Benchmarking discrete optimization heuristics: from building a sound experimental environment to algorithm configuration
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Bibliography

[1] Peyman Afshani, Manindra Agrawal, Benjamin Doerr, Carola Doerr, Kasper Green Larsen, and Kurt Mehlhorn. The query complexity of a permutation-based variant of mastermind. *Discrete Applied Mathematics*, 2019.

[2] Aldeida Aleti and Irene Moser. A systematic literature review of adaptive parameter control methods for evolutionary algorithms. *ACM Computing Surveys*, 49(3):1–35, 2016.

[3] Amine Aziz-Alaoui, Carola Doerr, and Johann Dreo. Towards large scale automated algorithm design by integrating modular benchmarking frameworks. In *Proc. of Genetic and Evolutionary Computation Conference (GECCO'21)*, pages 1365–1374. ACM, 2021.

[4] Thomas Bäck. Parallel optimization of evolutionary algorithms. In *Proc. of Parallel Problem Solving from Nature (PPSN'94)*, pages 418–427. Springer, 1994.

[5] Thomas Bäck. *Evolutionary Algorithms in Theory and Practice: Evolution Strategies, Evolutionary Programming, Genetic Algorithms.* Oxford University Press, USA, 1996.

[6] Thomas Bäck and Sami Khuri. An evolutionary heuristic for the maximum independent set problem. In *Proc. of Conference on Evolutionary Computation (CEC'94)*, pages 531–535. IEEE, 1994.

[7] Thomas Bäck and Martin Schütz. Intelligent mutation rate control in canonical genetic algorithms. In *Proc. of International Symposium on Foundations of Intelligent Systems (ISMIS'96)*, pages 158–167. Springer, 1996.

[8] Golnaz Badkobeh, Per Kristian Lehre, and Dirk Sudholt. Unbiased black-box complexity of parallel search. In *Proc. of Parallel Problem Solving from Nature (PPSN'14)*, pages 892–901. Springer, 2014.

[9] Barrie M Baker and MA Ayechew. A genetic algorithm for the vehicle routing problem. *Computers & Operations Research*, 30(5):787–800, 2003.

[10] Egon Balas and Paolo Toth. *Branch and bound methods for the traveling salesman problem.* Carnegie-Mellon University, 1983.

[11] Francisco Barahona. On the computational complexity of Ising spin glass models. *Journal of Physics A Mathematical General*, 15:3241–3253, 1982.

[12] Thomas Bartz-Beielstein, Carola Doerr, Jakob Bossek, Sowmya Chandrasekaran, Tome Eftimov, Andreas Fischbach, Pascal Kerschke, Manuel Lopez-Ibanez, Katherine M Malan, Jason H Moore, et al. Benchmarking in optimization: Best practice and open issues. *arXiv preprint arXiv:2007.03488*, 2020.

[13] Thomas Bartz-Beielstein, Christian WG Lasarczyk, and Mike Preuß. Sequential parameter optimization. In *Proc. of Congress on Evolutionary Computation (CEC'05)*, pages 773–780. IEEE, 2005.

[14] Maike Basmer and Timo Kehrer. Encoding adaptability of software engineering tools as algorithm configuration problem: A case study. In *Proc. of International Conference on Automated Software Engineering Workshop (ASEW'19)*, pages 86–89. IEEE, 2019.

[15] Jordan Bell and Brett Stevens. A survey of known results and research areas for n-queens. *Discrete Mathematics*, 309(1):1–31, 2009.

[16] Yoshua Bengio. Gradient-based optimization of hyperparameters. *Neural Computation*, 12(8):1889–1900, 2000.

[17] André Biedenkapp, H Furkan Bozkurt, Theresa Eimer, Frank Hutter, and Marius Lindauer. Dynamic algorithm configuration: foundation of a new meta-algorithmic framework. In *Proc. of European Conference on Artificial Intelligence (ECAI'20)*, pages 427–434. IOS Press, 2020.

[18] Mauro Birattari, Zhi Yuan, Prasanna Balaprakash, and Thomas Stützle. F-race and iterated f-race: An overview. *Experimental Methods for the Analysis of Optimization Algorithms*, pages 311–336, 2010.

[19] Endre Boros and Peter L Hammer. Pseudo-boolean optimization. *Discrete Applied Mathematics*, 123(1-3):155–225, 2002.

[20] Jakob Bossek, Pascal Kerschke, and Heike Trautmann. Anytime behavior of inexact tsp solvers and perspectives for automated algorithm selection. In *Proc. of Congress on Evolutionary Computation (CEC'20)*, pages 1–8. IEEE, 2020.

