# Bounding the Population Size of IPOP-CMA-ES on the Noiseless BBOB Testbed

Tianjun Liao IRIDIA, CoDE, Université Libre de Bruxelles (ULB), Brussels, Belgium tliao@ulb.ac.be Thomas Stützle
IRIDIA, CoDE, Université Libre de Bruxelles
(ULB), Brussels, Belgium
stuetzle@ulb.ac.be

#### **ABSTRACT**

A variant of CMA-ES that uses occasional restarts coupled with an increasing population size, which is called IPOP-CMA-ES, has shown to be a top performing algorithm on the BBOB benchmark set. In this paper, we test a mechanism that bounds the maximum size that the population may reach in IPOP-CMA-ES, and we experimentally explore the impact of a maximum population size on the BBOB benchmark set. In the proposed bounding mechanism, we use a maximum population size of  $10 \times D^2$ , where D is problem dimension. Once the maximum population size is reached or surpassed, the population size is reset to its default starting value  $\lambda$ , which is defined by the  $\lambda = 4 + \lfloor 3 \ln(D) \rfloor$ . Our experimental results show that our scheme for the population-size update can lead to improved performances on separable and weakly structured multi-modal functions.

# **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. INTRODUCTION

IPOP-CMA-ES [1] is a variant of CMA-ES [11, 10] that uses occasional restarts, which are triggered when the search process is deemed to stagnate, combined with an increasing population size. IPOP-CMA-ES and several of its variants [12, 3, 4, 2] have shown very good results on the BBOB

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. To copy otherwise, to republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee.

GECCO'13 Companion, July 6–10, 2013, Amsterdam, The Netherlands. Copyright 2013 ACM 978-1-4503-1964-5/13/07 ...\$15.00.

benchmark. In this paper, we base our analysis on IPOP-CMA-ES using its default parameter settings. In particular, the initial population size in IPOP-CMA-ES is set to  $\lambda = 4 + \lfloor 3 \ln(D) \rfloor$ , where D is dimension of the problem being tackled. At each restart, IPOP-CMA-ES increases the population size by a factor of two. This setting leads to an exponential increase of the population size in IPOP-CMA-ES in the number of restarts. In particular, on difficult, multi-modal functions many restarts may occur and, thus, very large population sizes may result if IPOP-CMA-ES doesn't find a solution better than the optimal threshold or a possible target value.

In this paper, we use a mechanism to bound the maximum population size that IPOP-CMA-ES may use; in fact, bounding the maximum population size is motivated by the fact that sometimes very large populations may, at least theoretically, decrease the performances [5]. However, occasionally CMA-ES may benefit from large populations [9], which is also the motivation for increasing the population size in IPOP-CMA-ES. Thus, in our bound on the population size, we do not want to be too restrictive. Thus, we set the upper bound of the population size to  $10 \times D^2$ , which leaves for higher dimensional problems the possibility to reach rather large populations (e.g.  $16\,000$  for D=40). Once this upper bound is reached, we reset the population size to its initial value, given by  $\lambda = 4 + |3\ln(D)|$ . Additionally, it gives some additional robustness with respect to the maximum bound on the population size we use. We label the resulting IPOP-CMA-ES variant IP-10DDr. The original IPOP-CMA-ES is labeled IP.

#### 2. EXPERIMENTAL PROCEDURE

We used the C version of IPOP-CMA-ES (last modification date 10/16/10) from Hansen's webpage http://www.lri.fr/~hansen/cmaesintro.html. To ensure that the final best solution is inside the bounds, the bound constraints are enforced by clamping each generated solution that violates the bound constraint to the nearest solution on the bounds. The default parameter settings of IPOP-CMA-ES were used. A maximum of  $10^6 \times D$  function evaluations was used for the experiments.

# 3. RESULTS

The results from the experiments that follow the experimental protocol [7] on the benchmark functions given in [6, 8] are presented in Figures 1, 3 and 4 and in Tables 1 and 2. The **expected running time (ERT)**, used in the figures and tables, depends on a given target function value,

 $f_{\rm t} = f_{\rm opt} + \Delta f$ , and it is computed across all relevant trials as the number of function evaluations executed during each trial while the best function value did not reach  $f_{\rm t}$ , summed over all trials and divided by the number of trials that actually reached  $f_{\rm t}$  [7, 13]. **Statistical significance** is tested with the rank-sum test for a given target  $\Delta f_{\rm t}$  ( $10^{-8}$  as in Figure 1) using, for each trial, either the number of needed function evaluations to reach  $\Delta f_{\rm t}$  (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.

In the experiments, we found that IP-10DDr reaches solutions below the optimal threshold of  $10^{-8}$  in various cases where the default version of IPOP-CMA-ES, here labeled IP, could not find such solutions. This was the case for functions  $f_4$  (D=3,5),  $f_{21}$  (D=40),  $f_{22}$  (D=10) and  $f_{24}$  (D=2,3). Compared to IP, IP-10DDr uses fewer function evaluations to reach optimal threshold in functions  $f_3$  (D=3,5,10),  $f_{16}$  (D=3),  $f_{21}$  (D=2,3,5,10,20),  $f_{22}$  (D=2,3,5),  $f_{23}$  (D=10,20); only in functions  $f_{19}$  (D=10) and  $f_{20}$  (D=5,10,20), IP-10DDr uses slightly more function evaluations to reach optimal threshold than IP.

We next examine the impact of the specific choice on the maximum population size. To do so, we explore another bound mechanism, where the maximum population size is set to a constant value of 500; a population size larger than 500 is then kept to 500. We label the resulting algorithm IP-500. Figure 1 shows that IP-10DDr clearly performs better than IP-500.

To situate the performance of IP-10DDr better with respect to other variants of IPOP-CMA-ES, in Figure 2 we show the comparisons between IP-10DDr and the performance data for the IPOP-CMA-ES variants, CMA\_mah [2] and IPOPsaACM [12] in the aforementioned functions  $f_3$ ,  $f_4, f_{16}, f_{19}, f_{20}, f_{21}, f_{22}, f_{23}, f_{24}$ . We find that IP-10DDr reaches the optimal threshold in functions  $f_4$  (D=5),  $f_{19}(D=40)$ ,  $f_{21}$  (D=40),  $f_{23}$  (D=20) and  $f_{24}$  (D=3) where both, CMA\_mah and IPOPsaACM, cannot reach optimal threshold. In functions  $f_3$  (D=3,5,10),  $f_4$  (D=2,3),  $f_{16}$  (D=3),  $f_{22}$  (D=3,5),  $f_{23}$  (D=3,5,10) IP-10DDr uses fewer function evaluations to reach optimal threshold than CMA\_mah and IPOPsaACM.

