



OASIS AI

Empower Operations

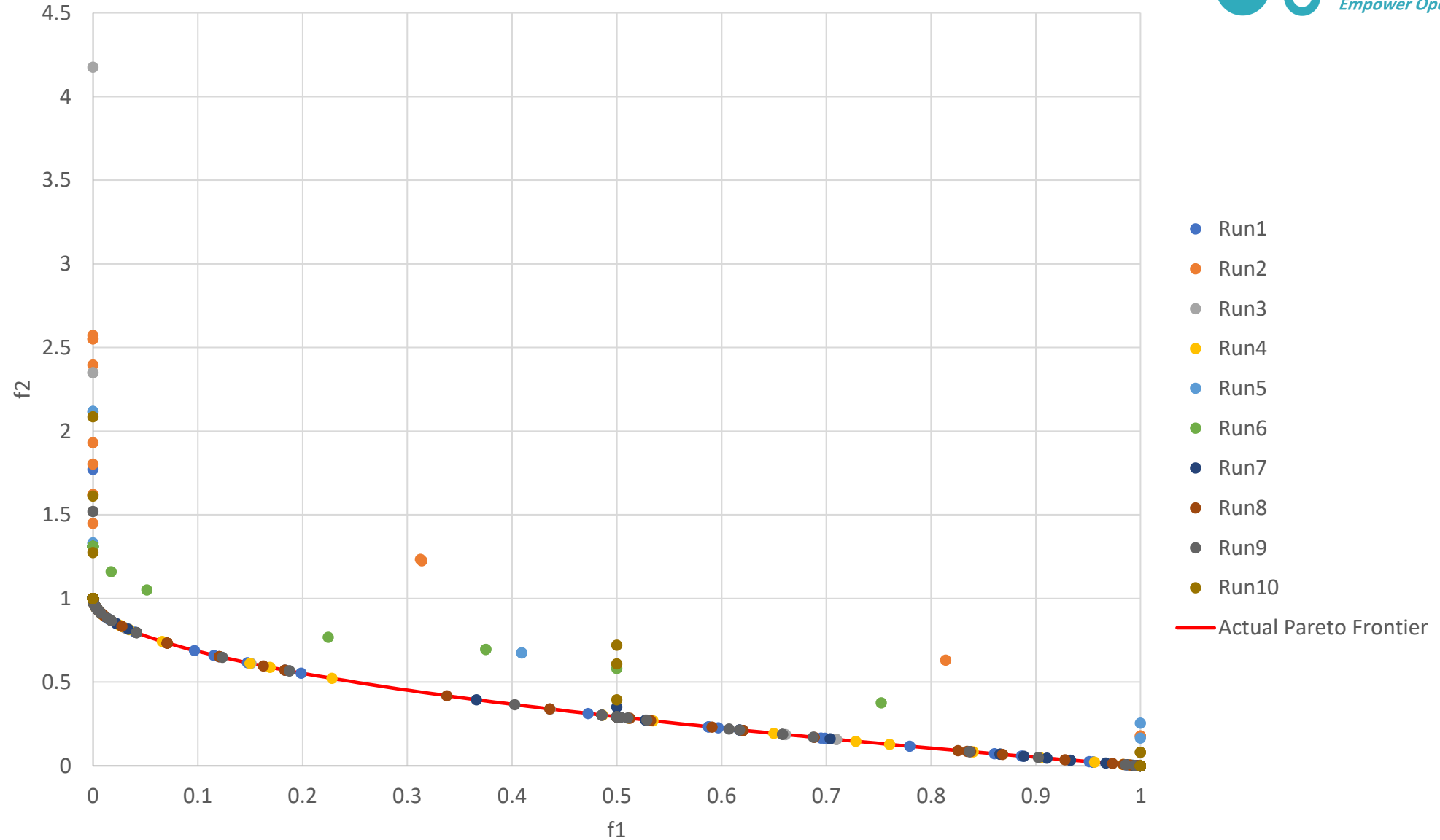
Technical Assessment November 2023

Test Cases

No	Problem Type	Benchmark	No. of Inputs	No. of Objectives	No. of Constraints	Budget (Func. Eval)
1	Multi-Objective, unconstrained	ZDT 1	30	2	0	250
2	Multi-Objective, unconstrained	ZDT 2	30	2	0	250
3	Multi-Objective, unconstrained	ZDT 3	30	2	0	250
4	Multi-Objective, unconstrained	ZDT 6	10	2	0	250
5	Multi-Objective, expensive constraints	OSY Exp. Cons.	6	2	6	500
6	Multi-Objective, cheap constraints	OSY Cheap Cons.	6	2	6	500
7	Multi-Objective, unconstrained	Geartrain	4 - Discrete	2	0	1000
8	Single Objective, expensive constraints	G7	10	1	8	500
9	Unimodal, unconstrained	Rosenbrock d10	10	1	0	1000
10	Unimodal, unconstrained	Rosenbrock d50	50	1	0	1000
11	Multimodal, unconstrained	Shubert d10	10	1	0	1000
12	Multimodal, unconstrained	Shubert d30	30	1	0	1000
13	Multimodal, unconstrained	Shubert d60	60	1	0	1000
14	Ill-shaped, unconstrained	Michalewicz d10	10	1	0	1000
15	Ill-shaped, unconstrained	Michalewicz d30	30	1	0	1000
16	Ill-shaped, unconstrained	Michalewicz d60	60	1	0	1000
17	Multimodal, high dimensional, highly constrained	Mopta08 - in progress	124	1	68	2000

