	151(12)	198(29)	15/15	R-SHADE	2.9(2)	1.5(1)	1.9(0.5)	<b>0.81(0.2)</b>	<b>0.94(1.0)</b>	1.1(1)	1.1(1)	15/15
<b>f6</b>	114	214	281	404	580	1038	1332	15/15	<b>f18</b>	103	378	3968	8451	928	10905	12469	15/15
SL-10	3.3(1)	4.2(0.8)	5.1(0.7)	4.8(0.5)	4.4(0.3)	3.7(0.2)	3.9(0.3)	15/15	SL-10	2.5(2)	2.5(0.8)	0.58(0.1)	<b>0.46(0.1)</b>	<b>0.57(0.1)</b>	<b>0.75(0.0)</b>	<b>0.84(0.0)</b>	15/15
SL-4-10	2.0(0.9)	2.3(0.4)	2.7(0.7)	2.6(0.5)	2.3(0.3)	1.8(0.2)	1.9(0.2)	15/15	SL-4-10	<b>1.0(0.6)</b>	1.7(1)	1.7(5)	0.98(1)	1.2(2)	4.6(9)	4.3(11)	15/15
R-SHADE	2.1(0.7)	2.5(0.8)	2.8(0.7)	2.6(0.4)	2.3(0.4)	1.8(0.2)	1.9(0.2)	15/15	R-SHADE	1.4(1)	<b>1.6(0.5)</b>	<b>0.32(0.2)</b>	0.64(1)	1.2(3)	2.6(3)	4.7(8)	15/15
<b>f7</b>	24	324	1171	1451	1572	1572	1597	15/15	<b>f19</b>	1	1	242	1.0e5	1.2e5	1.2e5	1.2e5	15/15
SL-10	<b>3.6(2)</b>	1.1(0.4)	0.58(0.2)	0.82(0.1)	0.80(0.2)	0.80(0.2)	0.89(0.1)	15/15	SL-10	<b>17(9)</b>	1626(2073)	150(79)	12(9)	20(17)	24(37)	25(24)	12/15
SL-4-10	3.6(2)	<b>0.82(0.3)</b>	0.49(0.1)	<b>0.60(0.3)</b>	0.70(0.5)	0.70(0.5)	0.72(0.5)	15/15	SL-4-10	21(20)	1423(673)	173(204)	<b>5.0(5)</b>	7.1(8)	<b>13(22)</b>	<b>19(21)</b>	12/15
R-SHADE	4.3(2)	1.3(2)	0.72(0.9)	0.75(0.4)	0.73(0.7)	0.73(0.5)	0.79(0.4)	15/15	R-SHADE	22(20)	1787(2597)	<b>111(165)</b>	21(21)	<b>∞</b>	<b>∞</b>	<b>∞</b> <sup>se5</sup>	0/15
<b>f8</b>	73	273	336	372	391	410	422	15/15	<b>f20</b>	16	851	38111	51362	54470	54861	55313	14/15
SL-10	7.3(2)	6.5(1)	7.4(1.0)	7.7(0.9)	7.8(0.9)	8.1(0.7)	8.6(0.8)	15/15	SL-10	3.5(2)	4.9(2)	<b>0.30(0.1)</b>	0.26(0.1)	0.27(0.2)	0.27(0.2)	0.27(0.1)	15/15
SL-4-10	3.7(1.0)	4.8(1)	5.8(6)	6.2(6)	6.4(3)	7.0(1)	7.6(3)	15/15	SL-4-10	<b>3.3(3)</b>	2.2(2)	0.40(0.4)	0.33(0.2)	0.32(0.3)	0.32(0.3)	0.32(0.3)	15/15
R-SHADE	4.9(2)	<b>4.7(5)</b>	5.3(2)	5.8(2)	<b>6.1(4)</b>	<b>6.7(3)</b>	7.5(3)	15/15	R-SHADE	3.9(2)	1.9(2)	0.33(0.2)	<b>0.26(0.3)</b>	<b>0.25(0.3)</b>	<b>0.25(0.1)</b>	<b>0.26(0.3)</b>	15/15
<b>f9</b>	35	127	214	263	300	335	369	15/15	<b>f21</b>	41	1157	1674	1692	1705	1729	1757	14/15
SL-10	15(4)	14(5)	11(2)	11(2)	10(2)	10(2)	10(1)	15/15	SL-10	2.1(2)	<b>1.2(0.6)</b>	<b>1.3(2)</b>	<b>1.5(0.7)</b>	<b>1.6(0.8)</b>	<b>1.7(2)</b>	<b>1.9(2)</b>	15/15
SL-4-10	8.1(2)	<b>7.6(3)</b>	<b>7.4(2)</b>	<b>7.4(2)</b>	<b>7.4(2)</b>	<b>7.8(2)</b>	<b>8.1(2)</b>	15/15	SL-4-10	<b>1.9(1)</b>	3.2(3)	3.0(3)	3.0(3)	3.1(2)	3.2(3)	3.2(3)	15/15