# 4. CPU TIMING EXPERIMENT

The IP-10DDr was run on  $f_8$  until at least 30 seconds have passed. These experiment were conducted with Intel Xeon E5410 (2.33 GHz) on Linux (kernel 2.6.9 - 78.0.22). The results were 3.1E-05, 1.5E-05, 1.2E-05, 9.5E-06, 1.5E-05 and 5.0E-05 seconds per function evaluation in dimensions 2, 3, 5, 10, 20, and 40, respectively.

#### 5. CONCLUSIONS

In this paper, we have studied the impact of bounding the population size in IPOP-CMA-ES together with re-initialization of the population size. Obviously, using a maximum population size of  $10 \times D^2$  does not worsen results on functions that are easy for IPOP-CMA-ES, that is, on functions where IPOP-CMA-ES within the first trial or very few restarts finds the optimum—in such cases the bounds do not take effect. However, for various difficult, multi-modal functions we observed improved performance of our new IPOP-CMA-ES

variants over the default IPOP-CMA-ES. Hence, these results would encourage us to explore bounds on the maximum population size also for other IPOP-CMA-ES variants such as Bipop-CMA-ES. Finally, one may further explore different settings for the bounds on the maximum population size, which may lead to further improvements in performance.

#### 6. ACKNOWLEDGMENTS

The authors would like to thank the great and hard work of the BBOB team. This work was supported by the Meta-X project funded by the Scientific Research Directorate of the French Community of Belgium. Thomas Stützle acknowledges support from the Belgian F.R.S.-FNRS, of which he is a Research Associate. Tianjun Liao acknowledges a fellowship from the China Scholarship Council.

### 7. REFERENCES

- [1] A. Auger and N. Hansen. A restart CMA evolution strategy with increasing population size. In *Proceedings of the IEEE Congress on Evolutionary Computation (CEC 2005)*, pages 1769–1776. IEEE Press, 2005.
- [2] D. Brockhoff, A. Auger, and N. Hansen. On the impact of active covariance matrix adaptation in the CMA-ES with mirrored mutations and small initial population size on the noiseless BBOB testbed. In GECCO 2012 (Companion), pages 291–296, 2010.
- [3] D. Brockhoff, A. Auger, and N. Hansen. Comparing mirrored mutations and active covariance matrix adaptation in the IPOP-CMA-ES on the noiseless BBOB testbed. In T. Soule, editor, GECCO 2012 (Companion), pages 297–303. ACM, 2012.
- [4] D. Brockhoff, A. Auger, and N. Hansen. On the impact of a small initial population size in the IPOP active CMA-ES with mirrored mutations on the noiseless BBOB testbed. In T. Soule, editor, GECCO 2012 (Companion), pages 291–296. ACM, 2012.
- [5] T. Chen, K. Tang, G. Chen, and X. Yao. A large population size can be unhelpful in evolutionary algorithms. *Theoretical Computer Science*, 436:54–70, 2012.
- [6] S. Finck, N. Hansen, R. Ros, and A. Auger. Real-parameter black-box optimization benchmarking 2009: Presentation of the noiseless functions. Technical Report 2009/20, Research Center PPE, 2009. Updated February 2010.
- [7] N. Hansen, A. Auger, S. Finck, and R. Ros. Real-parameter black-box optimization benchmarking 2012: Experimental setup. Technical report, INRIA, 2012.
- [8] N. Hansen, S. Finck, R. Ros, and A. Auger. Real-parameter black-box optimization benchmarking 2009: Noiseless functions definitions. Technical Report RR-6829, INRIA, 2009. Updated February 2010.
- [9] N. Hansen and S. Kern. Evaluating the CMA evolution strategy on multimodal test functions. In Parallel Problem Solving from Nature – PPSN VIII, volume 3242 of Lecture Notes in Computer Science, pages 282–291. Springer, Heidelberg, Germany, 2004.
- [10] N. Hansen, S. Muller, and P. Koumoutsakos. Reducing the time complexity of the derandomized evolution

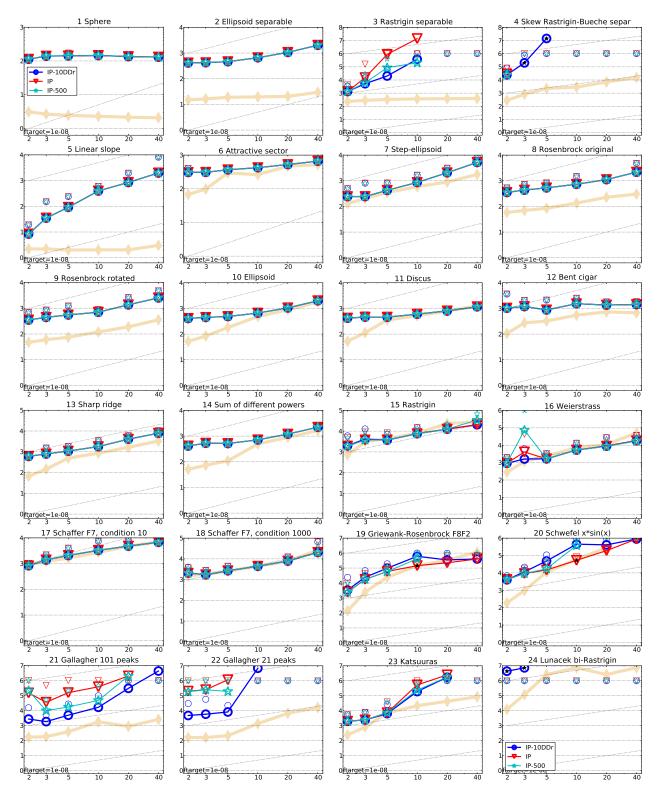


Figure 1: Expected running time (ERT in number of f-evaluations) divided by dimension for target function value  $10^{-8}$  as  $\log_{10}$  values versus dimension. Different symbols correspond to different algorithms given in the legend of  $f_1$  and  $f_{24}$ . Light symbols give the maximum number of function evaluations from the longest trial divided by dimension. Horizontal lines give linear scaling, slanted dotted lines give quadratic scaling. Black stars indicate statistically better result compared to all other algorithms with p < 0.01 and Bonferroni correction number of dimensions (six). Legend:  $\circ$ :IP-10DDr,  $\nabla$ :IP,  $\star$ :IP-500