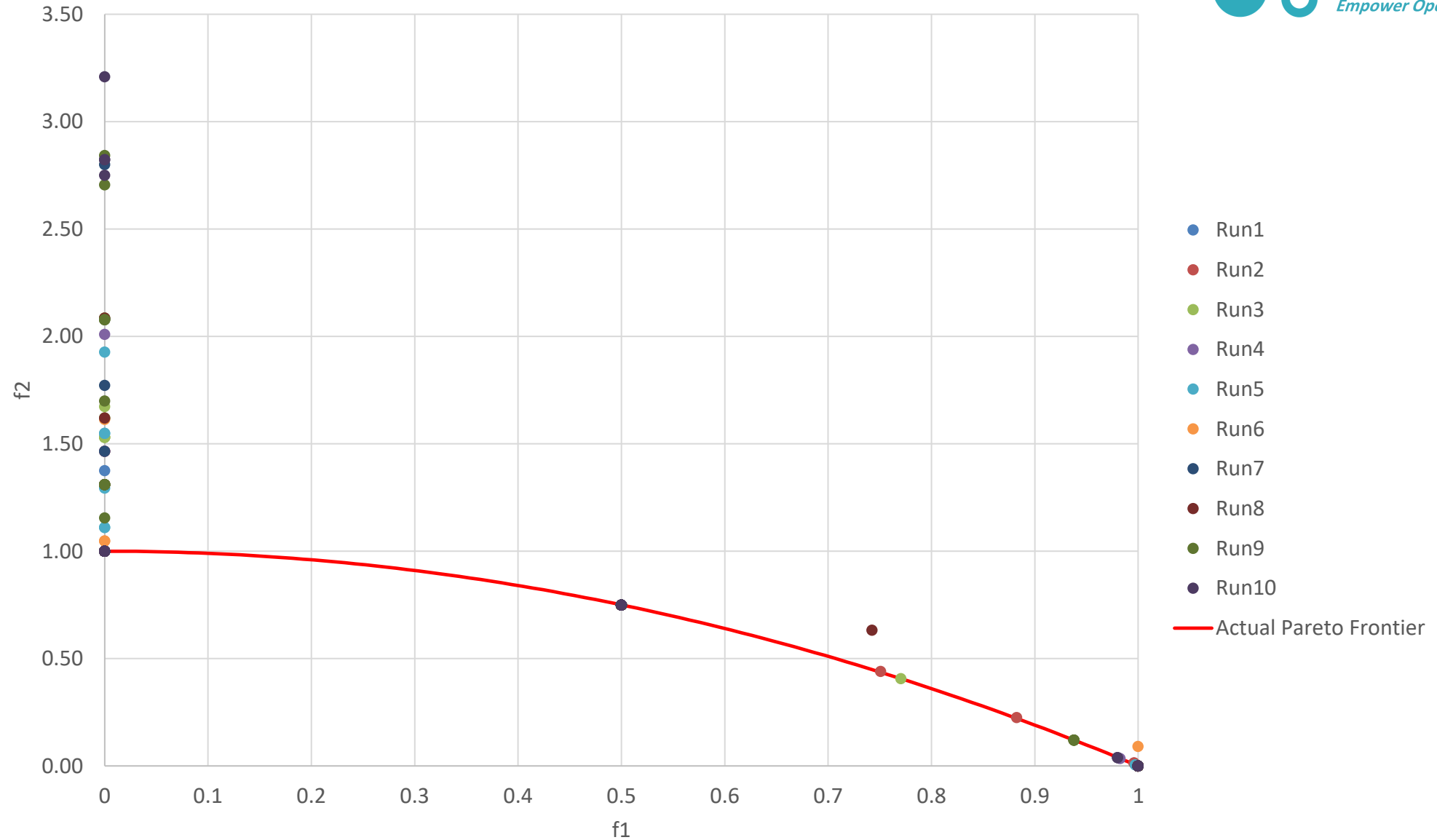
ZDT1

OASIS AI - ZDT1, 250 Func. Evals., Pareto Frontiers



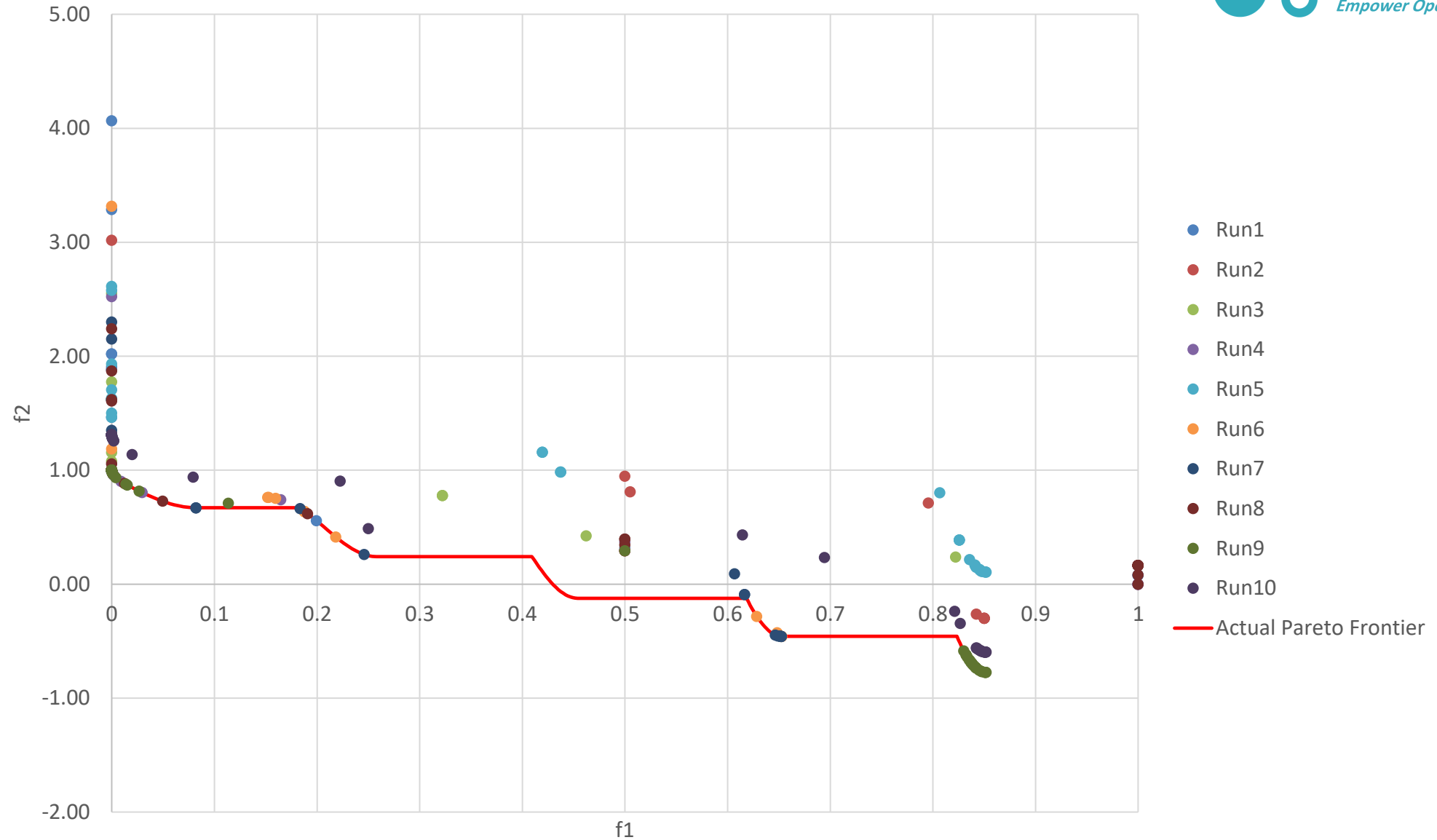
ZDT2

OASIS AI - ZDT2, 250 Func. Evals., Pareto Frontiers



ZDT3

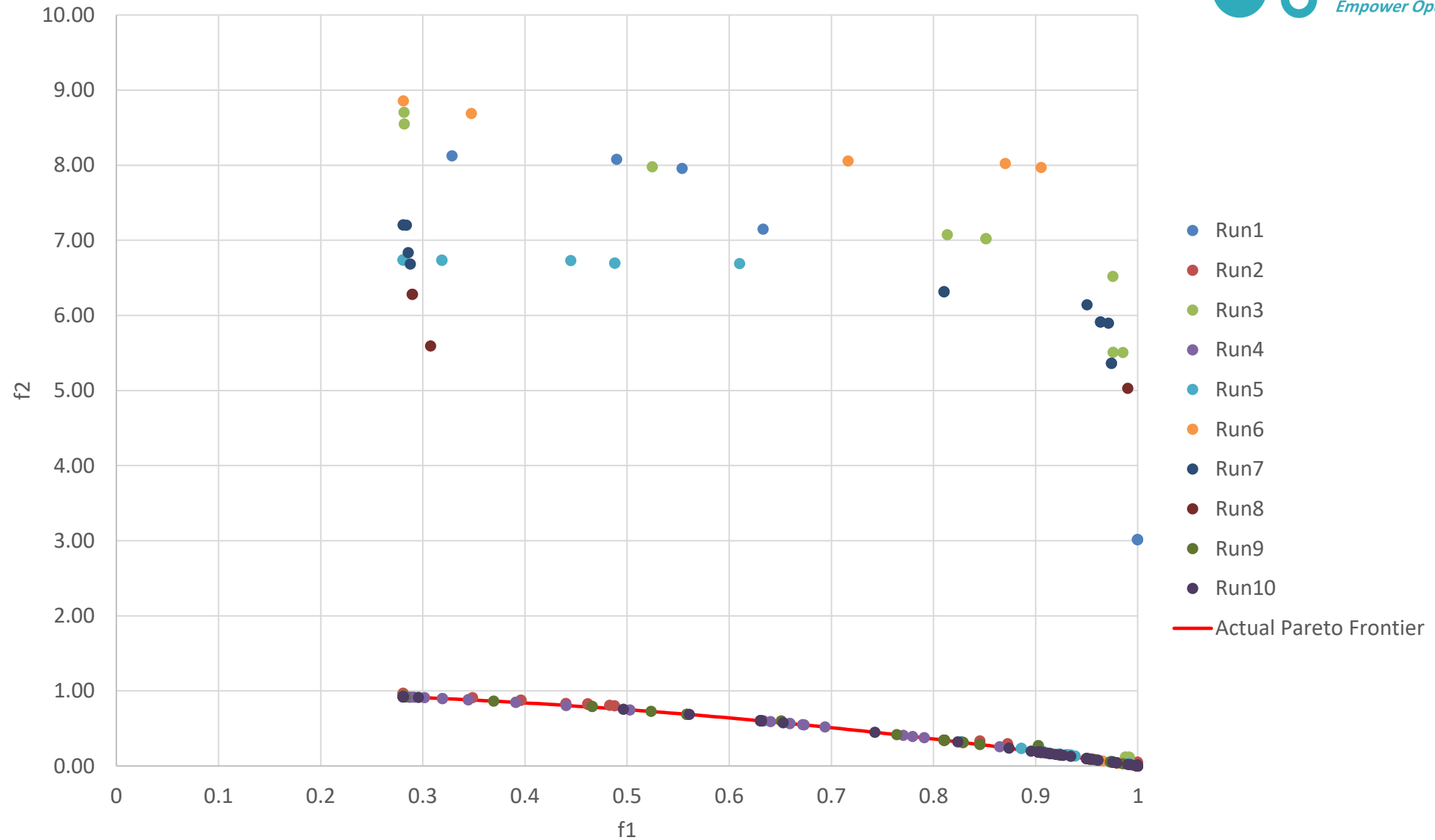
OASIS AI - ZDT3, 250 Func. Evals., Pareto Frontiers