R-SHADE	<b>8.0(2)</b>	11(14)	9.4(6)	9.0(7)	8.7(4)	9.0(4)	9.3(1)	15/15	R-SHADE	2.0(2)	2.6(3)	3.3(2)	3.3(3)	3.4(2)	3.4(2)	3.5(3)	15/15
<b>f10</b>	349	500	574	607	626	829	880	15/15	<b>f22</b>	71	386	938	980	1008	1040	1068	14/15
SL-10	2.40(9)	<b>2.1(0.5)</b>	2.2(0.4)	2.5(0.2)	2.6(0.3)	2.5(0.2)	<b>2.8(0.2)</b>	15/15	SL-10	2.7(3)	5.1(3)	5.9(9)	6.1(8)	6.0(9)	6.1(5)	6.4(5)	15/15
SL-4-10	2.4(1)	2.5(2)	2.8(2)	3.4(2)	3.7(2)	3.4(2)	3.8(2)	15/15	SL-4-10	1.6(0.6)	3.9(7)	3.3(5)	3.3(4)	3.5(3)	3.6(5)	3.6(5)	15/15
R-SHADE	2.2(2)	2.3(1)	2.4(0.6)	2.6(0.7)	2.9(1)	2.9(0.9)	3.2(0.8)	15/15	R-SHADE	<b>1.5(1)</b>	<b>3.2(6)</b>	5.5(7)	5.5(7)	5.5(7)	5.6(6)	5.6(6)	15/15
<b>f11</b>	143	202	763	977	1177	1467	1673	15/15	<b>f23</b>	3.0	518	14249	27890	31654	33030	34256	15/15
SL-10	4.4(2)	4.9(1)	1.4(0.2)	<b>1.2(0.3)</b>	<b>1.2(0.2)</b>	<b>1.3(0.2)</b>	<b>1.3(0.2)</b>	15/15	SL-10	<b>2.5(3)</b>	13(16)	2.5(3)	1.3(1)	1.2(1)	1.2(1)	1.2(1)	15/15
SL-4-10	3.2(1)	3.7(1)	1.3(0.4)	1.3(0.4)	1.3(0.5)	1.4(0.4)	1.6(0.4)	15/15	SL-4-10	3.2(3)	10(7)	2.4(3)	1.4(1)	1.3(1)	1.3(1)	1.3(1)	15/15
R-SHADE	3.1(0.7)	<b>3.5(1)</b>	1.3(0.3)	1.3(0.8)	1.2(0.7)	1.3(0.5)	1.4(0.5)	15/15	R-SHADE	2.9(3)	6.2(5)	1.7(3)	<b>0.93(2)</b>	<b>0.83(0.4)</b>	<b>0.82(0.7)</b>	<b>0.82(1)</b>	15/15
<b>f12</b>	108	268	371	413	461	1303	1494	15/15	<b>f24</b>	1622	2.2e5	6.4e6	9.6e6	9.6e6	1.3e7	1.3e7	3/15
SL-10	12(4)	10(11)	11(11)	12(12)	13(11)	5.8(5)	6.1(4)	15/15	SL-10	4.1(1)	2.4(3)	5.4(4)	3.6(3)	3.6(4)	2.7(2)	2.7(3)	2/15
SL-4-10	<b>10(9)</b>	9.5(9)	12(13)	14(14)	15(18)	6.8(5)	7.1(7)	15/15	SL-4-10	1.7(0.7)	<b>1.8(3)</b>	5.3(6)	<b>∞</b>	<b>∞</b>	<b>∞</b>	<b>∞</b> <sup>se6</sup>	0/15
R-SHADE	10(7)	7.1(3)	8.0(6)	8.9(9)	10(5)	5.0(3)	5.3(3)	15/15	R-SHADE	1.7(1)	2.6(3)	<b>∞</b>	<b>∞</b>	<b>∞</b>	<b>∞</b>	<b>∞</b> <sup>se5</sup>	0/15

**Table 2: Expected runtime (ERT in number of function evaluations) divided by the respective best ERT measured during BBOB-2009 in dimension 5. This ERT ratio and, in braces as dispersion measure, the half difference between 10 and 90%-tile of bootstrapped run lengths appear for each algorithm and target, the corresponding reference ERT in the first row. The different target  $\Delta f$ -values are shown in the top row. #succ is the number of trials that reached the (final) target  $f_{\text{opt}} + 10^{-8}$ . The median