VEHICLE DYNAMICS IN PRACTICE: SELECTION OF THE BEST CMA-ES CONFIGURATION

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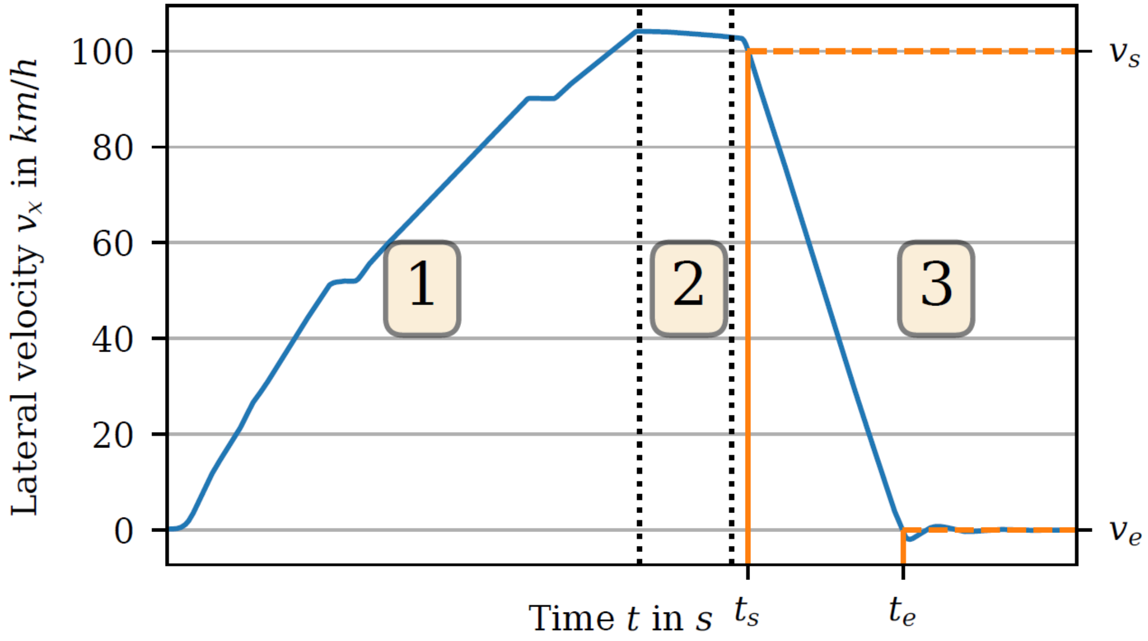
REAL-WORLD PROBLEM

emergency straight-line full-stop braking maneuver



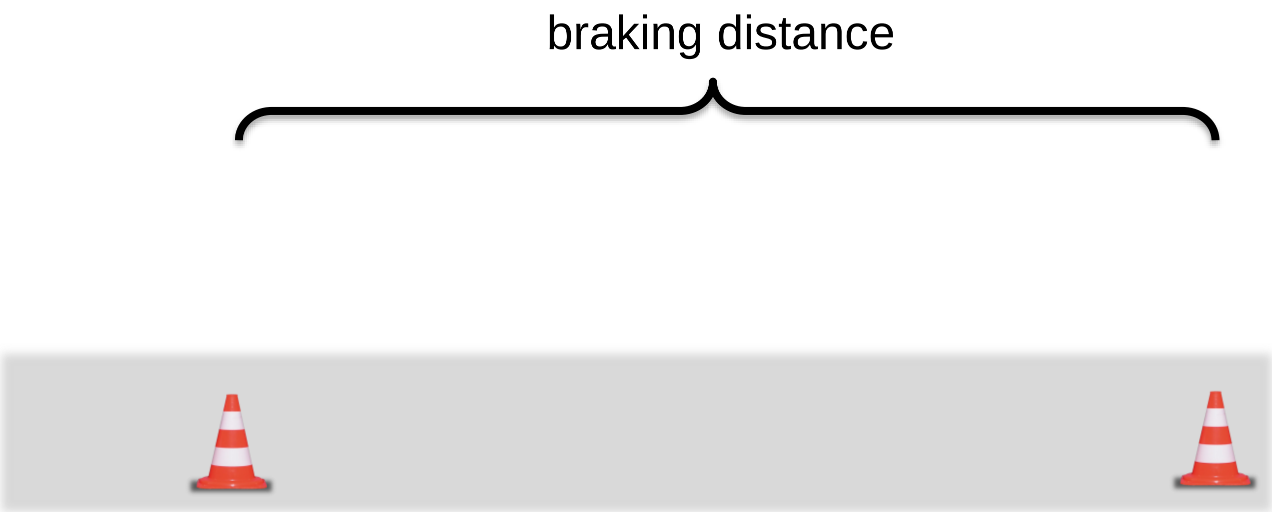
Maneuver phases

1) Acceleration of vehicle to 103.5 km/h
2) No acceleration or deceleration until 103 km/h
3) Applying brakes until vehicle stop

Average braking distance $y = \frac{1}{10}\sum_{k=1}^{10}\int_{t_s}^{t_e} v(t)dt$

$$\underset{x \in X}{\text{minimize}}\, y(x), \qquad X = \{x \in \mathbb{R}^2 : B_{lb} \leq x \leq B_{ub}\}$$

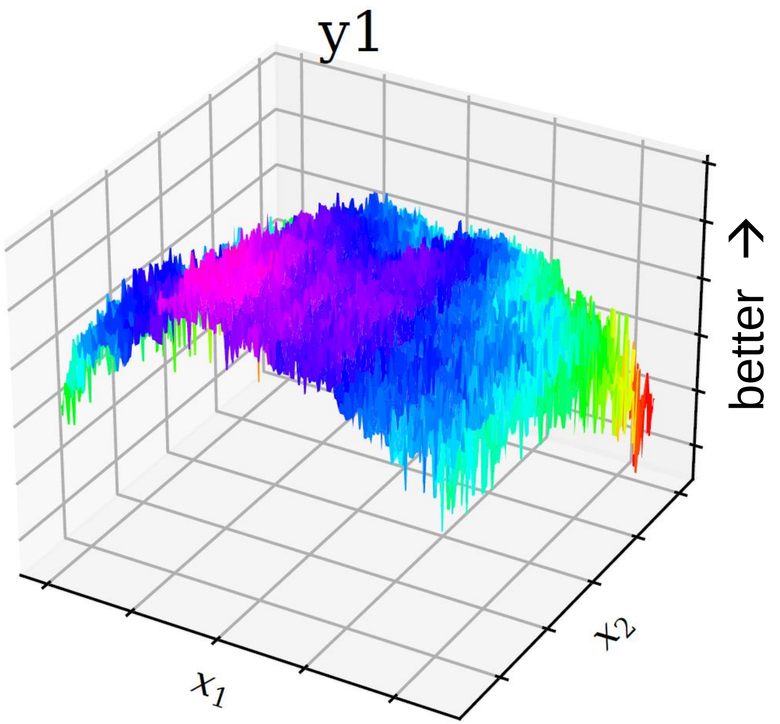
SIMULATION



over
100 000
simulations

brute force

2 weeks
(50 parallel)