ZDT6

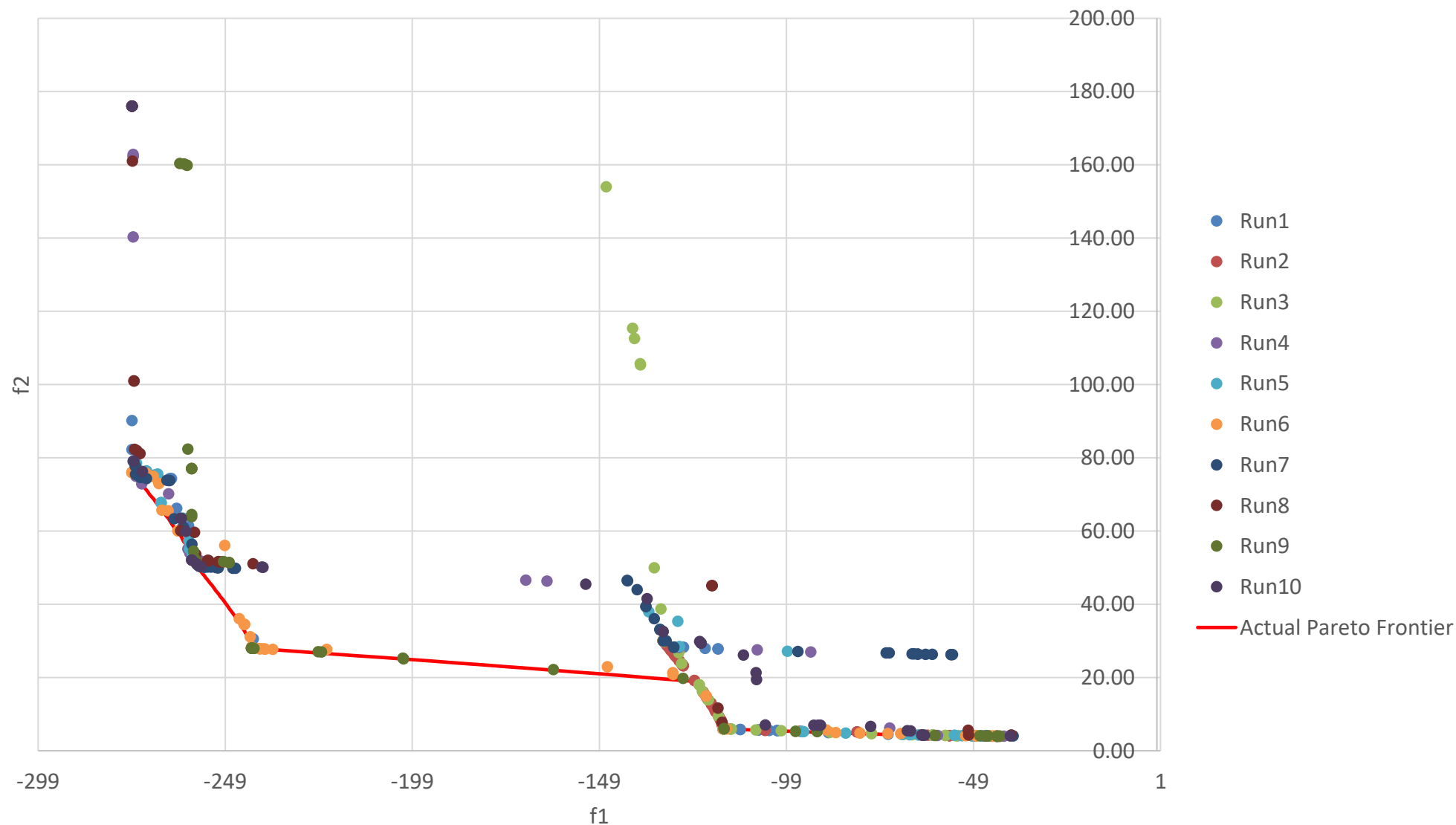


OASIS AI - ZDT6, 250 Func. Evals., Pareto Frontiers

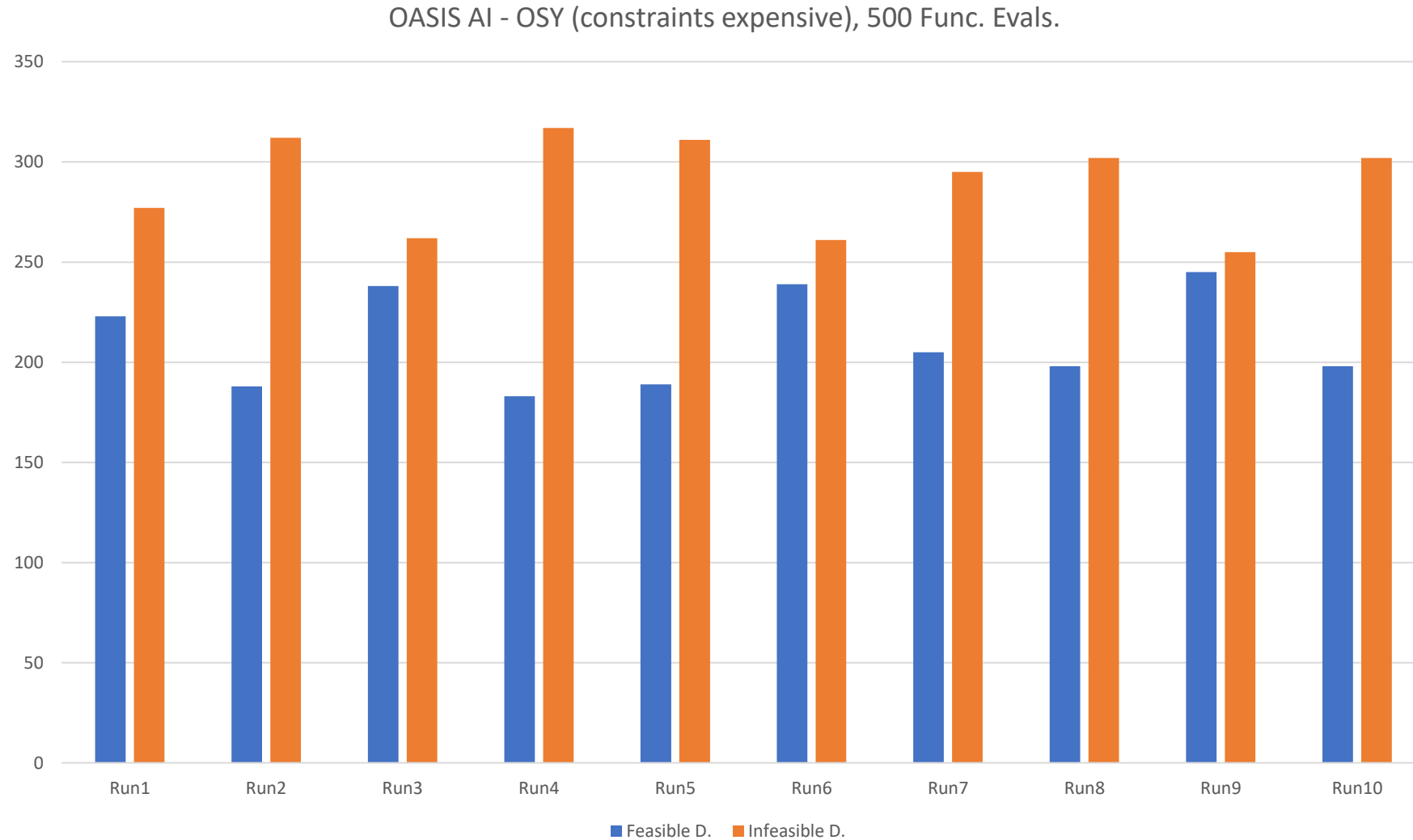


OSY – (constraints expensive)

OASIS AI - OSY (constraints expensive), 500 Func. Evals.,
Pareto Frontiers, Feasible Designs



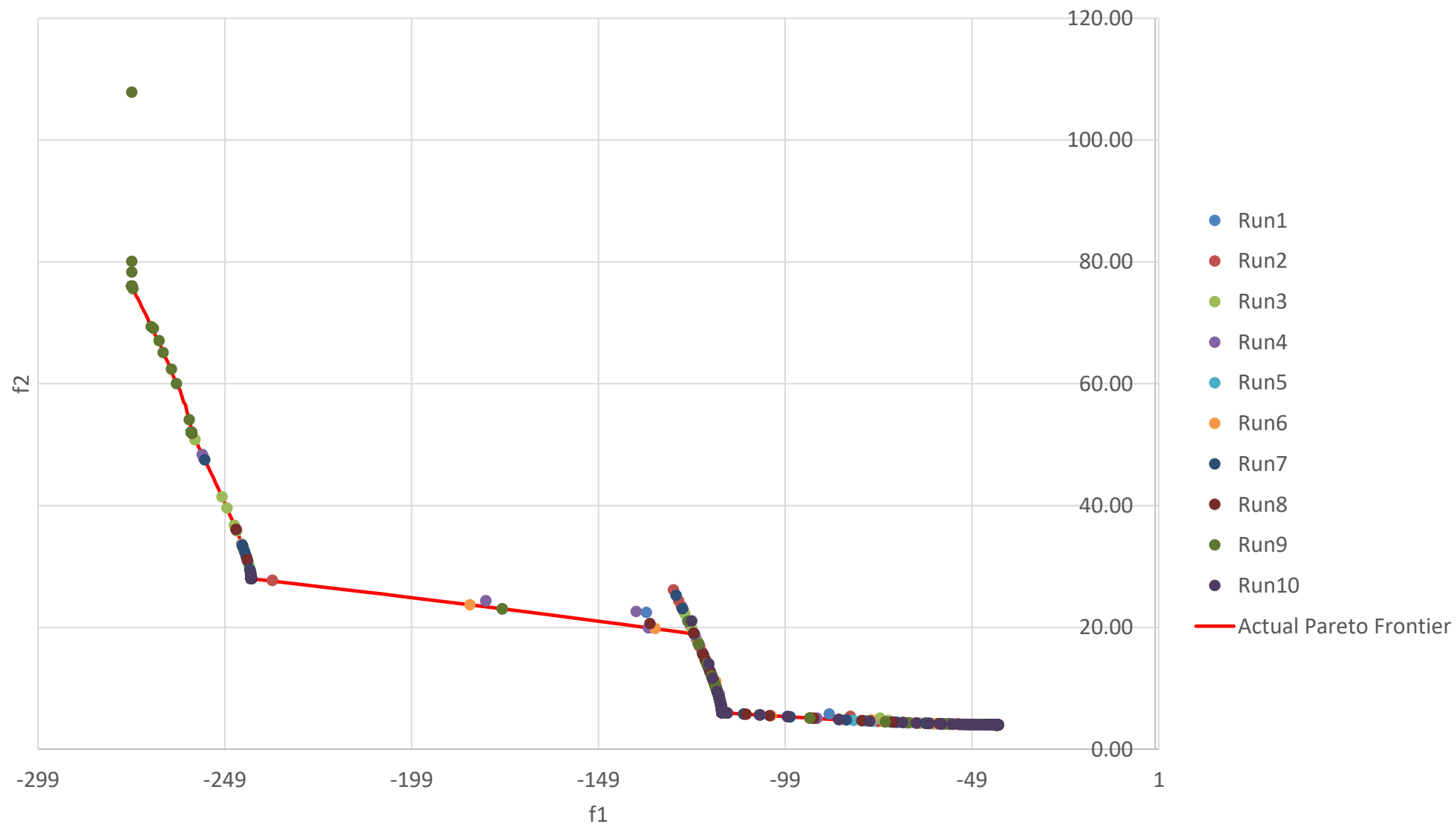
OSY – (constraints expensive) continued



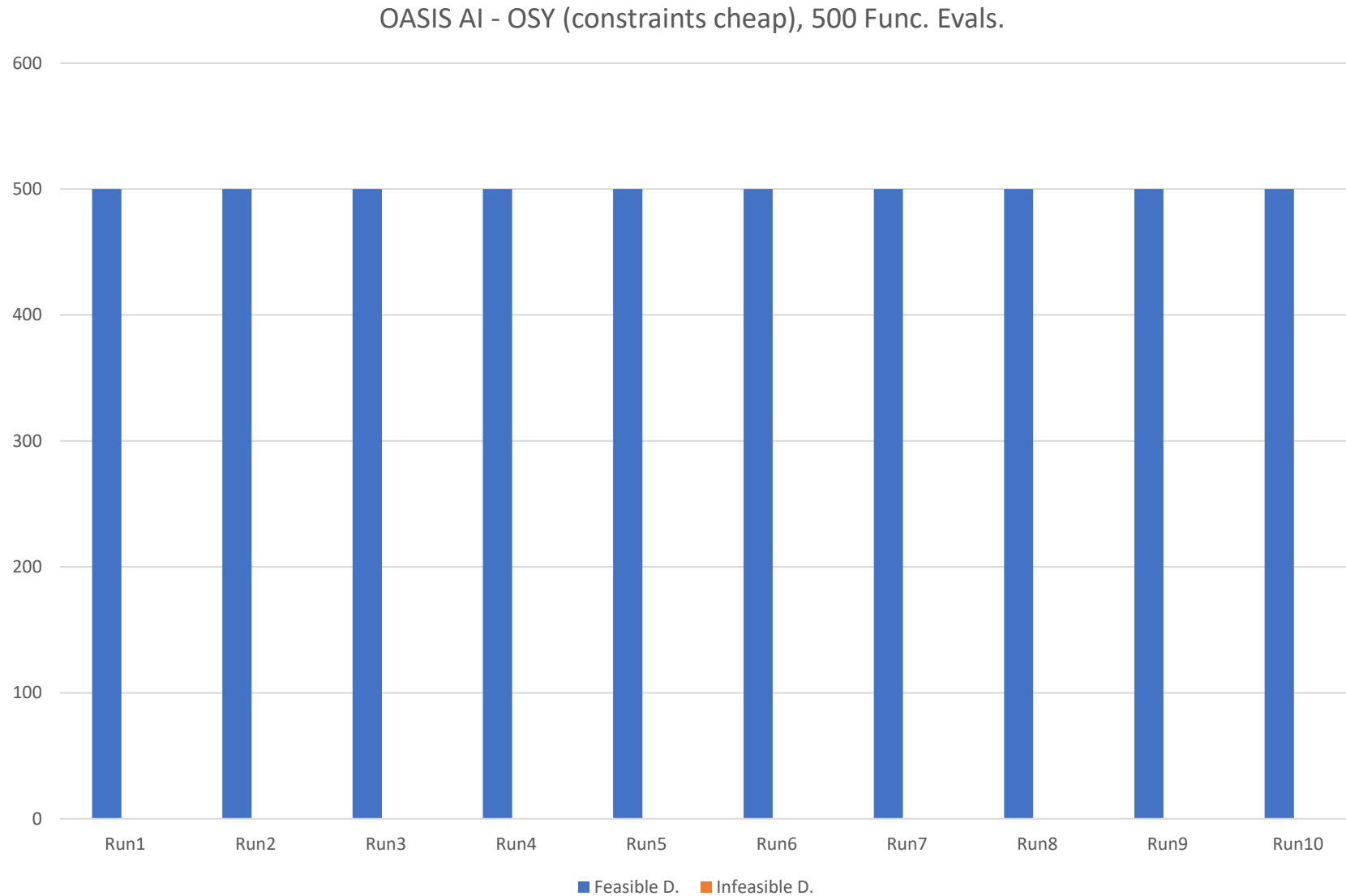
OSY – (constraints cheap)



OASIS AI - OSY (constraints cheap), 500 Func. Evals.,
Pareto Frontiers, Feasible Designs