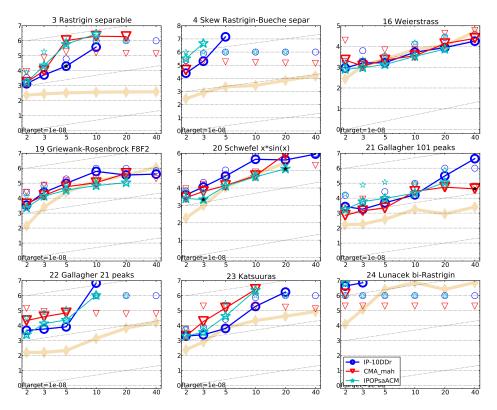


Figure 2: Comparing IP-10DDr to CMA\_mah and IPOPsaACM. CMA\_mah is the active covariance matrix adaptation version of IPOP-CMA-ES with mirrored mutation and a small initial population size. CMA\_sa is self-adaptive surrogate-assisted version of IPOP-CMA-ES. Expected running time (ERT) divided by dimension for target function value  $10^{-8}$  as  $\log_{10}$  values. Different symbols correspond to different algorithms given in legend of  $f_{24}$ . Light symbols give the maximum number of function evaluations from all trials divided by the dimension. Horizontal lines give linear scaling, the slanted dotted lines give quadratic scaling.

- strategy with covariance matrix adaptation (CMA-ES). *Evolutionary Computation*, 11(1):1–18, 2003.
- [11] N. Hansen and A. Ostermeier. Completely derandomized self-adaptation in evolution strategies. *Evolutionary Computation*, 9(2):159–195, 2001.
- [12] I. Loshchilov, M. Schoenauer, and M. Sebag. Black-box optimization benchmarking of IPOP-SaACM-ES and Bipop-SaACM-ES on the BBOB-2012 noiseless testbed.

- In T. Soule, editor,  $GECCO\ 2012\ (Companion)$ , pages 175–182. ACM, 2012.
- [13] K. Price. Differential evolution vs. the functions of the second ICEO. In *Proceedings of the IEEE* International Congress on Evolutionary Computation, pages 153–157, 1997.

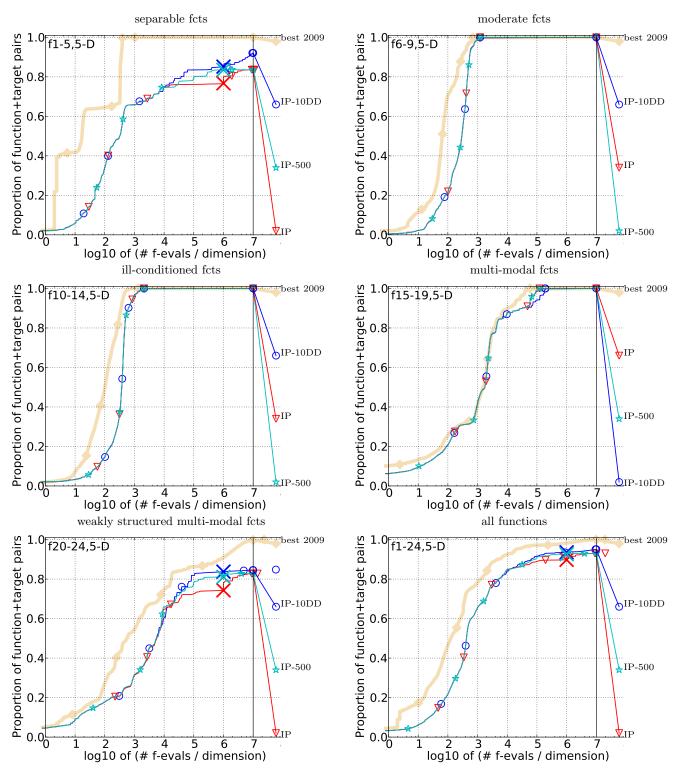


Figure 3: Bootstrapped empirical cumulative distribution of the number of objective function evaluations divided by dimension (FEvals/D) for 50 targets in  $10^{[-8..2]}$  for all functions and subgroups in 5-D. The "best 2009" line corresponds to the best ERT observed during BBOB 2009 for each single target.

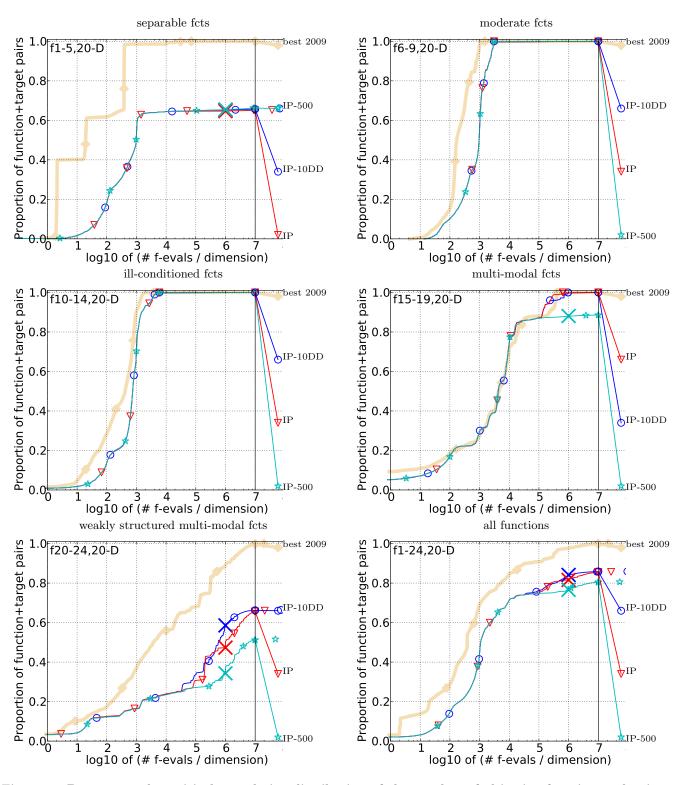


Figure 4: Bootstrapped empirical cumulative distribution of the number of objective function evaluations divided by dimension (FEvals/D) for 50 targets in  $10^{[-8..2]}$  for all functions and subgroups in 20-D. The "best 2009" line corresponds to the best ERT observed during BBOB 2009 for each single target.

