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Ye, F.

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Acronyms

AC Algorithm Configuration

AS Algorithm Selection

AUC Area Under the empirical cumulative distribution function Curve

BDA Best Dynamic Algorithm selection policy

BSA Best Static Algorithm

COCO COmparing Continuous Optimizers

DoE Design of Experiment

dynAS dynamic Algorithm Selection

EC Evolutionary Computation

ECDF Empirical Cumulative Distribution Function

EDA Estimation of Distribution Algorittm

ERT Expected Running Time

ES Evolution Strategy

Acronyms

fGA fast Genetic Algorithm

GA Genetic Algorithm

gHC greedy Hill Climber

GP Genetic Programming

GS Grid Search

IOH Iterative Optimization Heuristic

MIES Mixed Integer Evolution Strategies

MIP-EGO Mixed-Integer Parallel Efficient Global Optimization

PBO Pseudo-Boolean Optimization

RLS Randomized Local Search

SMAC Sequential Model-based Algorithm Configuration

UMDA Univariate Marginal Distribution Algorithm

vGA vanilla Genetic Algorithm