number of conducted function evaluations is additionally given in *italics*, if the target in the last column was never reached. Entries, succeeded by a star, are statistically significantly better (according to the rank-sum test) when compared to all other algorithms of the table, with  $p = 0.05$  or  $p = 10^{-k}$  when the number  $k$  following the star is larger than 1, with Bonferroni correction by the number of functions (24). A ↓ indicates the same tested against the best algorithm from BBOB 2009. Best results are printed in bold.**

Data produced with COCO v2.4

$\Delta f_{\text{opt}}$	1e1	1e0	1e-1	1e-2	1e-3	1e-5	1e-7	#succ	$\Delta f_{\text{opt}}^*$	1e1	1e0	1e-1	1e-2	1e-3	1e-5	1e-7	#succ
<b>f1</b>	43	43	43	43	43	43	43	15/15	<b>f13</b>	652	2021	2751	3507	18749	24455	30201	15/15
SL-10	<b>0.98(0)</b>	15/15	SL-10	11(4)	11(6)	14(9)	15(4)	3.4(0.8)	<b>3.3(0.7)*<sup>2</sup></b>	<b>3.3(0.5)*<sup>4</sup></b>	15/15						
SL-4-10	<b>0.98(0)</b>	15/15	SL-4-10	8.7(5)	<b>8.0(6)</b>	9.1(4)	<b>11(4)</b>	<b>3.0(2)</b>	6.2(3)	12(4)	15/15						
R-SHADE	27(5)	59(9)	89(12)	119(15)	149(18)	208(21)	264(26)	15/15	R-SHADE	12(7)	8.0(3)	10(5)	12(3)	3.4(1)	5.2(0.9)	25(26)	0/15
<b>f2</b>	385	386	387	388	390	391	393	15/15	<b>f1</b>	75	239	304	451	932	1648	15661	15/15
SL-10	12(1)	14(0.8)	15(0.9)	18(0.6)	19(0.6)	24(0.9)	28(0.7)	15/15	SL-10	14(5)	10(2)	10(2)	18(2)	14(1.0)	<b>14(2)*<sup>4</sup></b>	2.4(0.3)* <sup>4</sup>	15/15
SL-4-10	5.3(0.2)* <sup>4</sup>	6.2(0.4)* <sup>4</sup>	7.2(0.4)* <sup>4</sup>	8.1(0.4)* <sup>4</sup>	9.0(0.4)* <sup>4</sup>	11(0.5)* <sup>4</sup>	13(0.6)* <sup>4</sup>	15/15	SL-4-10	8.5(2)	<b>5.1(0.7)*<sup>4</sup></b>	<b>6.4(1)*<sup>4</sup></b>	<b>8.5(0.8)*<sup>4</sup></b>	<b>7.3(1)*<sup>3</sup></b>	48(21)	33(20)	15/15
R-SHADE	18(2)	21(3)	25(2)	28(2)	31(3)	37(3)	43(3)	15/15	R-SHADE	8.2(3)	9.4(2)	13(1)	13(2)	11(2)	58(37)	1861(1181)	0/15
<b>f3</b>	5066	7626	7635	7643	7646	7651	7651	15/15	<b>f15</b>	30378	1.5e5	3.1e5	3.2e5	4.5e5	4.6e5		15/15
SL-10	22(2)	21(1)	22(1)	22(2)	23(1)	23(2)	23(1)	15/15	SL-10	14(10)	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$	0/15
SL-4-10	7.9(0.8)	7.5(0.4)	8.0(0.4)	8.0(0.6)	<b>8.1(0.6)</b>	<b>8.2(0.5)</b>	<b>8.3(0.6)</b>	15/15	SL-4-10	13(11)	<b>1933(2388)</b>	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$	0/15