$\Delta f_{ m opt}$  1e1	1e0	1e-1	1e-3	1e-5	1e-7	#succ	$\Delta f_{ m opt}$	1e1	1e0	1e-1	1e-3	1e-5	1e-7	#succ
f1 11	12	12	12	12	12	15/15	f13	132	195	250	1310	1752	2255	15/15
IP-10DD 3.0(1) IP 3.0(1)	7.5(1) 7.5(1)	13(3) 13(3)	27(3) 27(3)	<b>40</b> (4) <b>40</b> (4)	<b>53</b> (6) <b>53</b> (6)	$\frac{15}{15}$	IP-10DI IP	4.7(4) 4.7(4)	5.8(4) $5.8(4)$	<b>5.7</b> (3) <b>5.7</b> (3)	1.5(0.7) 1.5(0.7)	1.9(0.8) 1.9(0.8)	1.9(0.8) 1.9(0.8)	$\frac{15}{15}$
IP-500 <b>3.0</b> (1)	7.5(1)	<b>13</b> (3)	<b>27</b> (3)	<b>40</b> (4)	<b>53</b> (6)	15/15	IP-500	4.7(4)	5.8(4)	<b>5.7</b> (3)	1.5(0.7)	1.9(0.8)	1.9(0.8)	15/15
$\Delta f_{ m opt}$ 1e1	1e0	1e-1	1e-3	1e-5	1e-7	#succ	$\Delta f_{ m opt}$	1e1	1e0	1e-1	1e-3	1e-5	1e-7	#succ
f2 83 IP-10DD <b>13</b> (4)	87 17(5)	88 19(4)	90 <b>21</b> (3)	92 <b>23</b> (3)	94 <b>24</b> (2)	15/15 15/15	<b>f14</b> IP-10DI	10	41 2.4(1)	58 <b>3.7</b> (1.0)	139 4.7(0.9)	251 5.7(0.4)	476 4.6(0.4)	15/15 15/15
IP <b>13</b> (4)	17(5) 17(5)	19(4)	21(3) 21(3)	<b>23</b> (3)	24(2) 24(2)	15/15	IP IDDI	1.2(1)	2.4(1) 2.4(1)	3.7(1.0) 3.7(1.0)	4.7(0.9)	5.7(0.4)	4.6(0.4)	15/15
IP-500 <b>13</b> (4)	<b>17</b> (5)	19(4)	<b>21</b> (3)	<b>23</b> (3)	<b>24</b> (2)	15/15	IP-500	1.2(1)	2.4(1)	<b>3.7</b> (1.0)	<b>4.7</b> (0.9)	<b>5.7</b> (0.4)	4.6(0.4)	15/15
$\Delta f_{ m opt}$ 1e1		1e-1	1e-3	1e-5	1e-7	#succ	$\Delta f_{ m opt}$	1e1	1e0	1e-1	1e-3	1e-5	1e-7	#succ
f3 716 IP-10DD 0.99(1)	1622 15(21)	1637 <b>60</b> (67)	1646 60(67)	1650 61(67)	1654 <b>61</b> (67)	15/15 15/15	f15	511 1.5(0.6)	9310 1.1(0.9)	19369 0.85(0.4	20073 ) <b>0.85</b> (0.4)	20769 0.85(0.4)	21359 0.86(0.4)	14/15 15/15
IP 0.99(1)				2670(4543)		8/15	IP	1.5(0.6)		0.86(0.4			0.87(0.4)	15/15
	18(11)	257(433)	258(433)	259(432)	259(432)	15/15	IP-500	<b>1.5</b> (0.6)		0.86(0.4)			0.87(0.4)	15/15
$\Delta f_{ m opt}$ 1e1	1e0	1e-1	1e-3	1e-5	1e-7	#succ	$\Delta f_{ m opt}$		1e0	1e-1	1e-3	1e-5	1e-7	#succ
f4 809	1633	1688	1817	1886	1903	15/15 4)*1 <sup>3</sup> /15	<b>f16</b> IP-10DI	120	612 2.2(3)	2662 1.1(1)	10449 <b>0.58</b> (0.5)	11644 <b>0.67</b> (0.3)	12095 <b>0.67</b> (0.3)	15/15 15/15
IP-10DD <b>2.6</b> (3) IP <b>2.6</b> (3)	2721(24 ∞	69) <sup>~</sup> 4.3e ∞	4(5e4) <b>4:0e4</b> ∞	(5e4) <b>3.8e4</b> (4 ∞	.e4) <b>3.8e4</b> (5e ∞ 5e6	0/15	IP IDDI	2.0(2)	2.2(3) 2.2(3)	1.1(1)	0.58(0.5)		<b>0.67</b> (0.3)	15/15
IP-500 <b>2.6</b> (3)	∞	∞	∞	∞	∞ 5e6	0/15	IP-500	2.0(2)	2.2(3)	1.1(1)	0.58(0.5)		0.67(0.3)	15/15
$\Delta f_{ m opt}$ [1e1	1e0	1e-1	1e-3	1e-5	1e-7	#succ	$\Delta f_{ m opt}$	1e1	1e0	1e-1	1e-3	1e-5	1e-7	#succ
f5 10	10	10	10	10	10	15/15	f17	5.2	215	899	3669	6351	7934	15/15
IP-10DD 6.2(3)	23(18)	30(25)	41(33)	<b>45</b> (43)	46(43)	15/15	IP-10DI IP	3.2(3) 3.2(3)	0.79(0.2 0.79(0.2				1.3(0.4) 1.3(0.4)	$\frac{15}{15}$ $\frac{15}{15}$
IP <b>6.2</b> (3) IP-500 <b>6.2</b> (3)	23(18) 23(18)	30(25) 30(25)	41(33) 41(33)	45(43) 45(43)	46(43) 46(43)	15/15 $15/15$	IP-500	3.2(3) 3.2(3)	0.79(0.2				1.3(0.4) 1.3(0.4)	15/15
$\Delta f_{ m opt}$  1e1	1e0	1e-1	1e-3	1e-5	1e-7	#succ	$\Delta f_{ m opt}$	1e1	1e0	1e-1	1e-3	1e-5	1e-7	#succ
f6 114	214	281	580	1038	1332	15/15	f18	103	378	3968	9280	10905	12469	15/15
IP-10DD 1.6(0.5)	1.8(0.4)		1.6(0.2)	1.2(0.1)	1.2(0.1)	15/15	IP-10DI	1.1(0.4)	1.8(0.3)	0.56(0.5	) <b>1.0</b> (0.3)	<b>0.97</b> (0.3)	1.0(0.1)	15/15
IP <b>1.6</b> (0.5)	1.8(0.4)	2.1(0.3)	1.6(0.2)	1.2(0.1)	1.2(0.1)	15/15	IP	1.1(0.4)		0.56(0.5		<b>0.97</b> (0.3)	1.0(0.1)	15/15
IP-500 <b>1.6</b> (0.5)	1.8(0.4)	<b>2.1</b> (0.3)	1.6(0.2)	1.2(0.1)	1.2(0.1)	15/15	IP-500	<b>1.1</b> (0.4)		<b>0.56</b> (0.5		<b>0.97</b> (0.3)	1.0(0.1)	15/15