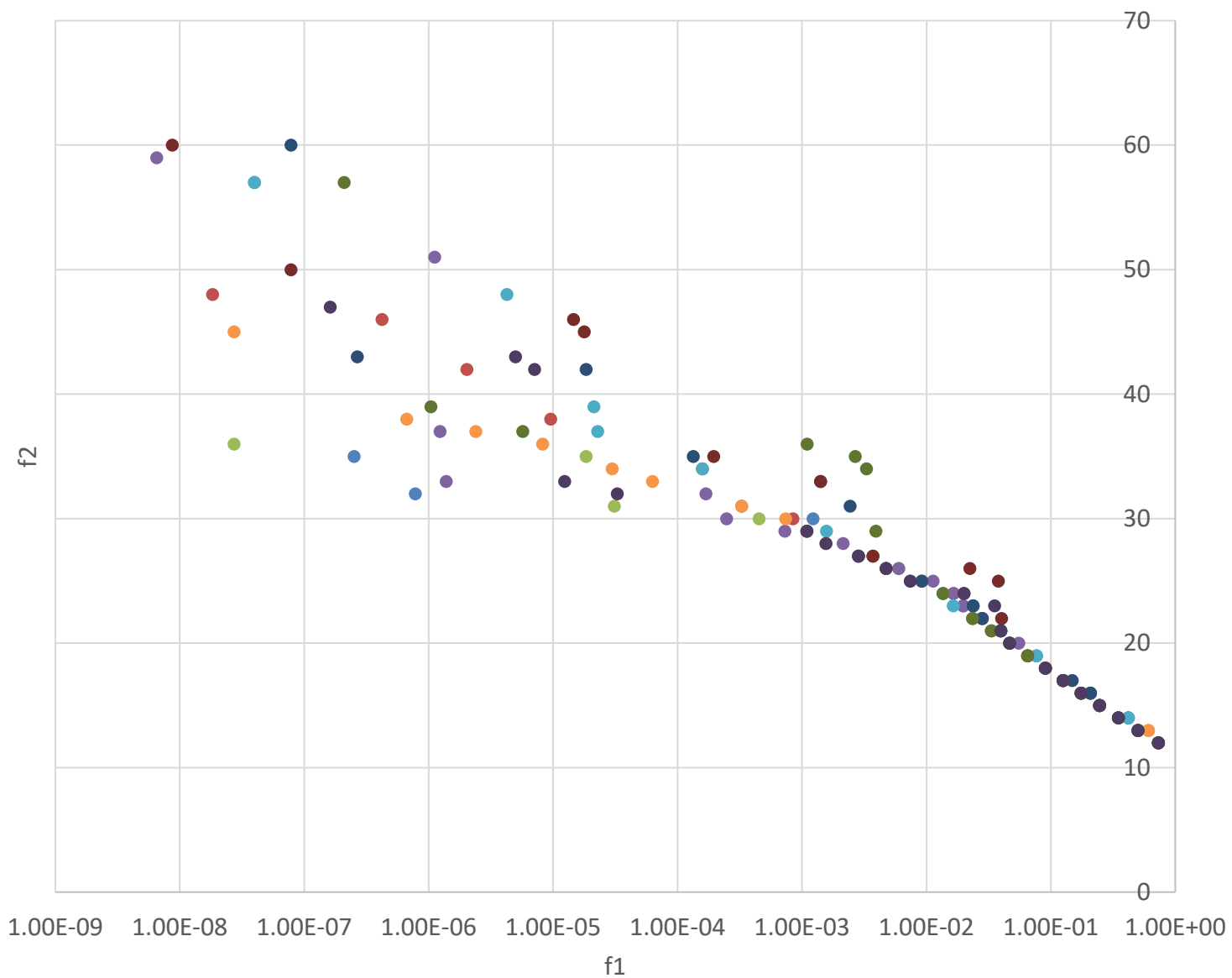


OSY – (constraints cheap) continued



Geartrain – Inputs discrete

Geartrain, 1000 Func. Evals., Pareto Frontiers



G7 – Single objective, expensive constraints

Inputs

Design Variables – $x_1 \dots x_{10}$

Ranges

$x_1 [-10,10]$

...

$x_{10} [-10,10]$

Python Script

$$\begin{aligned} f(\mathbf{x}) &= x_1^2 + x_2^2 + x_1 x_2 - 14x_1 - 16x_2 + (x_3 - 10)^2 \\ &\quad + 4(x_4 - 5)^2 + (x_5 - 3)^2 + 2(x_6 - 1)^2 + 5x_7^2 \\ &\quad + 7(x_8 - 11)^2 + 2(x_9 - 10)^2 + (x_{10} - 7)^2 + 45 \\ g_1(\mathbf{x}) &= -105 + 4x_1 + 5x_2 - 3x_7 + 9x_8 \leq 0 \\ g_2(\mathbf{x}) &= 10x_1 - 8x_2 - 17x_7 + 2x_8 \leq 0 \\ g_3(\mathbf{x}) &= -8x_1 + 2x_2 + 5x_9 - 2x_{10} - 12 \leq 0 \\ g_4(\mathbf{x}) &= 3(x_1 - 2)^2 + 4(x_2 - 3)^2 + 2x_3^2 - 7x_4 - 120 \leq 0 \\ g_5(\mathbf{x}) &= 5x_1^2 + 8x_2 + (x_3 - 6)^2 - 2x_4 - 40 \leq 0 \\ g_6(\mathbf{x}) &= x_1^2 + 2(x_2 - 2)^2 - 2x_1 x_2 + 14x_5 - 6x_6 \leq 0 \\ g_7(\mathbf{x}) &= 0.5(x_1 - 8)^2 + 2(x_2 - 4)^2 + 3x_5^2 - x_6 - 30 \leq 0 \\ g_8(\mathbf{x}) &= -3x_1 + 6x_2 + 12(x_9 - 8)^2 - 7x_{10} \leq 0 \end{aligned}$$

Outputs

Objectives – minimize $f(\mathbf{x})$

Expensive Constraints

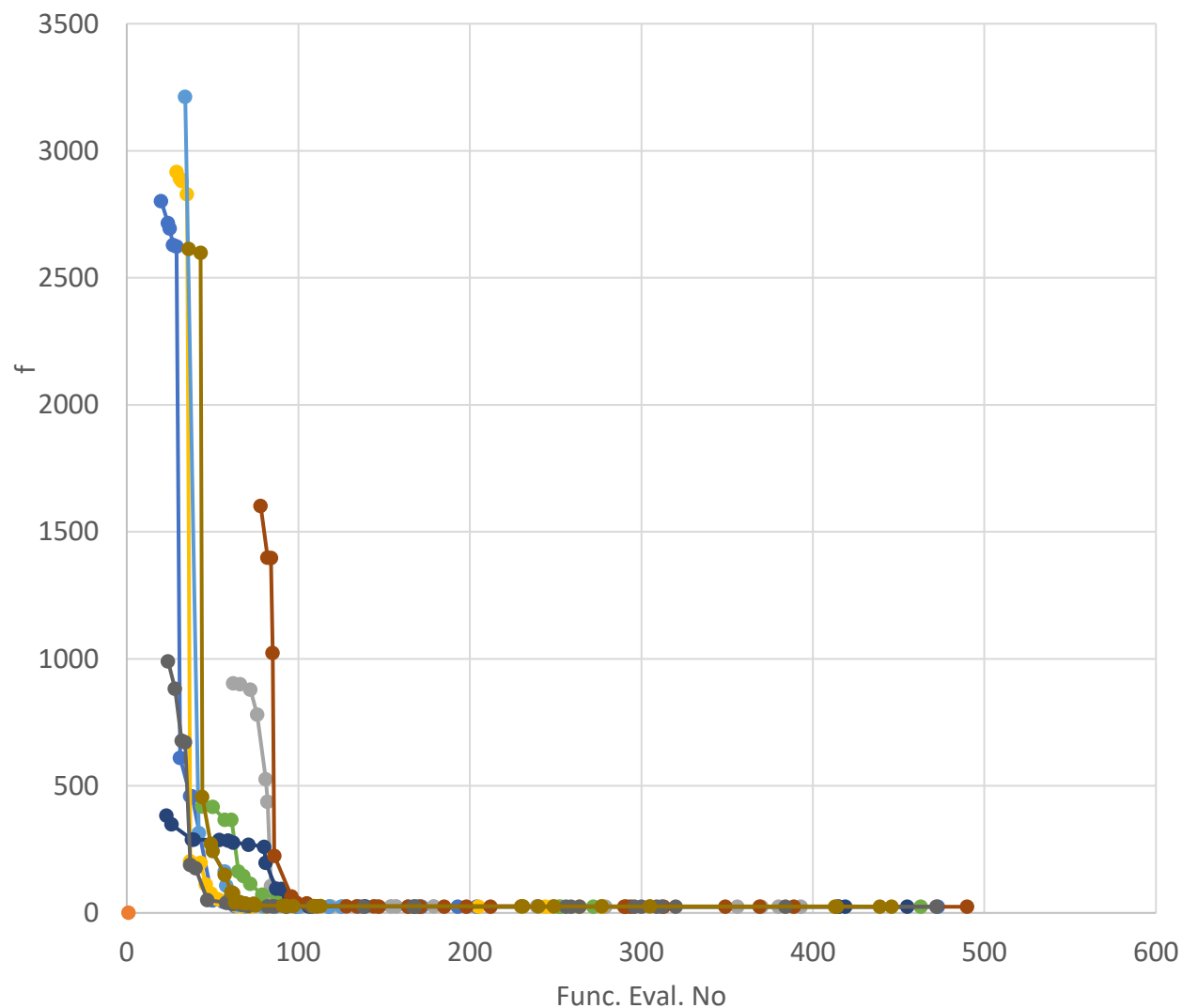
$g_1(\mathbf{x}) < 0$

...

$g_8(\mathbf{x}) < 0$

G7 – No initial designs provided

G7, 500 Func. Evals., Converge Plot Feasible Designs



Run No	First Feasible D. at Func. Eval.
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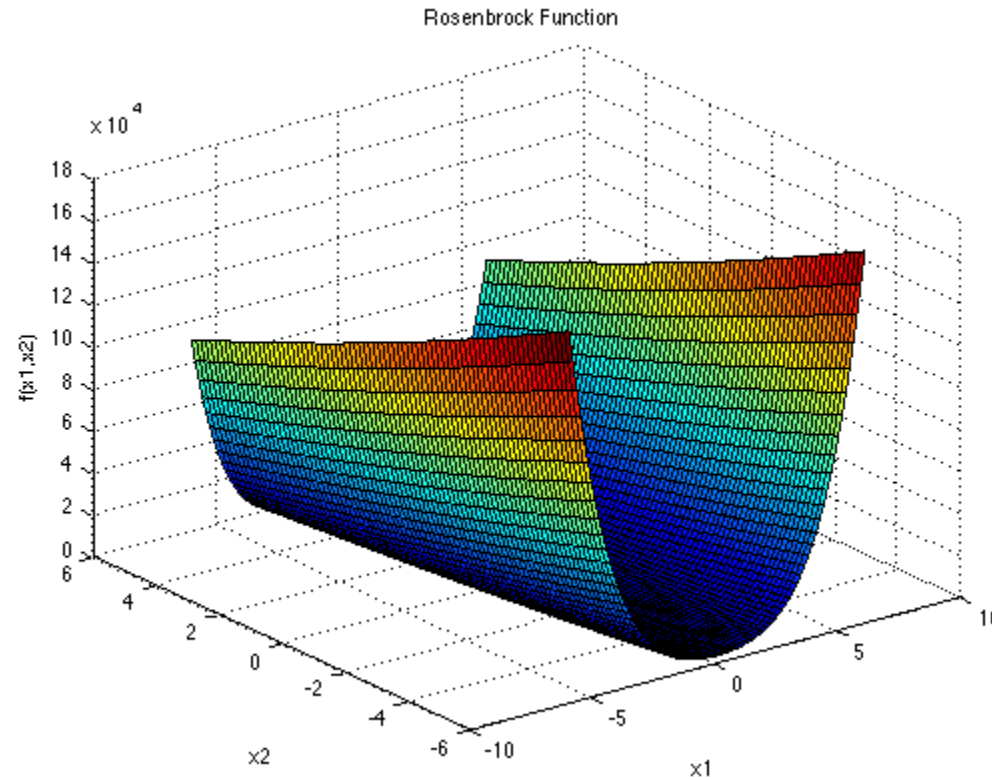
Run1	20
Run2	N/A
Run3	62
Run4	29
Run5	34
Run6	44
Run7	23
Run8	78
Run9	24
Run10	36