[21] Süntje Böttcher, Benjamin Doerr, and Frank Neumann. Optimal fixed and adaptive mutation rates for the LeadingOnes problem. In *Proc. of Parallel Problem Solving from Nature (PPSN'10)*, pages 1–10. Springer, 2010.

[22] Patrick Briest, Dimo Brockhoff, Bastian Degener, Matthias Englert, Christian Gunia, Oliver Heering, Thomas Jansen, Michael Leifhelm, Kai Plociennik, Heiko Röglin, et al. The Ising model: Simple evolutionary algorithms as adaptation schemes. In *Proc. of Parallel Problem Solving from Nature (PPSN'04)*, pages 31–40. Springer, 2004.

[23] Nathan Buskulic and Carola Doerr. Maximizing drift is not optimal for solving onemax. In *Proc. of Genetic and Evolutionary Computation Conference (GECCO'19)*, pages 425–426. ACM, 2019.

[24] Sébastien Cahon, Nordine Melab, and EG Talbi. Paradiseo: A framework for the reusable design of parallel and distributed metaheuristics. *Journal of Heuristics*, 10(3):357–380, 2004.

[25] Eduardo Carvalho Pinto and Carola Doerr. A simple proof for the usefulness of crossover in black-box optimization. In *Proc. of Parallel Problem Solving from Nature (PPSN'18)*, pages 29–41. Springer, 2018.

[26] Marco Cavazzuti. Design of experiments. In *Optimization Methods*, pages 13–42. Springer, 2013.

[27] Francisco Chicano, Andrew M. Sutton, L. Darrell Whitley, and Enrique Alba. Fitness probability distribution of bit-flip mutation. *Evolutionary Computation*, 23(2):217–248, 2015.

[28] David A Cohen, Martin C Cooper, Peter G Jeavons, and Andrei A Krokhin. The complexity of soft constraint satisfaction. *Artificial Intelligence*, 170(11):983–1016, 2006.

[29] Dogan Corus and Pietro Simone Oliveto. Standard steady state genetic algorithms can hillclimb faster than mutation-only evolutionary algorithms. *IEEE Transactions on Evolutionary Computation*, 22(5):720–732, 2018.

[30] Dogan Corus and Pietro Simone Oliveto. On the benefits of populations for the exploitation speed of standard steady-state genetic algorithms. In *Proc. of Genetic and Evolutionary Computation Conference (GECCO'19)*, pages 1452–1460. ACM, 2019.

[31] Duc-Cuong Dang, Tobias Friedrich, Timo Kötzing, Martin S Krejca, Per Kristian Lehre, Pietro S Oliveto, Dirk Sudholt, and Andrew M Sutton. Escaping local optima using crossover with emergent diversity. *IEEE Transactions on Evolutionary Computation*, 22(3):484–497, 2017.

[32] Nguyen Dang and Carola Doerr. Hyper-parameter tuning for the $(1 + (\lambda, \lambda))$ GA. In *Proc. of Genetic and Evolutionary Computation Conference (GECCO'19)*, pages 889–897. ACM, 2019.

[33] Lawrence Davis. Job shop scheduling with genetic algorithms. In *Proc. of International Conference on Genetic Algorithms*, pages 136–140. Lawrence Erlbaum Associates, 1985.

[34] Kenneth Alan De Jong. *An Analysis of the Behavior of a Class of Genetic Adaptive Systems.* PhD thesis, University of Michigan, Ann Arbor, MI, USA, 1975.

[35] Jacob de Nobel, Diederick Vermetten, Hao Wang, Carola Doerr, and Thomas Bäck. Tuning as a means of assessing the benefits of new ideas in interplay with existing algorithmic modules. In *Proc. of Genetic and Evolutionary Computation Conference (GECCO'21), Companion Material*, pages 1375–1384. ACM, 2021.

[36] Marcelo de Souza, Marcus Ritt, Manuel López-Ibáñez, and Leslie Pérez Cáceres. Acviz: A tool for the visual analysis of the configuration of algorithms with irace. *Operations Research Perspectives*, 8:100186, 2021.

[37] Benjamin Doerr. Analyzing randomized search heuristics: Tools from probability theory. In *Theory of Randomized Search Heuristics*, pages 1–20. World Scientific Publishing, 2011.

[38] Benjamin Doerr. Better runtime guarantees via stochastic domination. In *Proc. of Evolutionary Computation in Combinatorial Optimization (EvoCOP'18)*, pages 1–17. Springer, 2018.