$\Delta f_{ m opt}$ 1e1	1e0	1e-1	1e-3	1e-5	1e-7	#succ	$\Delta f_{ m opt}$	1e1	1e0	1e-1	1e-3	1e-5	1e-7	#succ
f7 24	324	1171	1572	1572	1597	15/15	<b>f19</b> IP-10DI	1	1 <b>1466</b> (13	242 10) 519(6	1.2e5 58) 4.0(3		1.2e5 4.0(3)	15/15 15/15
IP-10DD <b>5.3</b> (2) IP <b>5.3</b> (2)	1.1(0.4) 1.1(0.4)	1.2(0.9) 1.2(0.9)	1.2(0.7) 1.2(0.7)	1.2(0.7) 1.2(0.7)	1.3(0.8) 1.3(0.8)	$\frac{15}{15}$	IP IODI	13(14)	1466(13				2.4(2)	15/15
IP-500 <b>5.3</b> (2)	1.1(0.4)		1.2(0.7)	1.2(0.7)	1.3(0.8)	15/15	IP-500	13(14)	1466(13				2.4(2)	15/15
$\Delta f_{ m opt}$  1e1	1e0	1e-1	1e-3	1e-5	1e-7	#succ	$\Delta f_{ m opt}$	1e1	1e0	1e-1	1e-3	1e-5	1e-7	#succ
f8 73	273	336	391	410	422	15/15	f20	16	851	38111	54470	54861	55313	14/15
IP-10DD 3.2(1.0)	4.3(2)	5.1(1)	5.5(1)	5.8(1)	6.1(1)	15/15	IP-10DI		<b>12</b> (11)	6.2(5)	4.4(4)	4.4(4)	4.4(4)	15/15
IP 3.2(1.0)	4.3(2)	5.1(1)	5.5(1)	5.8(1)	6.1(1)	15/15	IP	3.4(1)	12(11)	1.7(2)	1.3(1)	1.3(1)	1.3(1)	15/15
IP-500  3.2(1.0)	4.3(2)	5.1(1)	<b>5.5</b> (1)	5.8(1)	6.1(1)	15/15	IP-500	3.4(1)  1e1	12(11) 1e0	2.1(3) 1e-1	1.5(2) 1e-3	1.5(2) 1e-5	1.5(2) 1e-7	15/15 #succ
$\frac{\Delta f_{\text{opt}}}{\mathbf{f9}}$   1e1	1e0 127	1e-1 214	1e-3 300	1e-5 335	1e-7 369	#succ 15/15	$\frac{\Delta f_{\text{opt}}}{\mathbf{f21}}$	41	1157	1674	1705	1729	1757	14/15
IP-10DD <b>6.1</b> (2)	10(10)	8.6(6)	<b>7.6</b> (5)	335 7.4(4)	<b>7.2</b> (4)	15/15	IP-10DI		11(12)	14(18)	14(18)	14(17)	14(17)	15/15
IP <b>6.1</b> (2)	10(10) 10(10)	8.6(6)	7.6(5)	7.4(4)	7.2(4)	15/15	IP	1.6(1)	8.7(9)	290(491)	458(1467)	452(1446)	445(1424)	13/15
IP-500 6.1(2)	<b>10</b> (10)	8.6(6)	7.6(5)	7.4(4)	7.2(4)	15/15	IP-500	1.6(1)	8.6(9)	51(11)	50(12)	50(12)	50(12)	15/15
$\Delta f_{ m opt}$ 1e1	1e0	1e-1	1e-3	1e-5	1e-7	#succ	$\Delta f_{ m opt}$			1e-1	1e-3	1e-5	1e-7	#succ
f10 349	500	574	626	829	880	15/15	<b>f22</b> IP-10DI	71	386 42(53)	938 <b>43</b> (59)	1008 40(55)	1040 <b>39</b> (53)	1068 39(52)	$\frac{14/15}{15/15}$
IP-10DD 3.4(0.9) IP 3.4(0.9)	3.1(0.6) 3.1(0.6)	3.1(0.3) 3.1(0.3)	3.2(0.3) 3.2(0.3)	2.6(0.2) 2.6(0.2)	2.7(0.2) 2.7(0.2)	$\frac{15/15}{15/15}$	IP-10DI	7.4(11)				5578(7225)	5438(7028)	7/15
IP-500 <b>3.4</b> (0.9)	3.1(0.6) 3.1(0.6)	3.1(0.3) 3.1(0.3)	3.2(0.3) 3.2(0.3)	2.6(0.2) 2.6(0.2)	2.7(0.2) 2.7(0.2)	15/15	IP-500	7.4(11)	92(27)	580(280)	962(2534)	933(2404)	910(2344)	13/15
$\Delta f_{ m opt}$  1e1	1e0	1e-1	1e-3	1e-5	1e-7	#succ	$\Delta f_{ m opt}$		1e0	1e-1	1e-3	1e-5	1e-7	#succ
f11 143	202	763	1177	1467	1673	15/15	f23	3.0	518	14249	31654	33030	34256	15/15
IP-10DD 7.4(4)	<b>7.1</b> (0.7)		1.6(0.1)	1.4(0.1)	1.3(0.1)	15/15	IP-10DI		7.2(5)	1.7(1)	0.96(0.8)		<b>0.93</b> (0.8)	15/15
IP <b>7.4</b> (4)	7.1(0.7)	2.1(0.2)	1.6(0.1)	1.4(0.1)	1.3(0.1)	15/15	IP IP-500	2.1(2) 2.1(2)	7.2(5) 7.2(5)	2.0(1)	1.1(0.8) 1.1(0.8)	1.1(0.8) 1.1(0.8)	1.1(0.8) $1.1(0.8)$	$\frac{15}{15}$
IP-500 <b>7.4</b> (4)	<b>7.1</b> (0.7)	, ,	1.6(0.1)	1.4(0.1)	1.3(0.1)	15/15			1.2(5) 1e0	2.0(1) 1e-1	1.1(0.8) 1e-3	1.1(0.8) 1e-5	1.1(0.8) 1e-7	#succ
$\frac{\Delta f_{\rm opt}}{{\bf f12}} \frac{1 {\rm e1}}{108}$	1e0 268	1e-1 371	1e-3 461	1e-5 1303	1e-7 1494	#succ 15/15	$\frac{\Delta f_{\text{opt}}}{\mathbf{f24}}$	1622	2.2e5	6.4e6	9,6e6	1.3e7	1.3e7	3/15
F12   108 IP-10DD <b>7.9</b> (5)	268 <b>5.9</b> (3)	371 6.0(3)	461 <b>6.3</b> (4)	1303 2.8(2)	1494 2.8(2)	$\frac{15/15}{15/15}$	IP-10DI		2.2e3 104(111		∞	1.3e1 ∞	1.3e1 ∞ 5e6	0/15
IP 7.9(5)	<b>5.9</b> (3)	6.0(3)	6.3(4)	2.8(2) 2.8(2)	2.8(2) 2.8(2)	15/15	IP-10DI	2.0(2) 2.0(2)	∞	) ∞ ∞	∞	∞	$\infty$ 5e6	0/15
IP-500 <b>7.9</b> (5)	<b>5.9</b> (3)	6.0(3)	6.3(4)	2.8(2)	2.8(2)	15/15	IP-500	2.0(2)	∞	∞	∞	∞	$\infty$ 5e6	0/15
/	. /		. ,			•								• •