Run1
Run2 - No Feasible D.
Run3
Run4
Run5
Run6
Run7
Run8
Run9
Run10

Rosenbrock – Unimodal, unconstrained

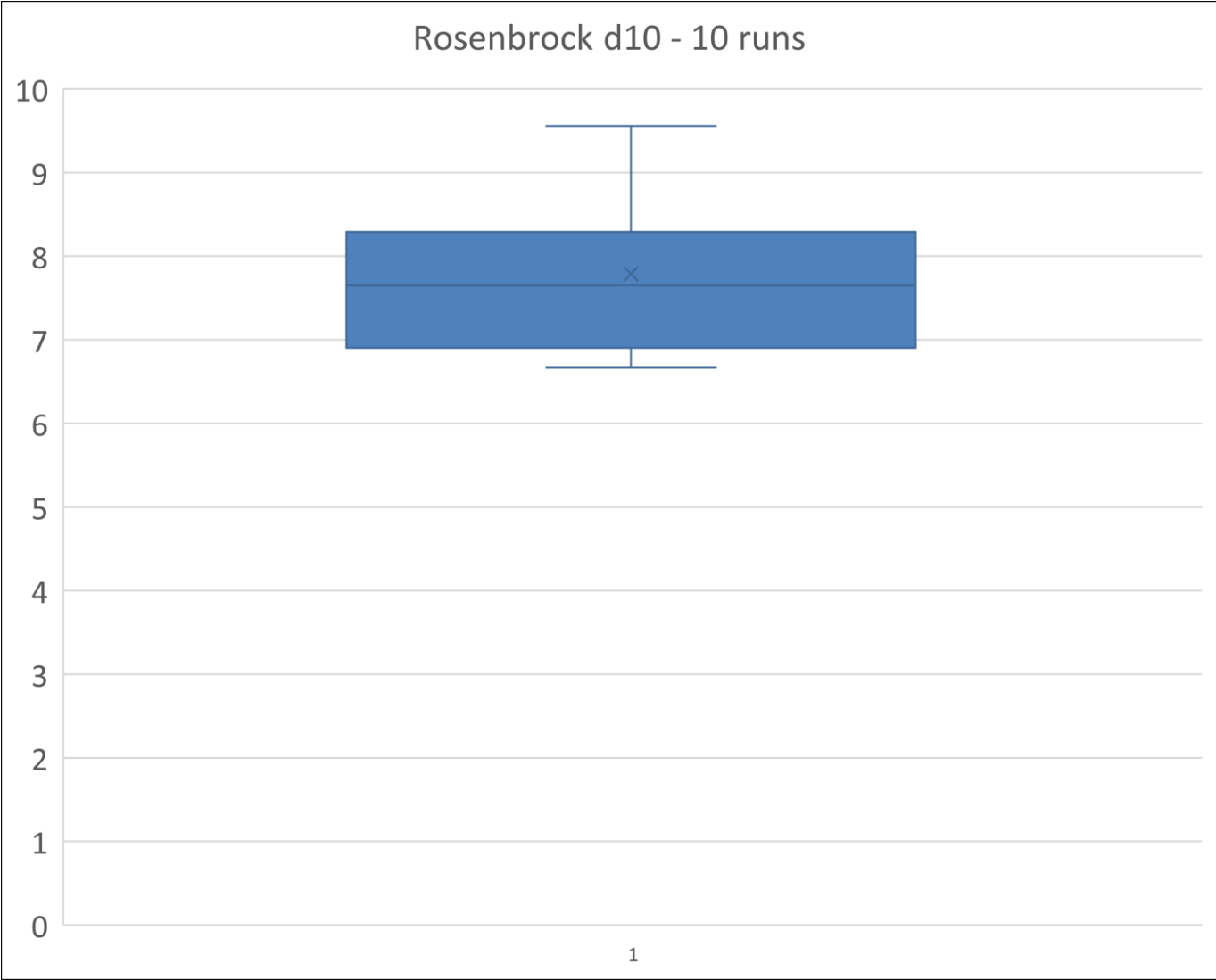
$$f(x) = \sum_{i=1}^d [100(x_i^2 - x_{i+1})^2 + (x_i - 1)^2]$$

$-10 \leq x_i \leq 10, d = \# \text{ of variables}$



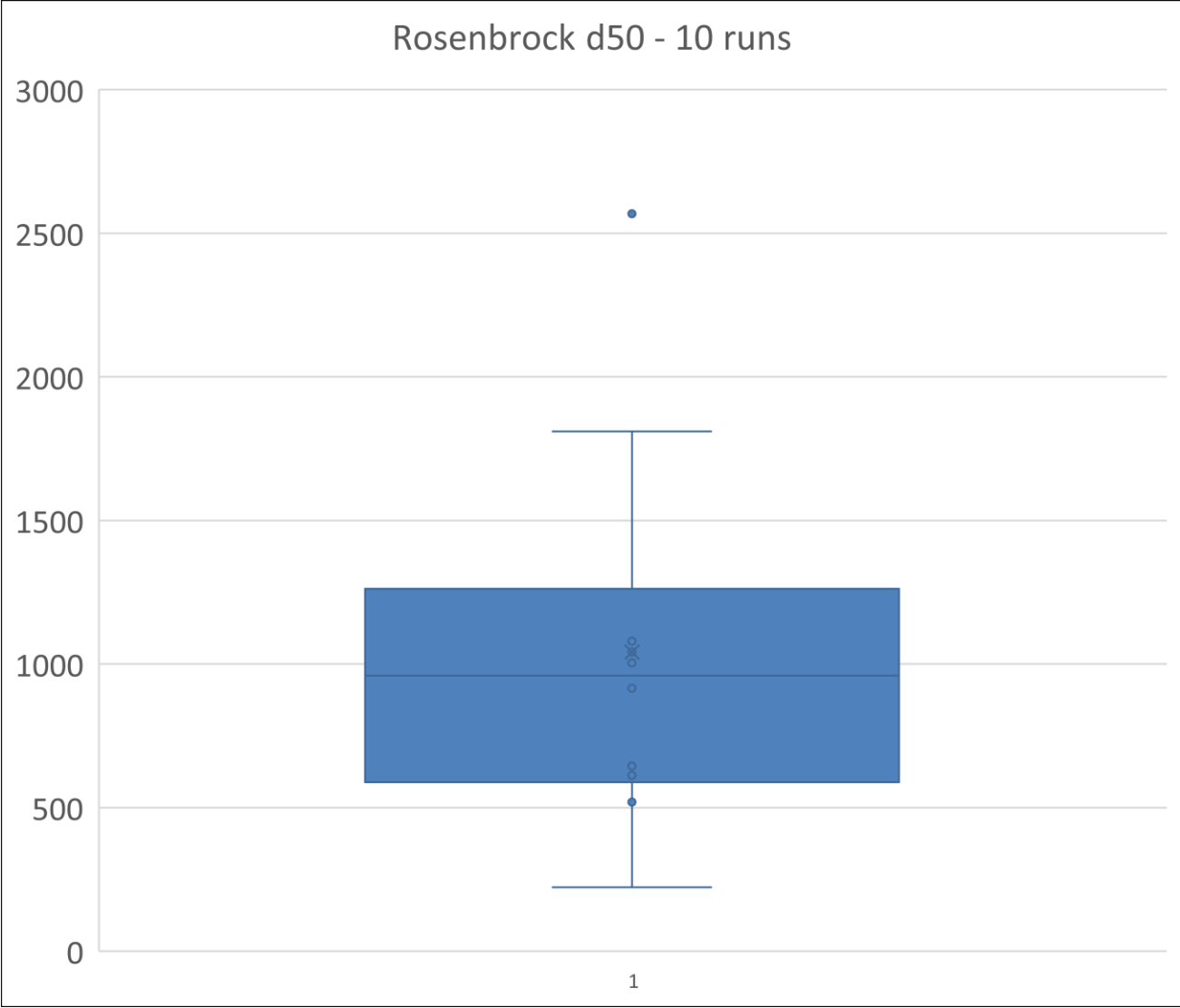
Rosenbrock d10

	f
Run1	6.919334
Run2	7.398033
Run3	6.864139
Run4	9.559364
Run5	7.855866
Run6	7.954235
Run7	9.264648
Run8	7.446289
Run9	7.967622
Run10	6.666425
Average	7.789595
Std.	0.922907
Median	7.651078



Rosenbrock d50

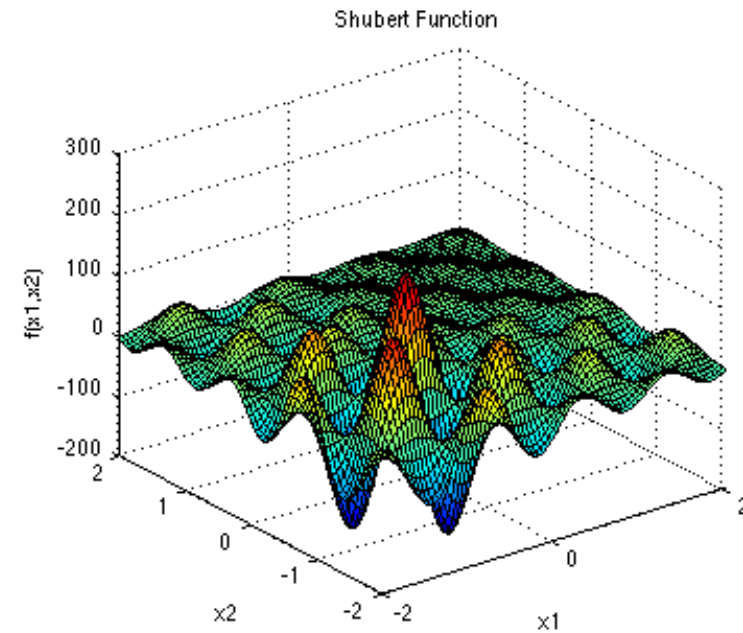
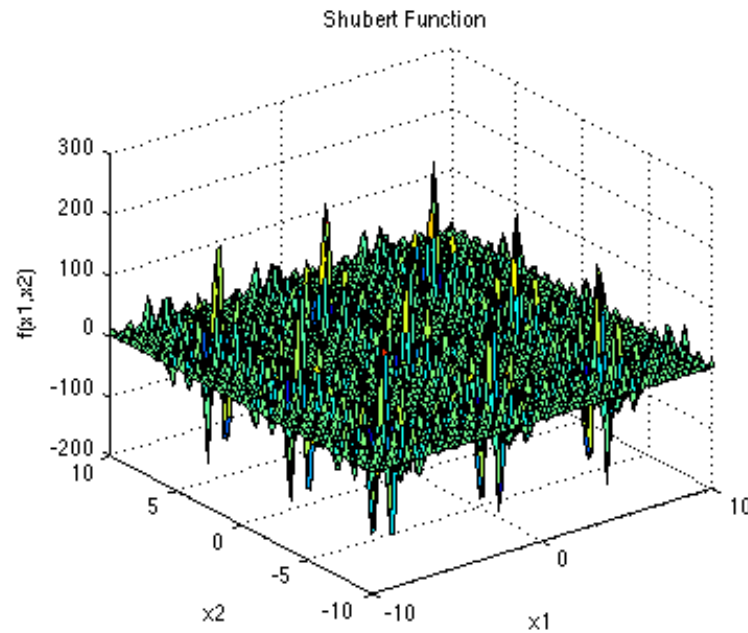
	f
Run1	222.6451
Run2	1079.161
Run3	1003.654
Run4	519.3808
Run5	916.0565
Run6	611.9465
Run7	644.763
Run8	1810.185
Run9	1041.664
Run10	2567.793
Average	1041.725
Std.	649.9294
Median	959.8552