Simulation Information

- Two-track model (16 degrees of freedom)
- Tire model MF-Swift (Pacejka's Magic Formula)*
- Control systems Anti-lock Braking System (ABS)

$$\underset{x \in X}{\text{minimize}}\, y(x), X = \{x \in \mathbb{R}^2 : B_{lb} \leq x \leq B_{ub}\}$$

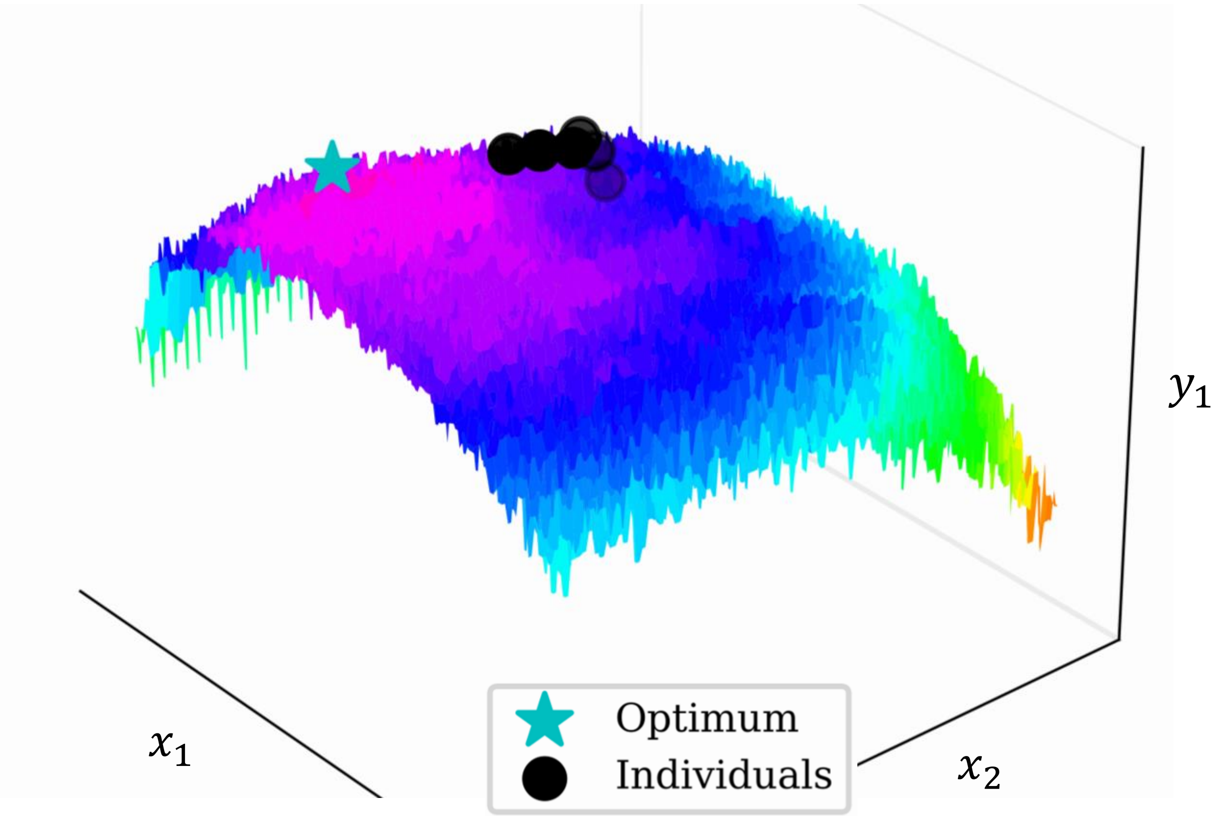
Vehicle Settings

Name	Tires	Vehicle Load
y1	High performance	Partially loaded
y2	Medium performance	Partially loaded
y3	Under performance	Partially loaded
y4	High performance	Fully loaded
y5	High performance	Little loaded

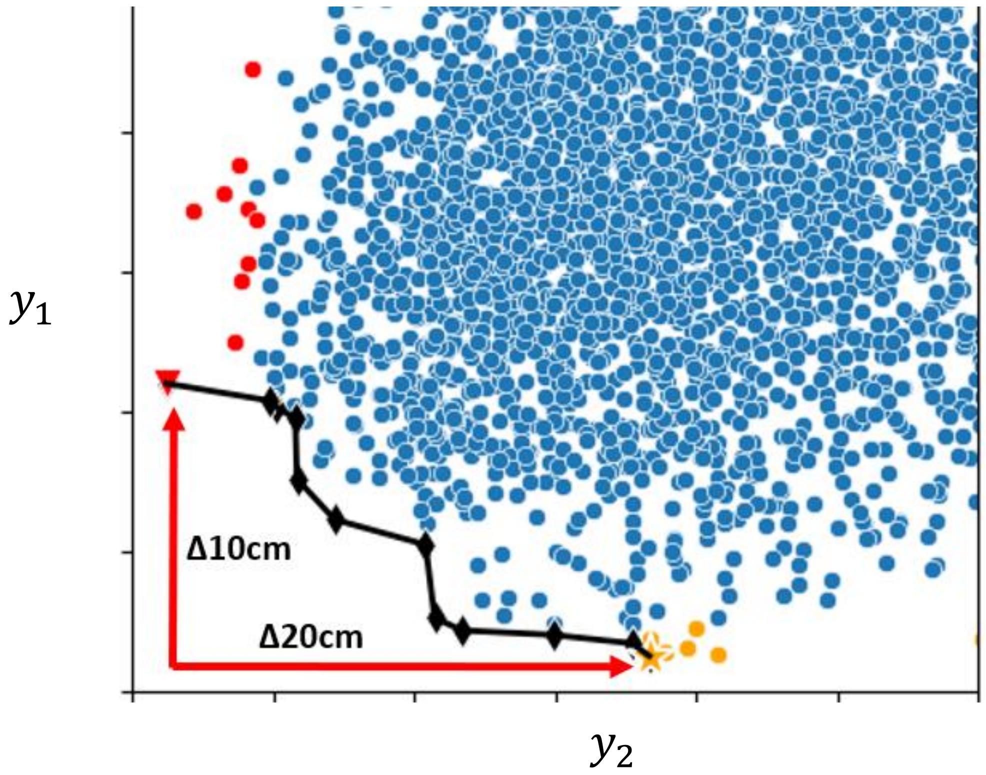
*Siemens Digital Industries Software. 2020. Tire Simulation & Testing. https://www.plm.automation.siemens.com/global/en/products/simulationtest/ tire-simulation-testing.html