Table 1: Expected running time (ERT in number of function evaluations) divided by the respective best ERT measured during BBOB-2009 (given in the respective first row) for different  $\Delta f$  values in dimension 5. The central 80% range divided by two is given in braces. The median number of conducted function evaluations is additionally given in italics, if  $\text{ERT}(10^{-7}) = \infty$ . #succ is the number of trials that reached the final target  $f_{\text{opt}} + 10^{-8}$ . Best results are printed in bold. IP-10DD in the table denotes IP-10DDr.

$\Delta f_{ m opt}$  1e1	1e0	1e-1	1e-3	1e-5	1e-7	#succ	$\Delta f_{ m opt}$	l1e1	1e0	1e-1	1e-3	1e-5	1e-7	#succ
f1 43	43	43	43	43	43	15/15	f13	652	2021	2751	18749	24455	30201	15/15
IP-10DD 7.5(0.6)	14(0.7)	<b>20</b> (2)	<b>32</b> (3)	<b>45</b> (2)	<b>57</b> (3)	15/15	IP-10DD	<b>2.4</b> (0.3)	4.3(5)	6.4(4)	1.7(1)	2.2(0.9)	2.3(0.9)	15/15
IP <b>7.5</b> (0.6)	14(0.7)	<b>20</b> (2)	<b>32</b> (3)	<b>45</b> (2)	<b>57</b> (3)	15/15	IP	<b>2.4</b> (0.3)	<b>4.3</b> (5)	6.4(4)	1.7(1)	<b>2.2</b> (0.9)	<b>2.3</b> (0.9)	15/15
IP-500 <b>7.5</b> (0.6)	14(0.7)	20(2)	<b>32</b> (3)	<b>45</b> (2)	<b>57</b> (3)	15/15		2.4(0.3)	4.3(5)	6.4(4)	1.7(1)	2.2(0.9)	<b>2.3</b> (0.9)	15/15
$\frac{\Delta f_{\mathrm{opt}}}{\mathbf{f2}}$ 1e1	1e0 386	1e-1 387	1e-3 390	1e-5 391	1e-7 393	#succ 15/15	$\frac{\Delta f_{\text{opt}}}{\text{f14}}$	1e1 75	1e0 239	1e-1 304	1e-3 932	1e-5 1648	1e-7 15661	#succ 15/15
IP-10DD 35(4)	<b>42</b> (4)	48(4)	<b>51</b> (2)	<b>52</b> (2)	<b>53</b> (2)	15/15	IP-10DD		2.7(0.5)	3.4(0.4)	4.2(0.4)	<b>6.3</b> (0.4)	1.2(0.1)	15/15
IP 35(4)	42(4)	48(4)	51(2)	<b>52</b> (2)	53(2)	15/15	IP	3.8(0.7)	2.7(0.5)	3.4(0.4)	4.2(0.4)	6.3(0.4)	1.2(0.1)	15/15
IP-500 <b>35</b> (4)	<b>42</b> (4)	48(4)	<b>51</b> (2)	<b>52</b> (2)	<b>53</b> (2)	15/15	IP-500	3.8(0.7)	<b>2.7</b> (0.5)	3.4(0.4)	4.2(0.4)	6.3(0.4)	1.2(0.1)	15/15
$\Delta f_{ m opt}$ 1e1	1e0	1e-1	1e-3	1e-5	1e-7	#succ	$\Delta f_{ m opt}$	1e1	1e0	1e-1	1e-3	1e-5	1e-7	#succ
f3 5066 IP-10DD 15(16)	$7626$ $\infty$	7635 ∞	7643	7646 ∞	7651 ∞ 2e7	15/15 0/15	f15 IP-10DD	30378	1.5e5 0.99(0.5)	3.1e5 0.70(0.2)	3.2e5 0.71(0.2)	4.5e5	4.6e5	15/15
IP <b>15</b> (16)	∞	∞	∞ ∞	∞	∞ 2e7 ∞ 2e7	0/15	IP IDDL	1.1(0.7) 1.1(0.7)	0.99(0.5)	0.70(0.2)	0.71(0.2)		$2^{0.54(0.2)}$	
IP-500 <b>15</b> (16)	1.9e4(2		∞	∞	∞ 2e7	0/15	IP-500	1.1(0.7) 1.1(0.7)	0.99(0.5)	0.70(0.2) $0.71(0.2)$	0.71(0.2)		$30.54(0.1)_{13}$	
$\Delta f_{ m opt}$  1e1	1e0	1e-1	1e-3	1e-5	1e-7	#succ		11e1	1e0	1e-1	1e-3	1e-5	1e-7	#succ
f4 4722	7628	7666	7700	7758	1.4e5	9/15	$\frac{\Delta f_{\text{opt}}}{\mathbf{f} 16}$	1384	27265	77015	1.9e5	2.0e5	2.2e5	#succ 15/15
IP-10DD 2.9e4(3e		$\infty$	$\infty$	$\infty$	$\infty 2e7$	0/15	IP-10DD		0.27(0.3)		1.363 1.20.78(0.6)	0.85(0.6)	0.79(0.5)	15/15