Shubert – Multimodal, unconstrained

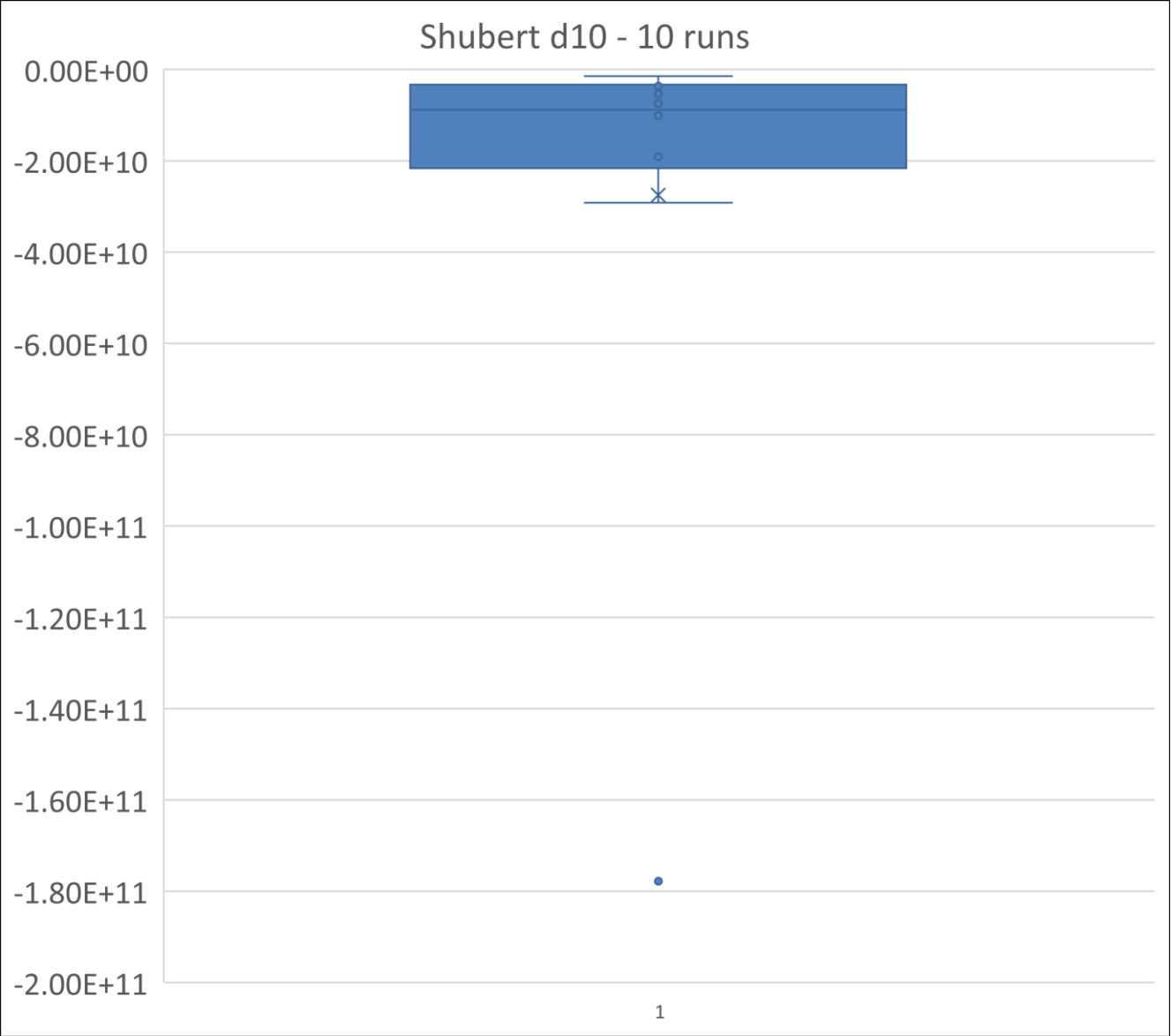
$$f(\mathbf{x}) = \prod_{i=1}^d \sum_{j=1}^5 j \cos((j+1)x_i + j)$$

$x \in [-5.12, 5.12]$; $d = \# \text{ variables}$



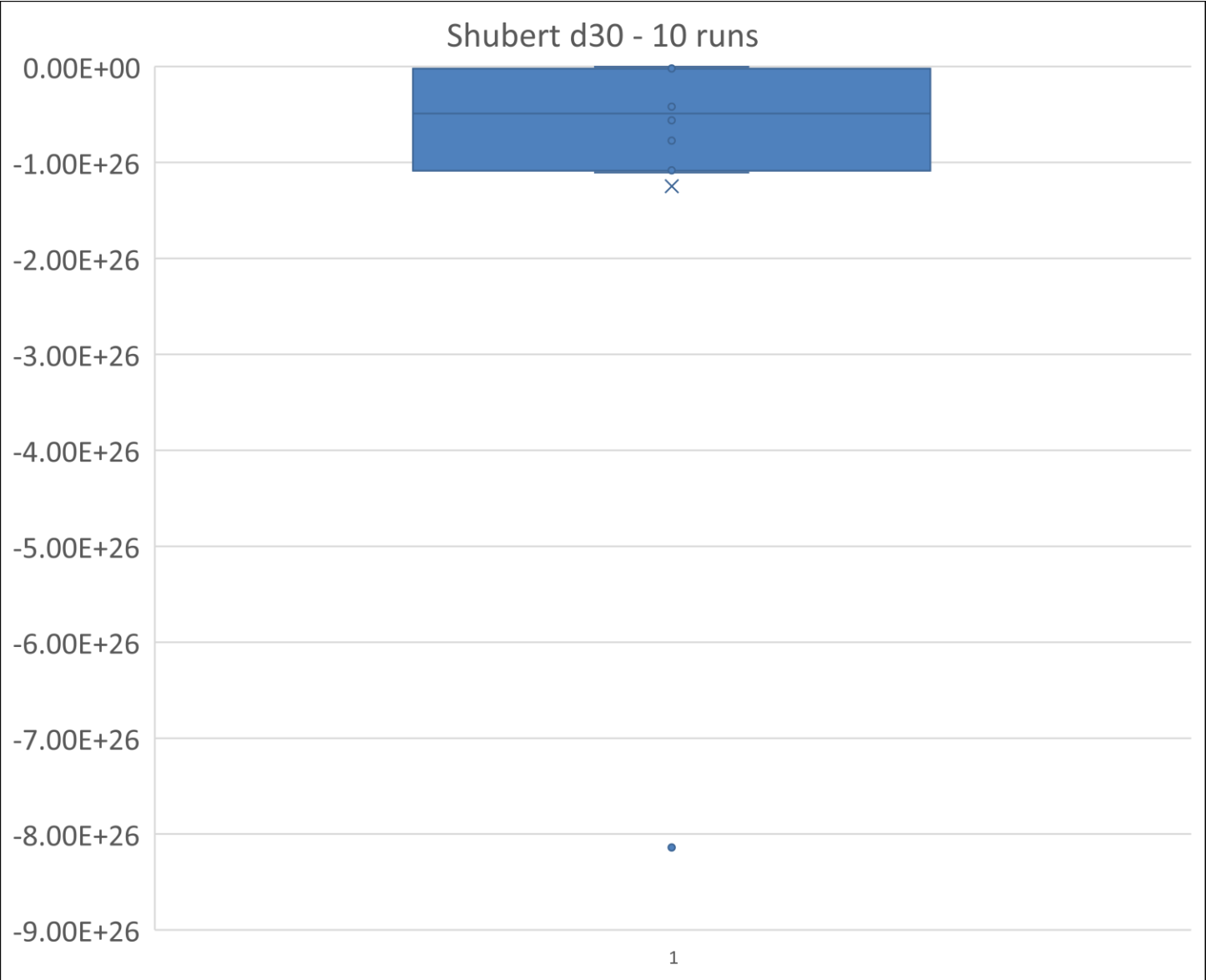
Shubert d10

	f
Run1	-1.78E+11
Run2	-1.91E+10
Run3	-7.51E+09
Run4	-5.38E+09
Run5	-1.86E+10
Run6	-1.01E+10
Run7	-3.66E+09
Run8	-2.92E+10
Run9	-1.47E+09
Run10	-2.17E+09
Average	-2.75E+10
Std.	5.08E+10
Median	-8.81E+09



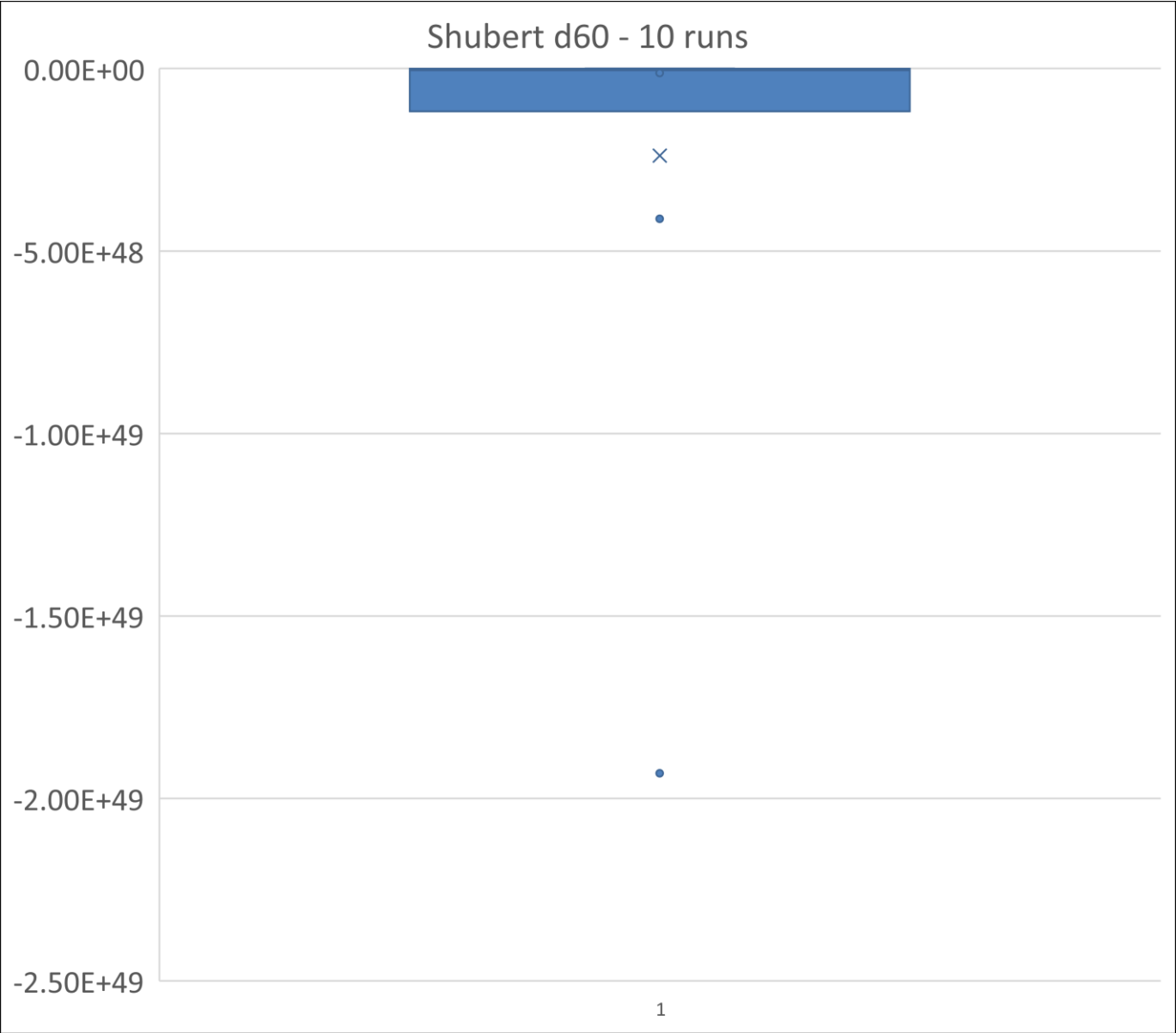
Shubert d30

	f
Run1	-7.72E+25
Run2	-4.18E+25
Run3	-5.61E+25
Run4	-1.08E+26
Run5	-2.08E+24
Run6	-1.59E+23
Run7	-1.64E+24
Run8	-8.14E+26
Run9	-3.59E+25
Run10	-1.10E+26
Average	-1.25E+26
Std.	2.33E+26
Median	-4.89E+25