DATA AS BENCHMARK PROBLEMS

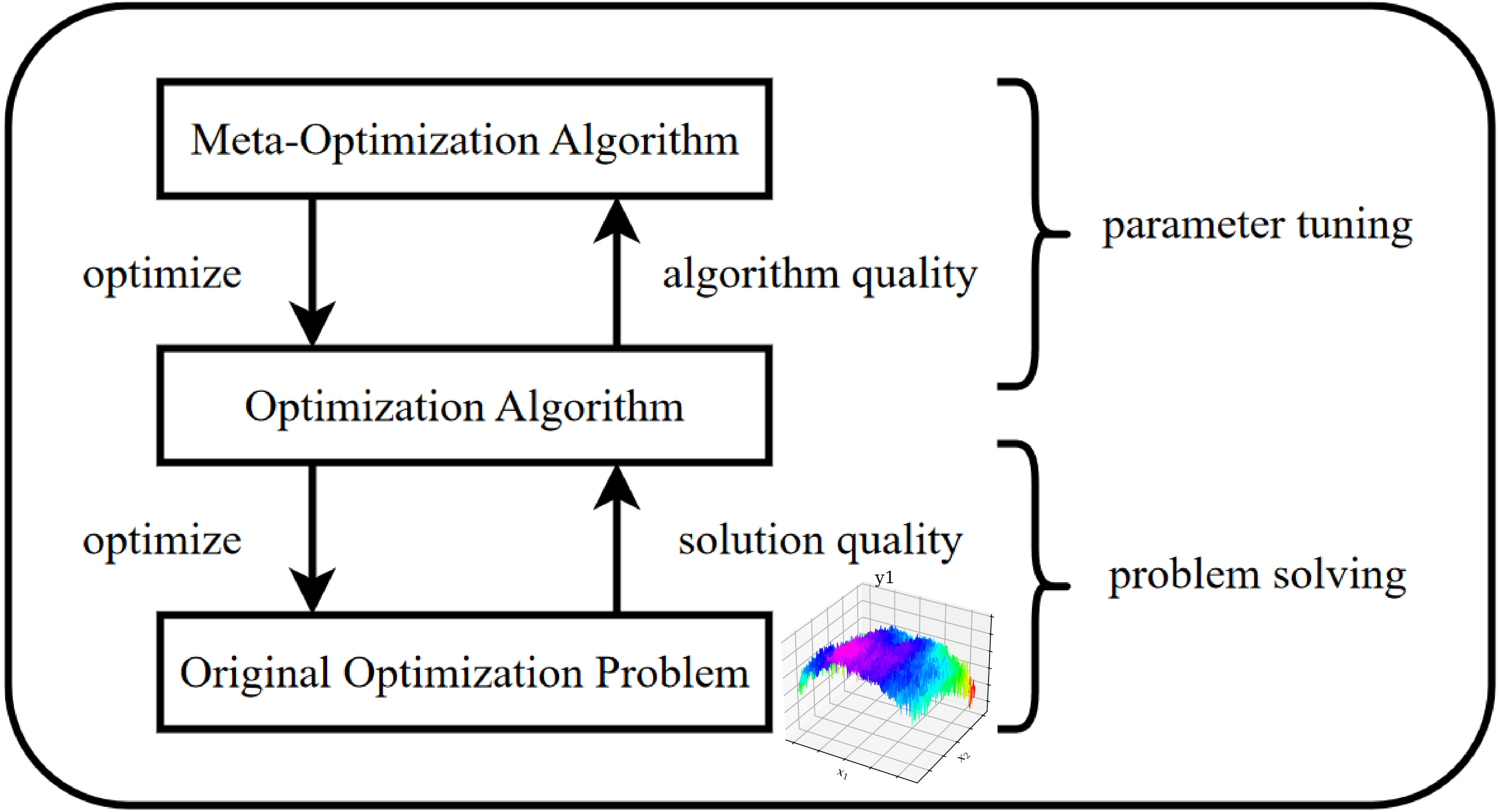
CMA-ES run (without further simulation)