IP ∞	$\infty$	$\infty$	$\infty$	$\infty$	$\infty 2e7$	0/15	IP	1.2(0.3)	0.27(0.3)		$12^{0.78}(0.6)$	0.85(0.6)	0.79(0.5)	15/15
IP-500 ∞	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$ 2e7	0/15	IP-500	1.2(0.3)	0.27(0.3)		120.78(0.6)	0.83(0.6)	0.77(0.5)	15/15
$\frac{\Delta f_{\text{opt}}}{\text{f5}}$ 1e1	1e0 41	1e-1 41	1e-3 41	1e-5 41	1e-7 41	#succ 15/15	$\Delta f_{ m opt}$	1e1	1e0	1e-1	1e-3	1e-5	1e-7	#succ
IP-10DD <b>51</b> (35)	111(93)	165(106)	233(151)	309(245)	403(293)	15/15	f17	63	1030	4005	30677	56288	80472	15/15
IP <b>51</b> (35)	111(93)	165(106)	233(151)	309(245)	403(293)	15/15	IP-10DD			<b>0.67</b> (0.1)		1.1(0.4)	1.1(0.5)	15/15
IP-500 <b>51</b> (35)	<b>111</b> (93)	<b>165</b> (106)	<b>233</b> (151)	<b>309</b> (245)	<b>403</b> (293)	15/15	IP	1.9(0.8)		0.67(0.1)		1.1(0.4)	1.1(0.5)	15/15
$\Delta f_{ m opt}$ [1e1	1e0	1e-1	1e-3	1e-5	1e-7	#succ	IP-500	1.9(0.8)		0.67(0.1)	<b>0.93</b> (0.4)	1.1(0.4)	1.1(0.5)	15/15
f6 1296	2343	3413	5220	6728	8409	15/15	$\Delta f_{ m opt}$	1e1	1e0	1e-1	1e-3	1e-5	1e-7	#succ
IP-10DD 1.3(0.2)	1.1(0.2)	1.1(0.2)	1.1(0.1)	1.1(0.1)	1.1(0.1)	15/15	f18	621	3972	19561	67569	1.3e5	1.5e5	15/15
IP <b>1.3</b> (0.2) IP-500 <b>1.3</b> (0.2)	1.1(0.2) 1.1(0.2)	1.1(0.2) 1.1(0.2)	1.1(0.1) 1.1(0.1)	1.1(0.1) 1.1(0.1)	1.1(0.1) 1.1(0.1)	$\frac{15/15}{15/15}$		0.87(0.2)		0.66(0.4)		<b>0.96</b> (0.4)	1.0(0.4)	15/15
! ` ′	` ′	` ′	, ,	` /	` ′		IP	0.87(0.2)		0.66(0.4)	1.2(0.8)	<b>0.96</b> (0.4)	1.0(0.4)	15/15
$\frac{\Delta f_{ m opt}}{{ m f7}} \frac{1{ m e}1}{1351}$	1e0 4274	1e-1 9503	1e-3 16524	1e-5 16524	1e-7 16969	#succ 15/15		0.87(0.2)  1e1	0.46(0.2) 1e0	0.66(0.4) 1e-1	1.2(0.8) 1e-3	0.96(0.4) 1e-5	1.0(0.4) 1e-7	15/15 #succ
IP-10DD 1.7(2)	6.2(3)	3.9(2)	2.4(1.0)	2.4(1.0)	2.4(1.0)	15/15	$\frac{\Delta f_{\mathrm{opt}}}{\mathbf{f19}}$	1	1	3.4e5	6.2e6	6.7e6	6.7e6	15/15
IP 1.7(2)	<b>6.2</b> (3)	3.9(2)	<b>2.4</b> (1.0)	<b>2.4</b> (1.0)	<b>2.4</b> (1.0)	15/15		178(144)		2e5 <b>4.0</b> (3)	0.84(0.6)		1.0(0.9)	15/15
IP-500 1.7(2)	6.2(3)	3.9(2)	<b>2.4</b> (1.0)	<b>2.4</b> (1.0)	<b>2.4</b> (1.0)	15/15	IP	178(144)		2e5 <b>4.0</b> (3)	0.67(0.3)	0.66(0.3)	0.66(0.3)	15/15
$\Delta f_{ m opt}$ 1e1	1e0	1e-1	1e-3	1e-5	1e-7	#succ	IP-500	<b>178</b> (144)	,	2e5 <b>4.0</b> (3)	$\infty$	$\infty$	$\infty$ 2e7	0/15
f8 2039 IP-10DD <b>4.1</b> (0.8)	3871 4.3(0.3)	4040 4.6(0.4)	4219 4.8(0.3)	4371 4.8(0.3)	4484 4.9(0.3)	15/15 15/15	$\Delta f_{ m opt}$	1e1	1e0	1e-1	1e-3	1e-5	1e-7	#succ
IP 4.1(0.8)	4.3(0.3)	4.6(0.4)	4.8(0.3)	4.8(0.3)	4.9(0.3)	15/15	f20	82	46150	3.1e6	5.5e6	5.6e6	5.6e6	14/15
IP-500 4.1(0.8)	4.3(0.3)	4.6(0.4)	4.8(0.3)	4.8(0.3)	4.9(0.3)	15/15	IP-10DD	5.4(1) 5.4(1)	<b>5.6</b> (3) <b>5.6</b> (3)	0.91(0.6) <b>0.86</b> (0.4)	1.5(1) <b>0.66</b> (0.2)	1.5(1) <b>0.66</b> (0.2)	1.5(1) <b>0.67</b> (0.2)	$\frac{15}{15}$
$\Delta f_{ m opt}$  1e1	1e0	1e-1	1e-3	1e-5	1e-7	#succ	IP-500	5.4(1)	5.8(3)	∞	∞	∞	∞ 2e7	0/15