Shubert d60

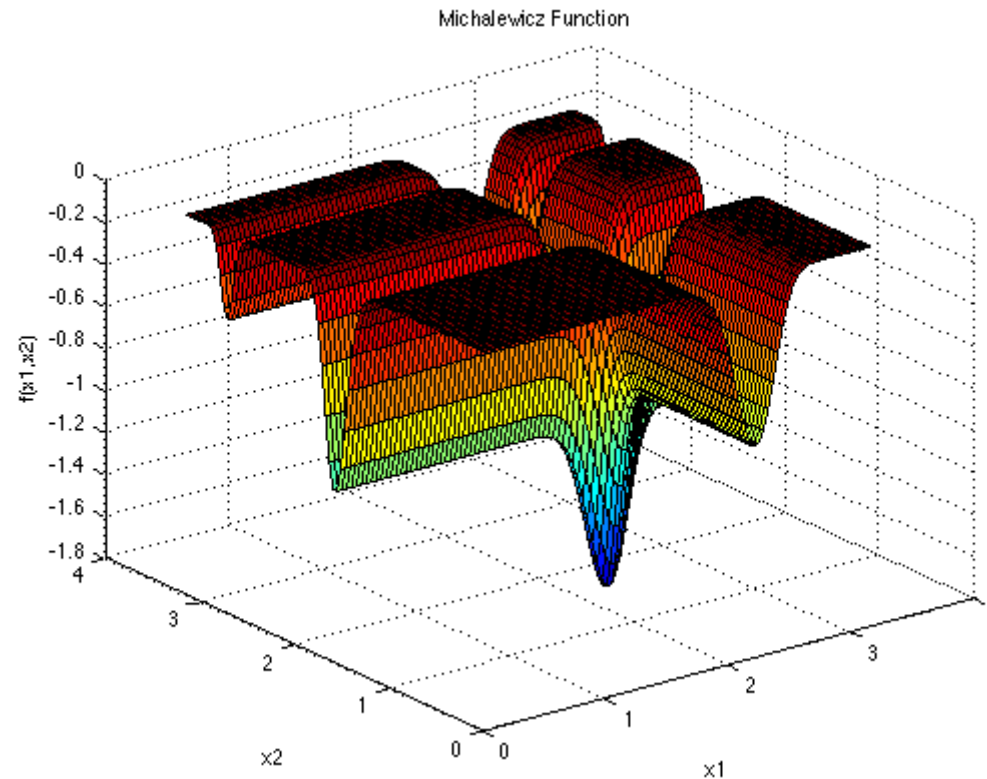
	f
Run1	-4.12E+48
Run2	-1.89E+47
Run3	-3.19E+45
Run4	-7.48E+46
Run5	-8.24E+43
Run6	-3.85E+45
Run7	-1.93E+49
Run8	-1.18E+47
Run9	-2.45E+46
Run10	-1.02E+45
Average	-2.38457E+48
Std.	5.77208E+48
Median	-4.96167E+46



Michalewicz – Ill-Shaped, unconstrained

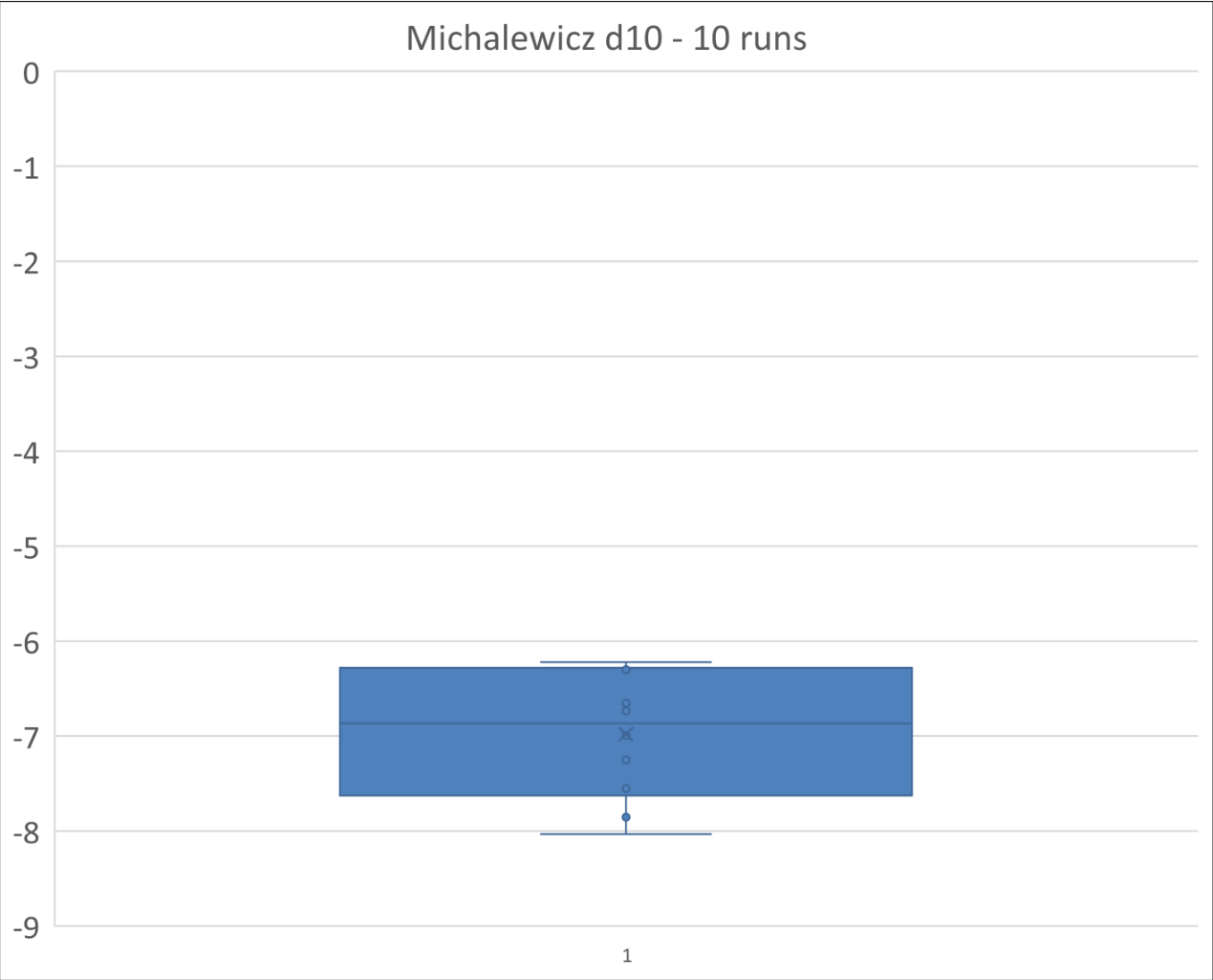
$$f(x) = - \sum_{i=1}^d \sin(x_i) \sin^{2m}\left(\frac{ix_i^2}{\pi}\right)$$

$m = 10; x \in [0, \pi]; d = \# \text{ of variables}$



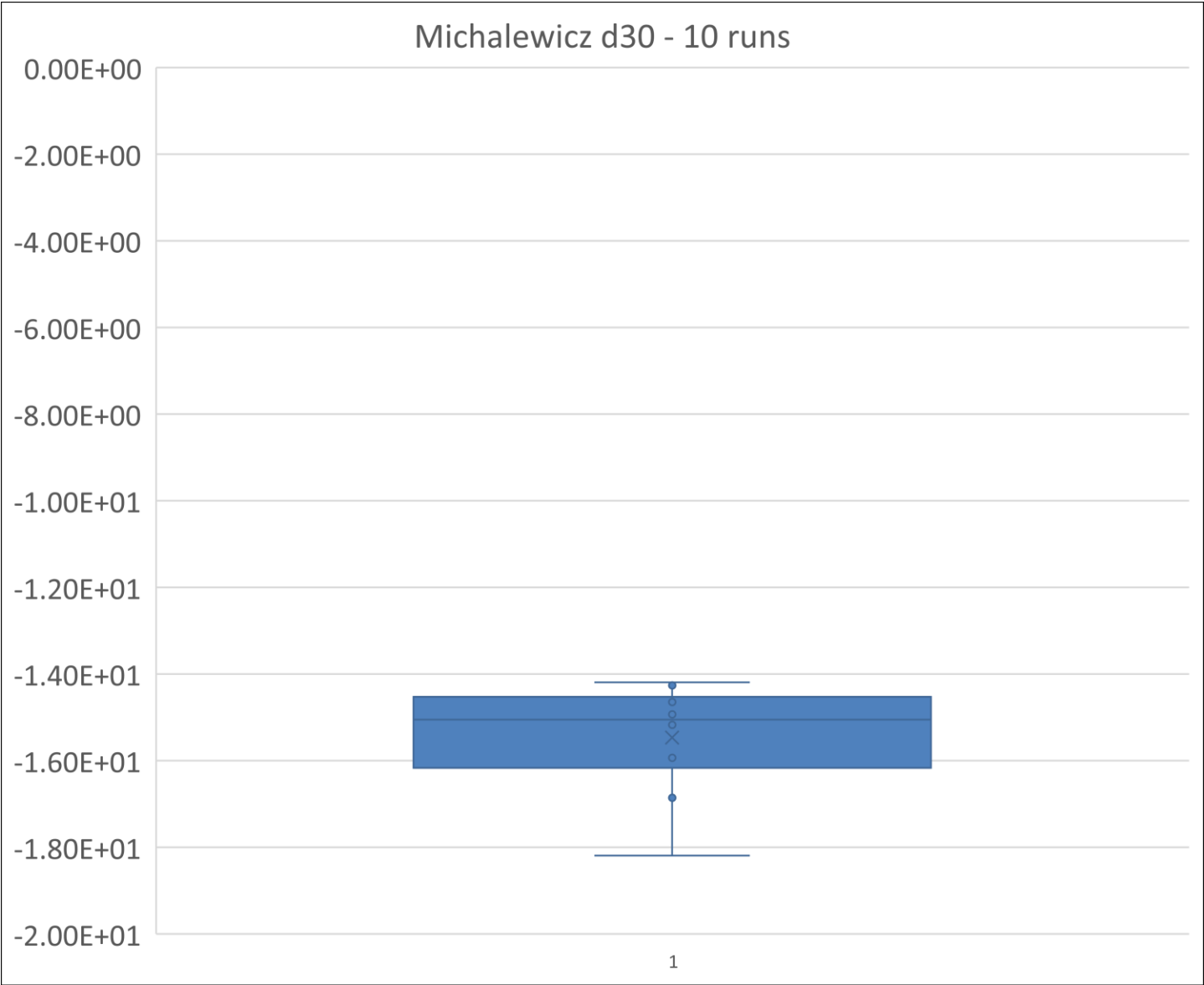
Michalewicz d10

	f
Run1	-7.852177076
Run2	-6.228031066
Run3	-6.734286674
Run4	-6.995044189
Run5	-8.032482593
Run6	-7.249619292
Run7	-6.654006129
Run8	-6.221074724
Run9	-7.551919436
Run10	-6.300118156
Average	-6.98E+00
Std.	6.36E-01
Median	-6.86E+00