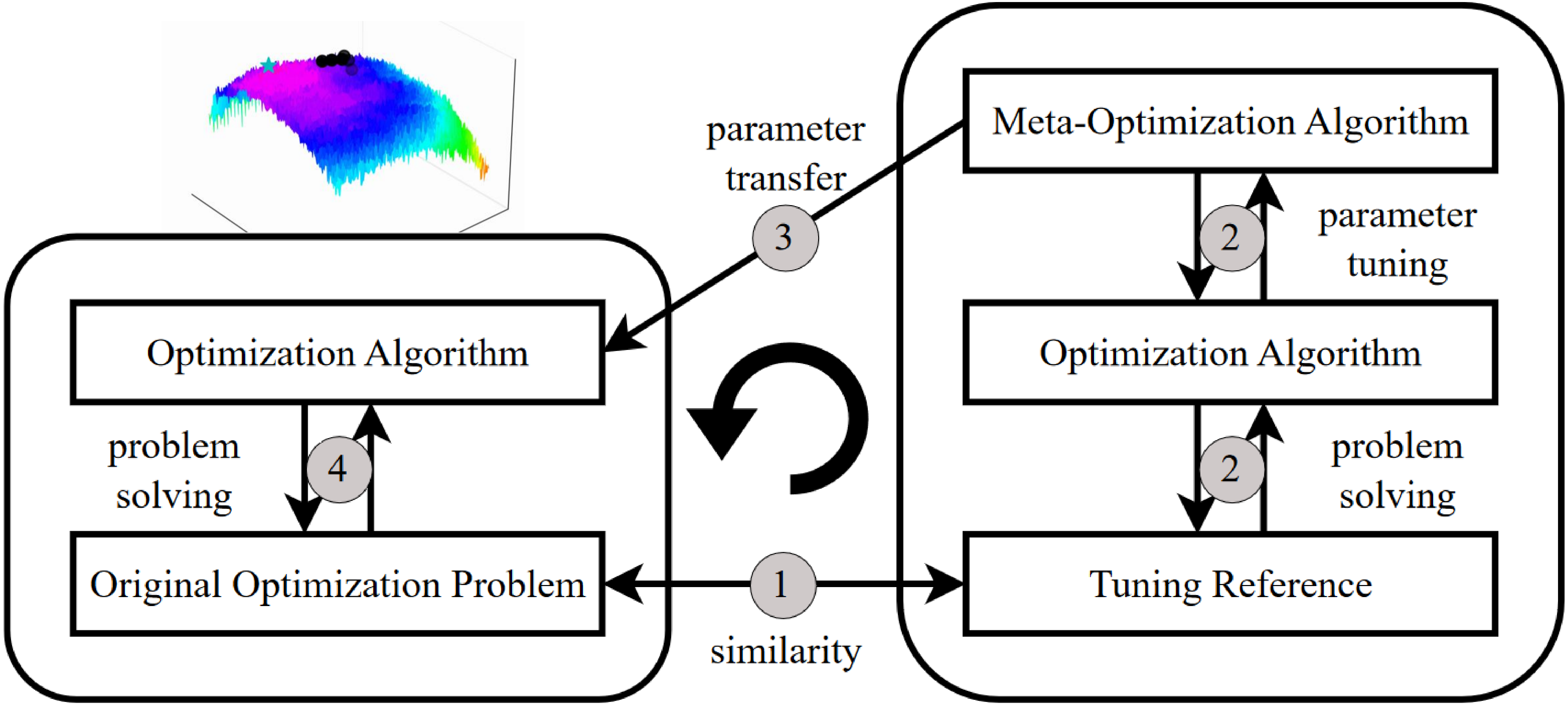
Multi-objective – Pareto Front



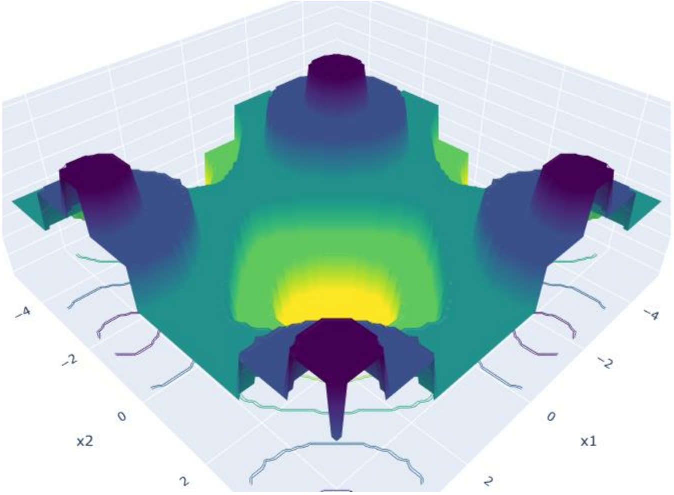
PARAMTER TUNING

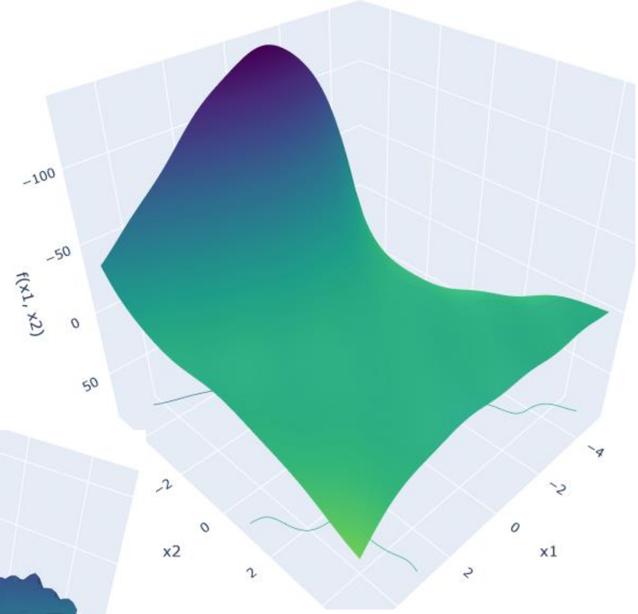


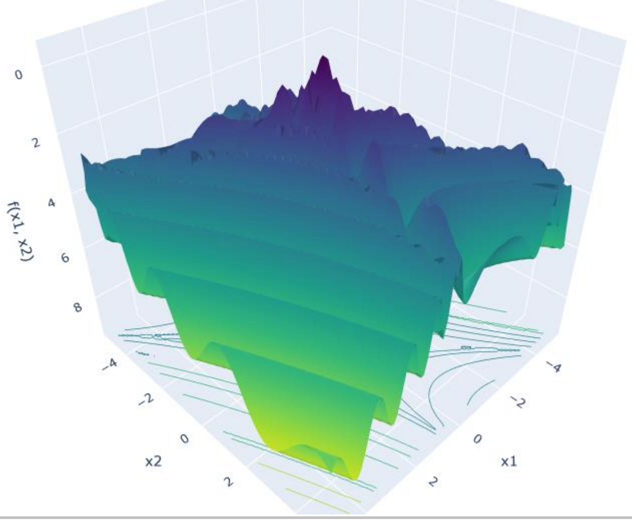
PARAMTER TUNING - TRANSFER



ARTIFICIAL FUNCTION GENERATOR*



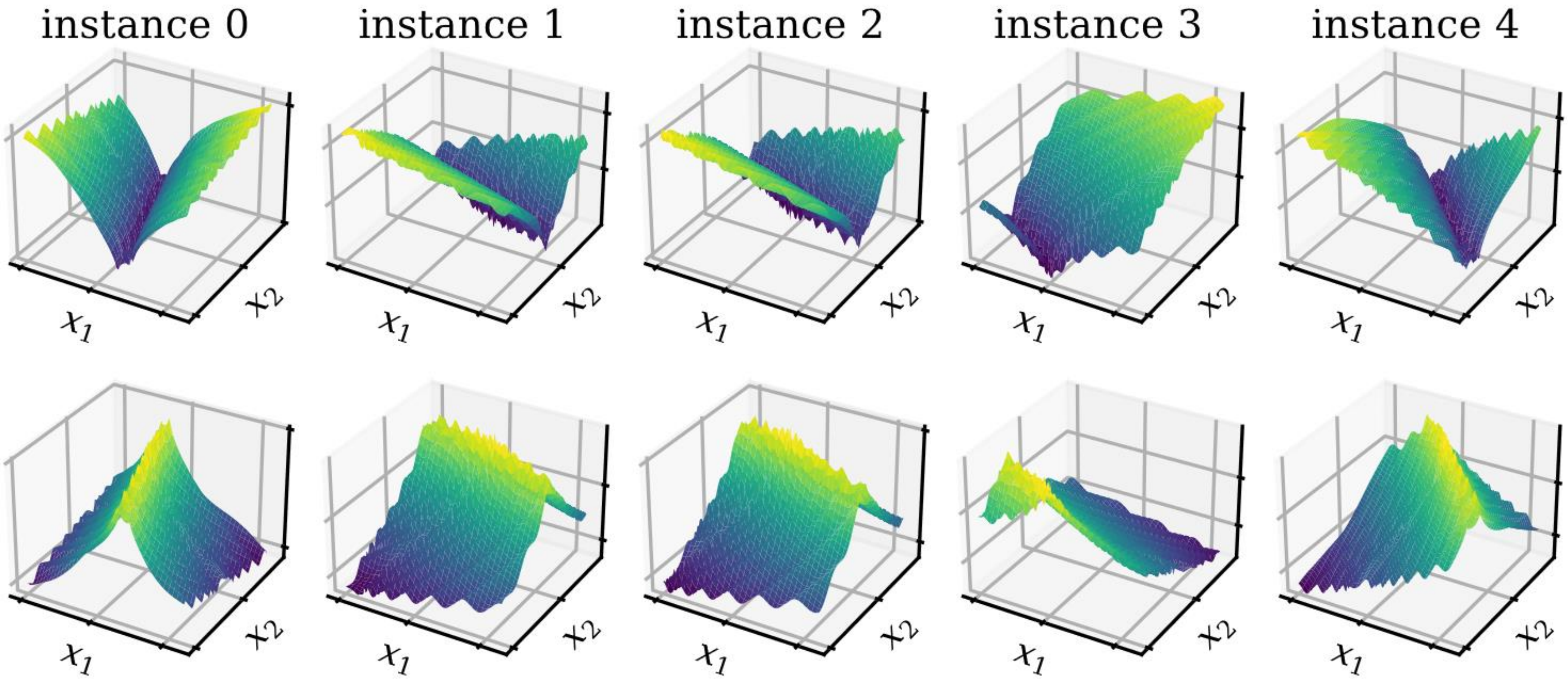




Notation	Meaning	Syntax
	Numbers	
a	A real constant	a
rand	A random number	$rand$
	Decision variables	
x	Decision vector	$(x_1, \dots, x_d)$
x1	First variable	x_1
xt	Translated decision vector	$(x_2, \dots, x_d, 0)$
xr	Rotated decision vector	$\mathbf{xr}$
index	Index vector	$(1, \dots, d)$
	Binary operators	
add	Addition	$a + x$
sub	Subtraction	$a - x$
mul	Multiplication	$a \cdot x$
div	Division	a/x
	Unary operators	
neg	Negative	$-x$
rec	Reciprocal	$1/x$
multen	Multiplying by ten	$10x$
square	Square	x^2
sqrt	Square root	$\sqrt{\|x\|}$
abs	Absolute value	$\|x\|$
exp	Exponent	e^x
log	Logarithm	$\ln \|x\|$
sin	Sine	$\sin(2\pi x)$
cos	Cosine	$\cos(2\pi x)$
round	Rounded value	$\lceil x \rceil$
	Vector-oriented operators	
sum	Sum of vector	$\sum_{i=1}^{d} x_i$
mean	Mean of vector	$\frac{1}{d}\sum_{i=1}^{d} x_i$
cum	Cumulative sum of vector	$(\sum_{i=1}^{1} x_i, \dots, \sum_{i=1}^{d} x_i)$
prod	Product of vector	$\prod_{i=1}^{d} x_i$
max	Maximum value of vector	$\max_{i=1,\dots,d} x_i$

*Tian et al. A Recommender System for Metaheuristic Algorithms for Continuous Optimization Based on Deep Recurrent Neural Networks