R-SHADE	7.7(0.3)	7.1(0.3)	7.7(0.3)	7.9(0.3)	8.1(0.3)	8.4(0.2)	8.7(0.2)	15/15	R-SHADE	52(51)	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$	0/15
<b>f4</b>	4722	7628	7666	7686	7700	7758	1.4e5	9/15	<b>f16</b>	1384	27265	77015	1.4e5	1.9e5	2.0e5	2.2e5	15/15
SL-10	27(3)	24(2)	26(2)	26(2)	26(2)	27(2)	1.5(0.1)	15/15	SL-10	52(16)	1116(1838)	<b>3685(5194)</b>	$\infty$	$\infty$	$\infty$	$\infty$	0/15
SL-4-10	10(0.9)	8.4(0.6)	<b>11(3)</b>	11(4)	11(3)	<b>11(3)</b>	<b>0.64(0.4)</b>	15/15	SL-4-10	24(17)	4786(4034)	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$	0/15
R-SHADE	9.4(0.8)	<b>8.3(0.6)</b>	12(8)	12(3)	12(5)	13(6)	0.72(0.4)	15/15	R-SHADE	27(18)	<b>246(370)</b>	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$	0/15
<b>f5</b>	41	41	41	41	41	41	41	15/15	<b>f17</b>	63	1030	4005	12242	30677	56288	80472	15/15
SL-10	<b>0.54(0)</b>	15/15	SL-10	7.7(4)	3.7(0.8)	2.6(0.8)	<b>1.6(0.5)</b>	<b>3.8(5)</b>	<b>2.9(6)*<sup>2</sup></b>	<b>2.7(4)*<sup>2</sup></b>	15/15						
SL-4-10	<b>0.54(0)</b>	15/15	SL-4-10	3.8(2)	<b>3.2(1)</b>	6.5(17)	5.8(10)	8.2(10)	45(122)	34(66)	14/15						
R-SHADE	117(14)	212(22)	308(29)	400(30)	489(31)	679(26)	862(33)	15/15	R-SHADE	3.7(2)	3.4(1)	3.9(0.5)	18(24)	45(41)	$\infty$	$\infty$	0/15
<b>f6</b>	1296	2343	3413	4255	5220	6728	8409	15/15	<b>f18</b>	621	19561	28555	67569	1.3e5	1.5e5		15/15
SL-10	7.4(2)	7.3(1)	6.8(0.8)	6.9(0.7)	6.8(0.4)	7.1(0.5)	7.2(0.3)	15/15	SL-10	3.7(1)	2.8(0.5)	<b>1.1(0.2)</b>	<b>1.3(0.3)*<sup>2</sup></b>	<b>86(99)</b>	<b>79(135)</b>	<b>128(81)</b>	9/15
SL-4-10	<b>4.0(0.5)</b>	<b>3.7(0.4)</b>	<b>3.5(0.3)</b>	<b>3.6(0.4)</b>	<b>3.6(0.3)</b>	<b>3.8(0.3)</b>	<b>3.9(0.3)</b>	15/15	SL-4-10	2.7(0.9)	<b>1.8(0.7)</b>	72(10)	192(370)	549(289)	2168(2603)	$\infty$	0/15
R-SHADE	4.2(0.5)	4.0(0.5)	3.8(0.4)	3.9(0.4)	3.9(0.4)	4.1(0.5)	4.1(0.3)	15/15	R-SHADE	3.1(0.9)	2.0(0.8)	30(32)	1050(700)	$\infty$	$\infty$	$\infty$	0/15
<b>f7</b>	1351	4274	9503	16523	16524	16524	16524	15/15	<b>f19</b>	1	1	3.4e5	4.7e6	6.2e6	6.7e6	6.7e6	15/15
SL-10	3.4(0.9)	<b>4.0(5)</b>	<b>4.3(6)</b>	<b>2.9(4)</b>	<b>2.9(3)</b>	<b>2.9(4)</b>	<b>2.9(2)</b>	15/15	SL-10	280(125)	1.1e7(1e7)	<b>381(277)</b>	$\infty$	$\infty$	$\infty$	$\infty$	0/15
SL-4-10	2.0(0.4)	7.5(4)	5.4(4)	4.6(3)	4.7(3)	4.7(2)	4.6(2)	15/15	SL-4-10	<b>186(68)*<sup>4</sup></b>	<b>1.5e5(4e4)*<sup>3</sup></b>	820(830)	$\infty$	$\infty$	$\infty$	$\infty$	0/15