[39] Benjamin Doerr. Analyzing randomized search heuristics via stochastic domination. *Theoretical Computer Science*, 773:115–137, 2019.

[40] Benjamin Doerr and Carola Doerr. A tight runtime analysis of the $(1{+}(\lambda,\lambda))$ genetic algorithm on OneMax. In *Proc. of Genetic and Evolutionary Computation Conference (GECCO'15)*, pages 1423–1430. ACM, 2015.

[41] Benjamin Doerr and Carola Doerr. Optimal static and self-adjusting parameter choices for the $(1 + (\lambda, \lambda))$ genetic algorithm. *Algorithmica*, 80:1658–1709, 2018.

[42] Benjamin Doerr and Carola Doerr. Theory of parameter control mechanisms for discrete black-box optimization: Provable performance gains through dynamic parameter choices. In Benjamin Doerr and Frank Neumann, editors, *Theory of Randomized Search Heuristics in Discrete Search Spaces*. Springer, 2019.

[43] Benjamin Doerr, Carola Doerr, and Franziska Ebel. From black-box complexity to designing new genetic algorithms. *Theoretical Computer Science*, 567:87–104, 2015.

[44] Benjamin Doerr, Carola Doerr, and Timo Kötzing. Unknown solution length problems with no asymptotically optimal run time. In *Proc. of Genetic and Evolutionary Computation Conference (GECCO'17)*, pages 1367–1374. ACM, 2017.

[45] Benjamin Doerr, Carola Doerr, and Jing Yang. Optimal parameter choices via precise black-box analysis. In *Proc. of Genetic and Evolutionary Computation Conference (GECCO'16)*, pages 1123–1130. ACM, 2016.

[46] Benjamin Doerr, Christian Gießen, Carsten Witt, and Jing Yang. The $(1 + \lambda)$ evolutionary algorithm with self-adjusting mutation rate. In *Proc. of Genetic and Evolutionary Computation Conference (GECCO'17)*, pages 1351–1358. ACM, 2017.

[47] Benjamin Doerr, Edda Happ, and Christian Klein. Crossover can provably be useful in evolutionary computation. *Theoretical Computer Science*, 425:17–33, 2012.

[48] Benjamin Doerr, Daniel Johannsen, Timo Kötzing, Frank Neumann, and Madeleine Theile. More effective crossover operators for the all-pairs shortest path problem. *Theoretical Computer Science*, 471:12–26, 2013.

[49] Benjamin Doerr, Daniel Johannsen, and Carola Winzen. Multiplicative drift analysis. *Algorithmica*, 64:673–697, 2012.

[50] Benjamin Doerr, Huu Phuoc Le, Régis Makhmara, and Ta Duy Nguyen. Fast genetic algorithms. In *Proc. of Genetic and Evolutionary Computation Conference (GECCO'17)*, pages 777–784. ACM, 2017.

[51] Benjamin Doerr and Frank Neumann. *Theory of Evolutionary Computation: Recent Developments in Discrete Optimization.* Springer, 2020.

[52] Benjamin Doerr and Carola Winzen. Black-box complexity: Breaking the $O(n \log n)$ barrier of LeadingOnes. In *Proc. of International Conference on Artificial Evolution (EA'11)*, pages 205–216. Springer, 2011.

[53] Carola Doerr. Dynamic parameter choices in evolutionary computation. In *Proc. of Genetic and Evolutionary Computation Conference (GECCO'18), Companion Material*, pages 800–830. ACM, 2018.

[54] Carola Doerr, Hao Wang, Furong Ye, Sander van Rijn, and Thomas Bäck. IOHprofiler: A benchmarking and profiling tool for iterative optimization heuristics. *arXiv preprint arXiv:1810.05281*, 2018.

[55] Carola Doerr, Furong Ye, Naama Horesh, Hao Wang, Ofer M Shir, and Thomas Bäck. Benchmarking discrete optimization heuristics with iohprofiler. *Applied Soft Computing*, 88:106027, 2020.

[56] Carola Doerr, Furong Ye, Sander van Rijn, Hao Wang, and Thomas Bäck. Towards a theory-guided benchmarking suite for discrete black-box optimization heuristics: profiling $(1+\lambda)$ EA variants on OneMax and LeadingOnes. In *Proc. of Genetic and Evolutionary Computation Conference (GECCO'18)*, pages 951–958. ACM, 2018.

[57] Devdatt P. Dubhashi and Alessandro Panconesi. *Concentration of Measure for the Analysis of Randomised Algorithms.* Cambridge University Press, 2009.