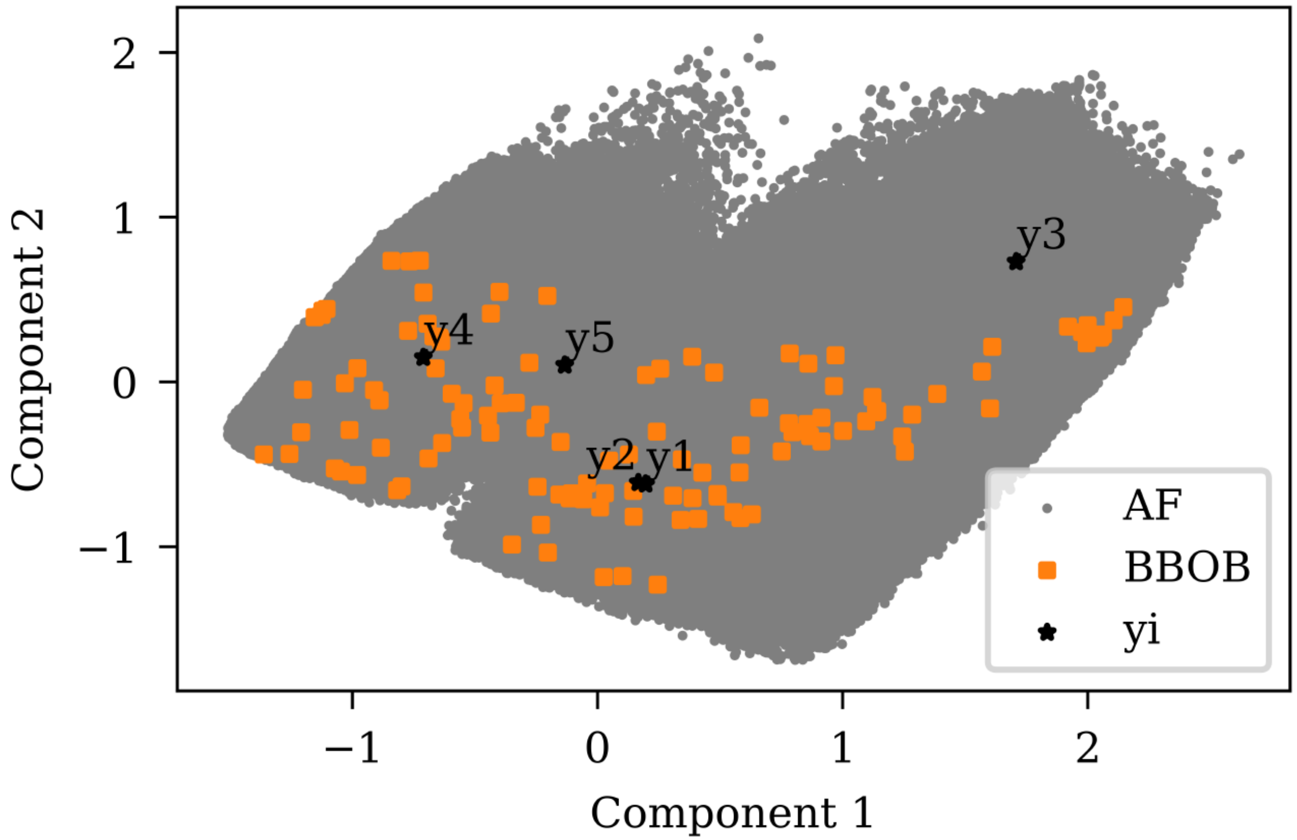
ARTIFICIAL FUNCTIONS



10^5 artificial functions (AF), 5 instance by rotation & shifting, inverse function (* -1) ➔ $\mathbf{10^6}$ **different AF**

EXPLORATORY LANDSCAPE ANALYSIS

Principal component analysis



Features

- 55 features (calculated with pflacco)
- 1000 samples
- PCA → dimensionality 31

Similarity of two problems p_1 and p_2:

$$d(p_1, p_2) = \left\| F_{p_1} - F_{p_2} \right\|_2$$

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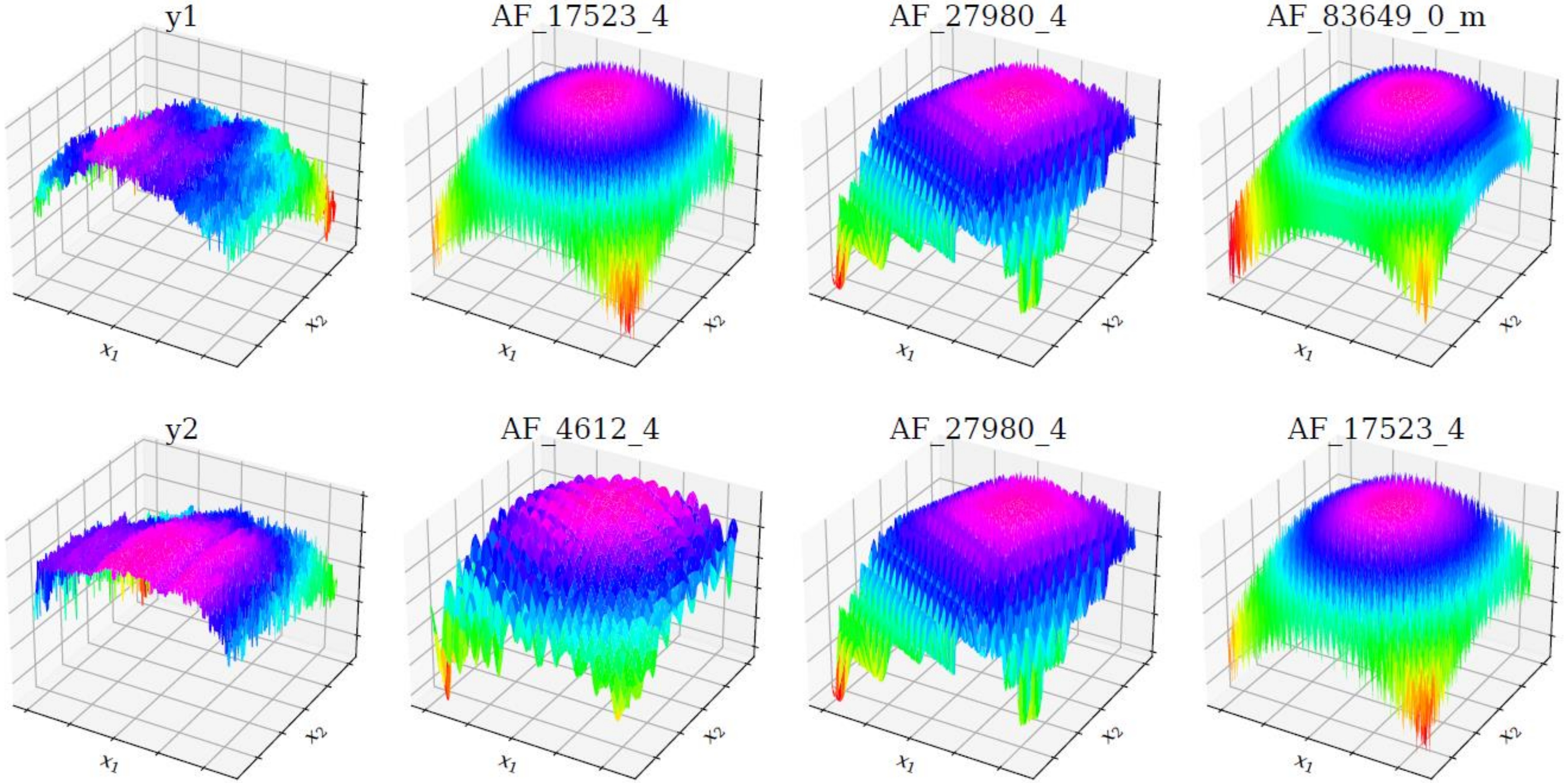
Similarity