f9 1716	3102	3277	3455	3594	3727	15/15	$\Delta f_{ m opt}$	1e1		le-1	1e-3	1e-5	1e-7	#succ
IP-10DD 5.0(1)	6.9(5)	7.2(5)	7.3(4)	7.3(4)	7.2(4)	15/15	f21	561	6541	4103	14643	15567	17589	15/15
IP <b>5.0</b> (1) IP-500 <b>5.0</b> (1)	6.9(5) 6.9(5)	7.2(5) 7.2(5)	<b>7.3</b> (4) <b>7.3</b> (4)	<b>7.3</b> (4) <b>7.3</b> (4)	7.2(4) 7.2(4)	15/15 15/15	IP-10DD			<b>430</b> (665)	<b>414</b> (641)	<b>390</b> (603)	345(533)	14/15
	1e0	1.2(3) 1e-1	1e-3		1.2(4) 1e-7		IP IP-500					2592(3264)	2295(2890) 2285(3411)	5/15
$\frac{\Delta f_{ m opt}}{{ m f10}}$ 1e1	8661	10735	14920	1e-5 17073	17476	#succ 15/15			856(1529) 2	, ,			` ,	5/15
IP-10DD 1.8(0.2)	1.9(0.2)	1.7(0.1)	1.3(0.0)	1.2(0.0)	1.2(0.0)	15/15	$\frac{\Delta f_{\text{opt}}}{\mathbf{f22}}$	1e1	1e0	1e-1	1e-3	1e-5	1e-7	#succ
IP 1.8(0.2)	1.9(0.2)	1.7(0.1)	1.3(0.0)	1.2(0.0)	1.2(0.0)	15/15		467 96(168)	5580 <b>1871</b> (35	2349 84) ∞	1 24948 ∞	26847 ∞	1.3e5 ∞ 2e7	12/15 0/15
IP-500 1.8(0.2)	1.9(0.2)	1.7(0.1)	1.3(0.0)	1.2(0.0)	1.2(0.0)	15/15	IP IODE	96(168)	2411(35		∞	∞	∞ 2e7	0/15
$\Delta f_{ m opt}$  1e1	1e0	1e-1	1e-3	1e-5	1e-7	#succ	IP-500	525(247)	2405(35		∞	∞	$\infty$ 2e7	0/15
f11 1002	2228	6278	9762	12285	14831	15/15	$\Delta f_{ m opt}$	1e1	1e0	1e-1	1e-3	1e-5	1e-7	#succ
IP-10DD 10(0.6)	5.1(0.2)	2.0(0.1)	1.4(0.0)	1.2(0.0)	1.1(0.0)	15/15	f23	3.2	1614	67457	4.9e5	8.1e5	8.4e5	15/15
IP 10(0.6) IP-500 10(0.6)	5.1(0.2) 5.1(0.2)	2.0(0.1) 2.0(0.1)	1.4(0.0) 1.4(0.0)	1.2(0.0) 1.2(0.0)	1.1(0.0) 1.1(0.0)	15/15 15/15	IP-10DD		<b>35</b> (39)	<b>5.3</b> (5)	71(66)	<b>43</b> (45)	<b>41</b> (43)	7/15
! ` ′	` /	` ′	, ,	` ′	` ′		IP FOO	1.7(2)	<b>35</b> (39)		100(102)	60(63)	58(62)	5/15
$\frac{\Delta f_{\rm opt}}{{\bf f12}}$ 1e1	1e0 1938	1e-1 2740	1e-3 4140	1e-5 12407	1e-7 13827	#succ 15/15	IP-500	1.7(2)	<b>35</b> (39)	<b>5.3</b> (5)	72(70)	44(42)	42(41)	7/15
IP-10DD <b>2.6</b> (2)	3.6(3)	4.1(3)	4.1(2)	1.8(0.6)	1.9(0.5)	15/15	$\Delta f_{\rm opt}$	1e1	1e0	1e-1	1e-3	1e-5	1e-7	#succ
IP <b>2.6</b> (2)	<b>3.6</b> (3)	4.1(3)	4.1(2)	1.8(0.6)	1.9(0.5)	15/15	<b>f24</b> IP-10DD	1.3e6	7.5e6	5.2e7 ∝	5.2e7	5.2e7 ~	5.2e7 ∞ 2e7	$\frac{3}{15}$ $\frac{0}{15}$
IP-500 <b>2.6</b> (2)	<b>3.6</b> (3)	<b>4.1</b> (3)	4.1(2)	1.8(0.6)	1.9(0.5)	15/15	IP-10DL	, ∞  ∞	∞ ∞	∞ ∞	∞	∞ ∞	$\infty$ 2e7 $\infty$ 2e7	0/15
							IP-500	∞	∞	∞	∞	∞	∞ 2e7	0/15

Table 2: Expected running time (ERT in number of function evaluations) divided by the respective best ERT measured during BBOB-2009 (given in the respective first row) for different  $\Delta f$  values in dimension 20. The central 80% range divided by two is given in braces. The median number of conducted function evaluations is additionally given in italics, if  $\text{ERT}(10^{-7}) = \infty$ . #succ is the number of trials that reached the final target  $f_{\text{opt}} + 10^{-8}$ . Best results are printed in bold. IP-10DD in the table denotes IP-10DDr.