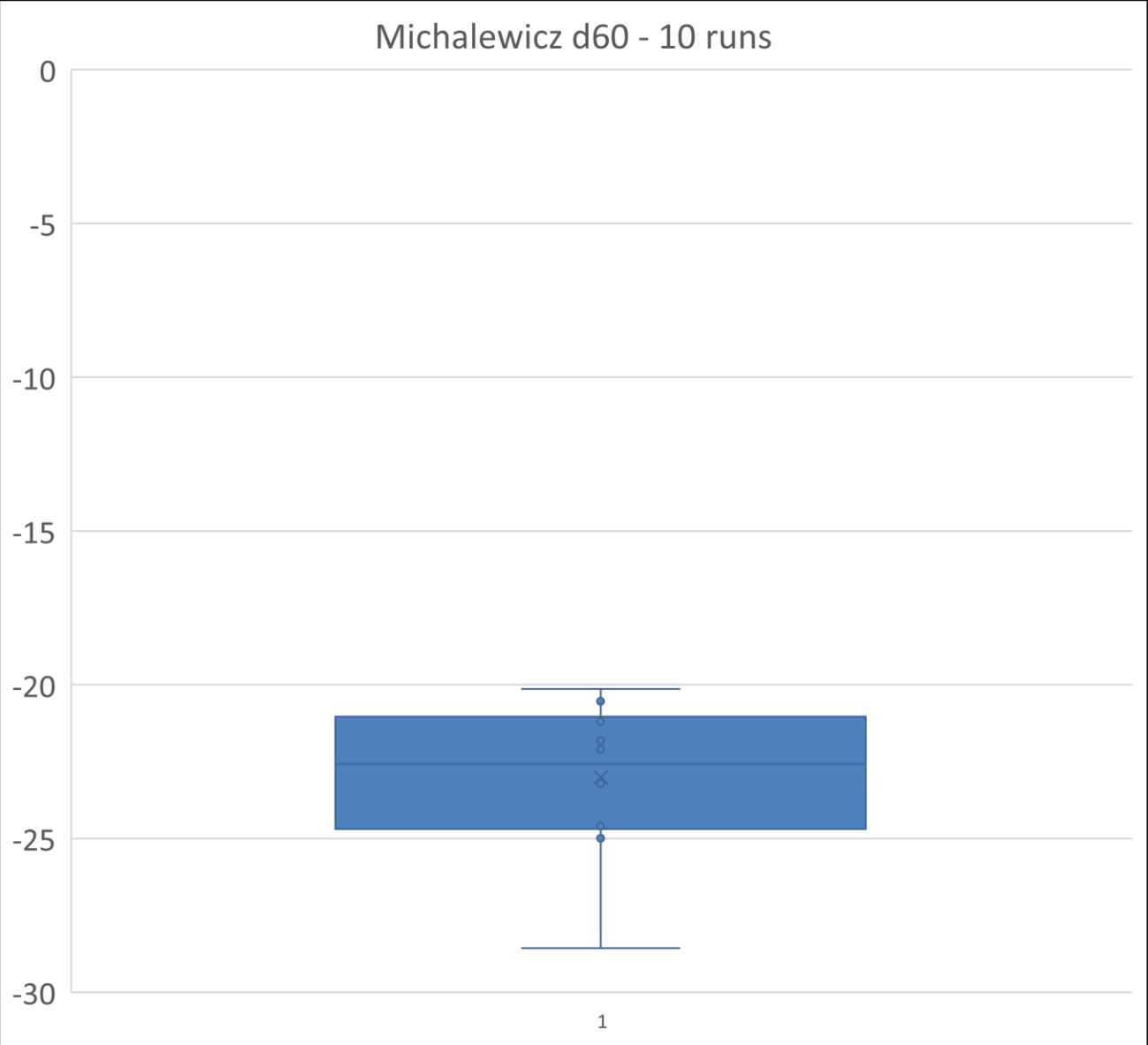
Michalewicz d30

	f
Run1	-15.88286757
Run2	-14.93024264
Run3	-15.93429641
Run4	-18.19228998
Run5	-14.26062751
Run6	-15.17177898
Run7	-14.6420262
Run8	-14.19045725
Run9	-16.85251075
Run10	-14.61121646
Average	-1.55E+01
Std.	1.21E+00
Median	-1.51E+01



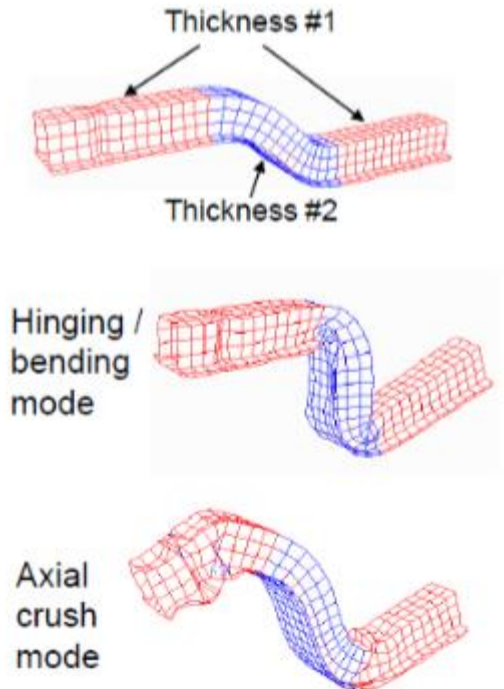
Michalewicz d60

	f
Run1	-23.04826589
Run2	-20.53611678
Run3	-24.985752
Run4	-21.20113662
Run5	-22.10367199
Run6	-20.13743591
Run7	-28.56081134
Run8	-24.59575895
Run9	-23.20783415
Run10	-21.81380351
Average	-23.01905872
Std.	2.390931657
Median	-22.57596894



MOPTA08, a multi disciplinary mass minimization problem from GM*

- 124 variables and 68 expensive constraints
- Variables – various thicknesses from car body
- Expensive Constraints – Outputs from Vehicle Simulations
 - Front – side - rear crash,
 - Noise vibration,
 - Durability.
- Based on a real automotive problem
- A challenging, tightly constrained problem

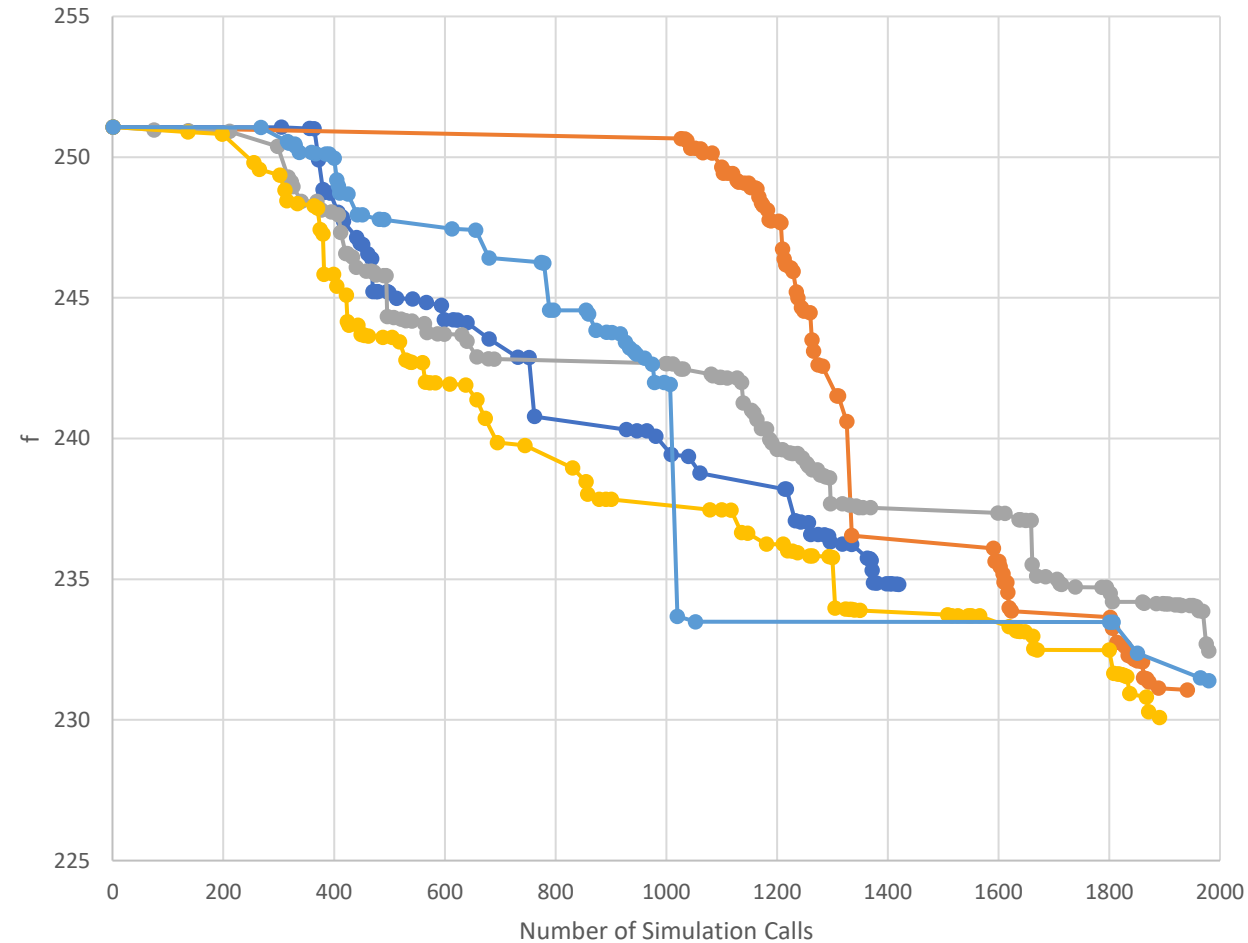


**Large-Scale Multi-Disciplinary Mass Optimization in the Auto Industry, Don Jones, MOPTA 2008 Conference, 2008*

Mopta08 - OASIS AI Accelerator Results



Mopta08 - OASIS AI Accelerator, 5 runs, Budget 2000,
Convergence Plot Feasible Designs



- WIP results by OASIS AI Accelerator, a R&D project to enhance OASIS AI robustness.

Thank You!