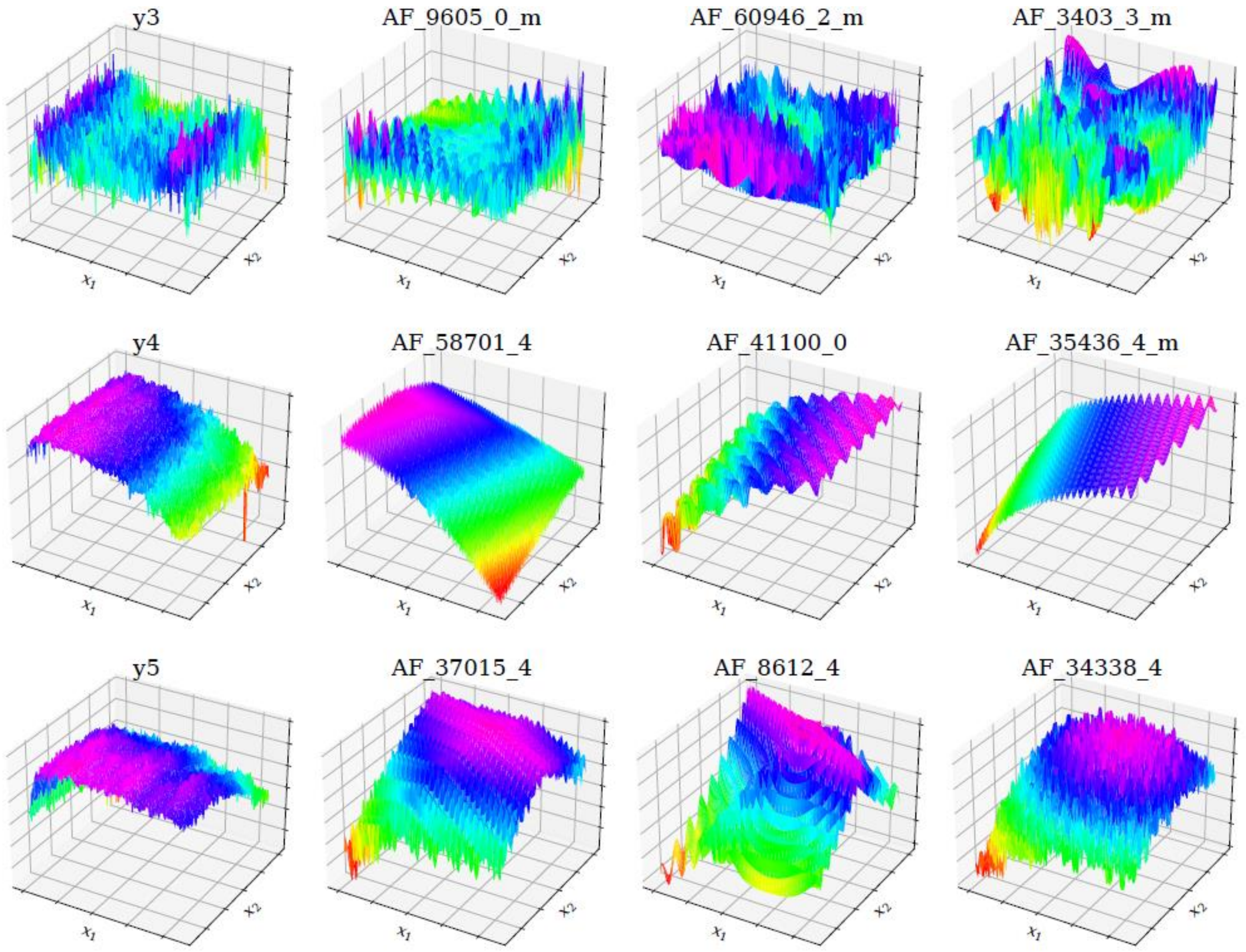
	$y1$	$y2$	$y3$	$y4$	$y5$
$y1$	0	0.84	6.3	4.3	4.2
$y2$	0.84	0	6.4	4.2	4.3
$y3$	6.3	6.4	0	6	6
$y4$	4.3	4.2	6	0	2.6
$y5$	4.2	4.3	6	2.6	0
$AF_{sim,1}$	0.95	1.1	1	0.74	1.3
$AF_{sim,2}$	1.1	1.2	1.1	0.91	1.4
$AF_{sim,3}$	1.1	1.2	1.2	1	1.4
$BBOB_{sim}$	2	2	2.9	2.3	2.6
Sphere	5.1	5.1	7.1	4.2	4.6

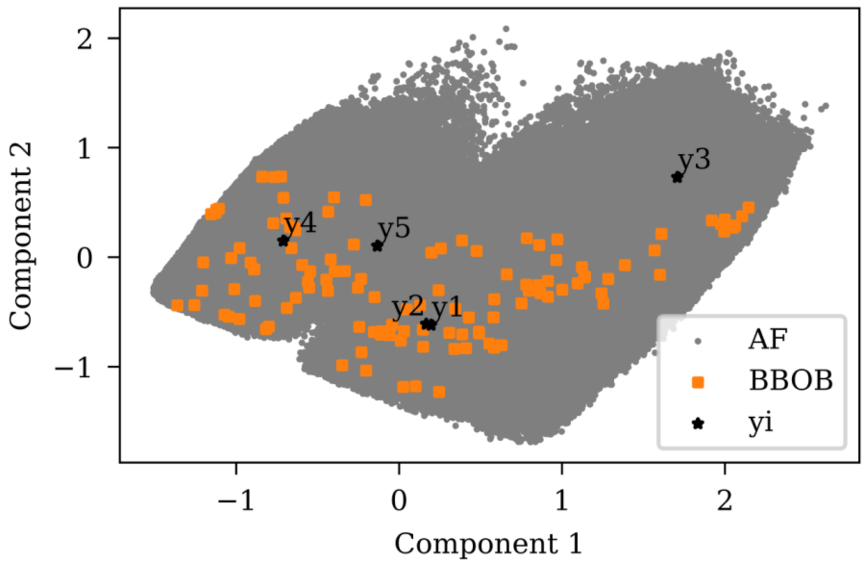
Name	Most similar BBOB Function
y1	Büche-Rastrigin Function f_4
y2	Büche-Rastrigin Function f_4
y3	Weierstrass Function f_{16}
y4	Rastrigin Function f_3
y5	Rastrigin Function f_3