R-SHADE	2.0(0.7)	29(41)	72(31)	1762(2149)	1761(2148)	1761(1543)	1715(330)	15/15	R-SHADE	344(68)	1.1e6(266)	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$	0/15
<b>f8</b>	2039	3871	4040	4148	4219	4371	4484	15/15	<b>f20</b>	82	46150	3.1e6	5.5e6	5.5e6	5.6e6	5.6e6	14/15
SL-10	14(0.5)	14(0.5)	15(0.6)	16(0.6)	16(0.4)	17(0.5)	18(0.5)	15/15	<b>f21</b>	561	6541	14103	14318	14643	15567	17589	15/15
SL-4-10	<b>7.7(1)*<sup>2</sup></b>	<b>8.0(0.9)*<sup>4</sup></b>	<b>8.7(1)*<sup>4</sup></b>	<b>9.1(1)*<sup>4</sup></b>	<b>9.5(1)*<sup>4</sup></b>	<b>10(0.8)*<sup>4</sup></b>	<b>11(0.9)*<sup>4</sup></b>	15/15	SL-10	5.4(2)	3.0(0.6)	<b>19(33)</b>	<b>51(52)</b>	<b>51(92)</b>	<b>50(84)</b>	<b>50(25)</b>	1/15
R-SHADE	11(4)	14(8)	15(6)	15(8)	15(6)	16(7)	16(5)	15/15	SL-4-10	5.6(2)	8.3(11)	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$	0/15
<b>f9</b>	1716	3102	3277	3379	3455	3594	3727	15/15	R-SHADE	10(3)	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$	0/15
SL-10	20(1)	21(0.8)	23(0.7)	24(0.5)	25(0.8)	26(0.7)	27(0.5)	15/15	<b>f21</b>	561	6541	14103	14318	14643	15567	17589	15/15
SL-4-10	<b>13(1)*<sup>2</sup></b>	<b>15(0.6)*<sup>3</sup></b>	<b>16(1)*<sup>3</sup></b>	<b>17(1.0)*<sup>3</sup></b>	<b>18(1)*<sup>3</sup></b>	<b>18(1)*<sup>3</sup></b>	<b>19(1)*<sup>3</sup></b>	15/15	SL-10	8.3(16)	55(180)	63(95)	63(174)	61(170)	58(104)	51(90)	15/15
R-SHADE	16(5)	20(8)	22(3)	23(8)	23(7)	24(3)	24(7)	15/15	SL-4-10	3.5(4)	116(394)	62(13)	61(44)	60(172)	56(191)	50(10)	15/15
<b>f10</b>	7413	8661	10735	13641	14920	17073	17476	15/15	R-SHADE	3.0(1)	<b>6.6(9)</b>	<b>6.5(7)</b>	<b>6.5(12)</b>	<b>6.4(12)</b>	<b>6.1(11)</b>	<b>5.5(10)</b>	15/15
SL-10	<b>3.4(0.7)*<sup>4</sup></b>	<b>3.6(0.5)*<sup>4</sup></b>	<b>3.3(0.4)*<sup>4</sup></b>	<b>3.0(0.4)*<sup>4</sup></b>	<b>3.0(0.4)*<sup>4</sup></b>	<b>3.1(0.4)*<sup>4</sup></b>	<b>3.5(0.4)*<sup>4</sup></b>	15/15	<b>f22</b>	467	5580	23491	24163	24948	26847	3.1e5	12/15
SL-4-10	20(8)	29(10)	30(9)	30(6)	35(10)	41(15)	51(13)	15/15	SL-10	7.3(10)	1401(1793)	1.2e4(1e4)	1.2e4(756)	1.1e4(2e4)	1.1e4(1e4)	2098(2003)	1/15
R-SHADE	16(6)	22(8)	25(6)	26(8)	29(9)	32(7)	40(11)	9/15	SL-4-10	7.0(17)	1853(2690)	5788(4389)	5627(3375)	5450(6351)	5065(4226)	1009(434)	2/15
<b>f11</b>	1002	2228	6278	8586	9762	12285	14831	15/15	R-SHADE	14(1)	<b>29(40)</b>	<b>1200(724)</b>	<b>1167(1842)</b>	<b>1130(2044)</b>	<b>1051(1229)</b>	<b>109(382)</b>	1/15
SL-10	10(2)	<b>6.6(0.9)*<sup>2</sup></b>	<b>3.0(0.4)*<sup>4</sup></b>	<b>2.7(0.3)*<sup>4</sup></b>	<b>2.8(0.3)*<sup>4</sup></b>	<b>2.9(0.3)*<sup>4</sup></b>	<b>2.9(0.3)*<sup>4</sup></b>	15/15	SL-10	2.6(3)	1005(2360)	350(493)	$\infty$	$\infty$	$\infty$	$\infty$	0/15
SL-4-10	11(7)	16(8)	9.2(3)	9.4(2)	10(3)	12(2)	13(2)	15/15	SL-4-10	<b>1.5(2)</b>	<b>80(81)</b>	917(1117)	$\infty$	$\infty$	$\infty$	$\infty$	0/15
R-SHADE	7.6(5)	13(7)	8.2(4)	8.4(3)	10(2)	11(2)	12(2)	15/15	R-SHADE	2.3(1)	95(84)	<b>12(14)*<sup>2</sup></b>	$\infty$	$\infty$	$\infty$	$\infty$	0/15
<b>f12</b>	1042	1938	2740	3156	4140	12407	13827	15/15	<b>f24</b>	1.3e6	7.5e6	5.2e7	5.2e7	5.2e7	5.2e7	3/15	
SL-10	13(15)	17(15)	22(20)	25(15)	23(14)	11(4)	11(3)	15/15	SL-10	14(13)	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$	0/15
SL-4-10	<b>6.1(2)*<sup>2</sup></b>	<b>14(17)</b>	<b>18(18)</b>	<b>21(18)</b>	<b>21(12)</b>	<b>10(5)</b>	<b>11(5)</b>	15/15	SL-4-10	64(140)	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$	0/15
R-SHADE	8.5(0.9)	18(15)	23(15)	26(18)	25(16)	12(5)	13(5)	15/15	R-SHADE	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$	0/15

**Table 3: Expected runtime (ERT in number of function evaluations) divided by the respective best ERT measured during BBOB-2009 in dimension 20. This ERT ratio and, in braces as dispersion measure, the half difference between 10 and 90%-tile of bootstrapped run lengths appear for each algorithm and target, the corresponding reference ERT in the first row. The different target  $\Delta f$ -values are shown in the top row. #succ is the number of trials that reached the (final) target  $f_{\text{opt}} + 10^{-8}$ . The median number of conducted function evaluations is additionally given in *italics*, if the target in the last column was never reached. Entries, succeeded by a star, are statistically significantly better (according to the rank-sum test) when compared to all other algorithms of the table, with  $p = 0.05$  or  $p = 10^{-k}$  when the number  $k$  following the star is larger than 1, with Bonferroni correction by the number of functions (24). A ↓ indicates the same tested against the best algorithm from BBOB 2009. Best results are printed in bold.**

Data produced with COCO v2.4