SIMILAR FUNCTIONS



SIMILAR FUNCTIONS





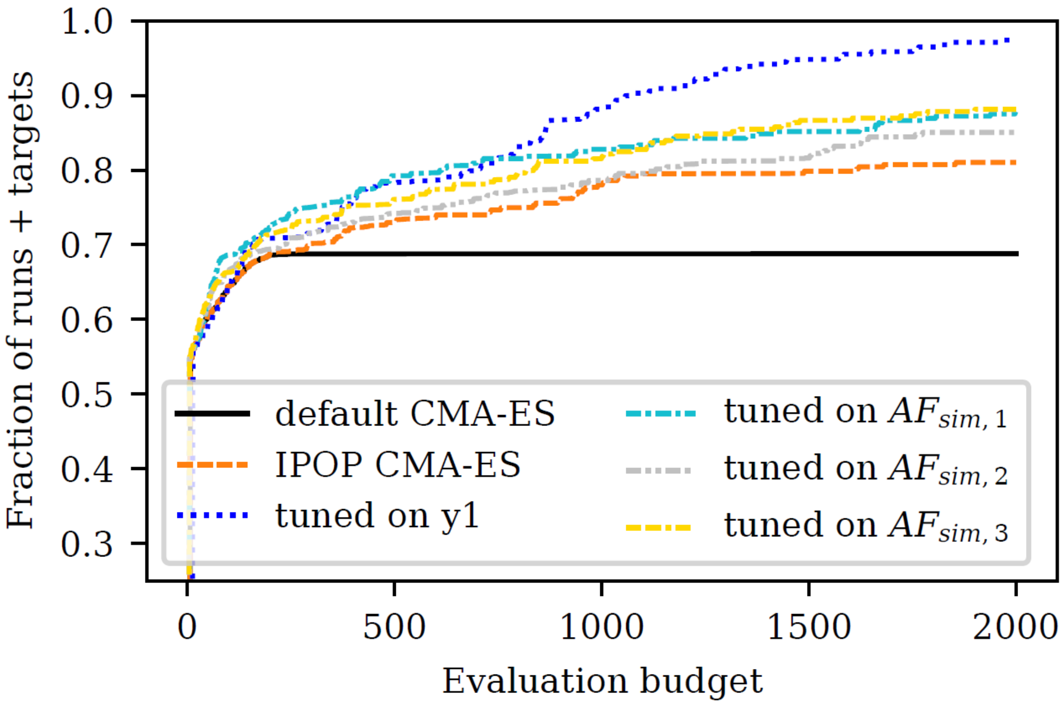
HYPERPARAMETER SPACE

Hyperparameter	Description	Space
λ	Number of children derived from parents	$\{4,6,..,20\}$
μ_r	Ratio of parents selected from population	$\{0.2,0.3,..,0.8\}$
σ_0	Initial standard deviation	$\{0.1,0.2,..,0.9\}$
Bound correction	Correction if individual out of bounds	{saturate, unif, COTN, toroidal, mirror}
Active update	Covariance matrix update variation	{on, off}
Elitism	Strategy of the evolutionary algorithm	$\{(\mu,\lambda),(\mu+\lambda)\}$
Mirrored sampling	Mutations are the mirror image of another	{on, off}
Orthogonal	Orthogonal sampling	{on, off}
Threshold	Length threshold for mutation vectors	{on, off}
Weights	Weights for recombination	$\{\text{default, equal}, \frac{1}{2}^{\lambda}\}$
Restart	Local restart of CMA-ES	{off, IPOP, BIPOP}

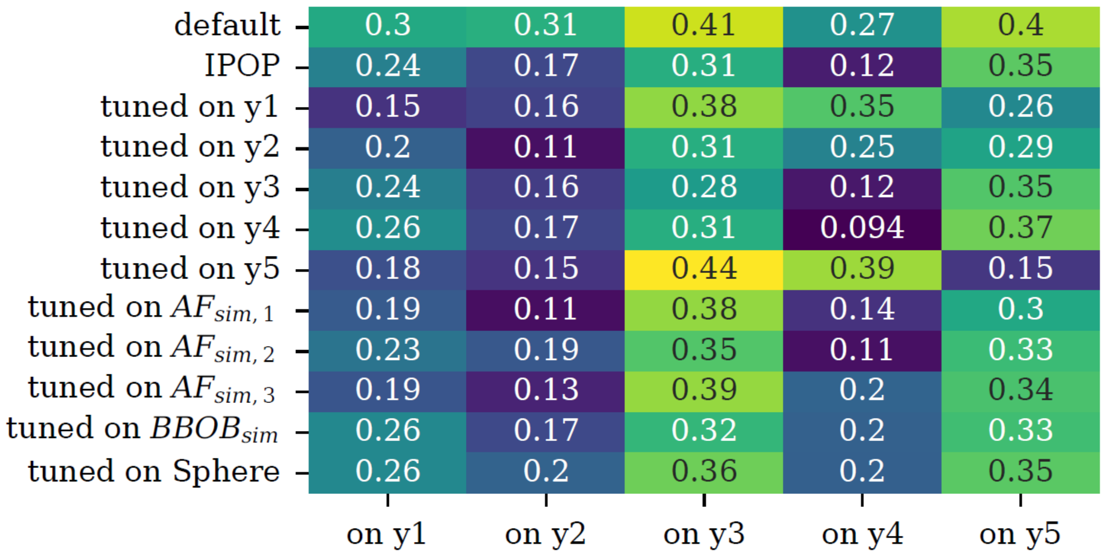
- Algorithm quality - AUC: Area under the ECDF curves (81 target values logarithmically distributed from 10^8 to 10^(−8))
- 100 CMA-ES runs on tuning reference

RESULTS

CMA-ES on real-world problem y1



Average 3 tuning runs per problem



➔ Goal: Minimize 1 - AUC

CONCLUSION

- Changing the vehicle setting changes the problem landscape
- Tuning CMA-ES to similar artificial functions improved performance on the five real-world problems
- Better performance compared to the default CMA-ES configuration, IPOP CMA-ES, and also to CMA-ES tuned to BBOB functions

Open Questions:

- Is the computational effort for computing the ELA justified?
- Does tuning on several similar functions increase the robustness?