[58] Juan J Durillo and Antonio J Nebro. jMetal: A Java framework for multi-objective optimization. *Advances in Engineering Software*, 42(10):760–771, 2011.

[59] Tome Eftimov, Gašper Petelin, and Peter Korošec. DSCTool: A web-service-based framework for statistical comparison of stochastic optimization algorithms. *Applied Soft Computing*, 87:105977, 2020.

[60] Katharina Eggensperger, Marius Lindauer, and Frank Hutter. Pitfalls and best practices in algorithm configuration. *Journal of Artificial Intelligence Research*, 64:861–893, 2019.

[61] Agoston Endre Eiben, Robert Hinterding, and Zbigniew Michalewicz. Parameter control in evolutionary algorithms. *IEEE Transactions on Evolutionary Computation*, 3:124–141, 1999.

[62] Hafsteinn Einarsson, Johannes Lengler, Marcelo Matheus Gauy, Florian Meier, Asier Mujika, Angelika Steger, and Felix Weissenberger. The linear hidden subset problem for the (1 + 1) EA with scheduled and adaptive mutation rates. In *Proc. of Genetic and Evolutionary Computation Conference (GECCO'18)*, pages 1491–1498. ACM, 2018.

[63] Saber M Elsayed, Ruhul A Sarker, and Daryl L Essam. Multi-operator based evolutionary algorithms for solving constrained optimization problems. *Computers & Operations Research*, 38(12):1877–1896, 2011.

[64] Thomas Elsken, Jan Hendrik Metzen, and Frank Hutter. Neural architecture search: A survey. *The Journal of Machine Learning Research*, 20(1):1997–2017, 2019.

[65] Simon Fischer and Ingo Wegener. The one-dimensional Ising model: Mutation versus recombination. *Theoretical Computer Science*, 344(2-3):208–225, 2005.

[66] Merrill M Flood. The traveling-salesman problem. *Operations Research*, 4(1):61–75, 1956.

[67] Peter I Frazier. A tutorial on bayesian optimization. *arXiv preprint arXiv:1807.02811*, 2018.

[68] Christian Gießen and Carsten Witt. The interplay of population size and mutation probability in the $(1 + \lambda)$ EA on OneMax. *Algorithmica*, 78(2):587–609, 2017.

[69] David Goldberg. *Genetic Algorithms in Search, Optimization, and Machine Learning*. Addison Wesley, 1989.

[70] Jens Gottlieb, Elena Marchiori, and Claudio Rossi. Evolutionary algorithms for the satisfiability problem. *Evolutionary Computation*, 10(1):35–50, 2002.

[71] John J Grefenstette. Optimization of control parameters for genetic algorithms. *IEEE Transactions on Systems, Man, and Cybernetics*, 16(1):122–128, 1986.

[72] Jun Gu, Paul W Purdom, John Franco, and Benjamin W Wah. Algorithms for the satisfiability (SAT) problem: A survey. Technical report, Cincinnati University, 1996.

[73] George T Hall, Pietro S Oliveto, and Dirk Sudholt. On the impact of the cutoff time on the performance of algorithm configurators. In *Proc. of Genetic and Evolutionary Computation Conference (GECCO'19)*, pages 907–915. ACM, 2019.

[74] George T Hall, Pietro S Oliveto, and Dirk Sudholt. Analysis of the performance of algorithm configurators for search heuristics with global mutation operators. In *Proc. of Genetic and Evolutionary Computation Conference (GECCO'20)*, pages 823–831. ACM, 2020.

[75] Julia Handl, Douglas B Kell, and Joshua Knowles. Multiobjective optimization in bioinformatics and computational biology. *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, 4(2):279–292, 2007.

[76] Nikolaus Hansen. A practical guide to experimentation. In *Proc. of Genetic and Evolutionary Computation Conference (GECCO'18), Companion Material*, pages 432–447. ACM, 2018.

[77] Nikolaus Hansen, Anne Auger, and Dimo Brockhoff. Data from the BBOB workshops. https://coco.gforge.inria.fr/doku.php?id=algorithms-bbob, 2020.

[78] Nikolaus Hansen, Anne Auger, Dimo Brockhoff, Dejan Tušar, and Tea Tušar. Coco: Performance assessment. *arXiv preprint arXiv:1605.03560*, 2016.

[79] Nikolaus Hansen, Anne Auger, Raymond Ros, Olaf Mersmann, Tea Tušar, and Dimo Brockhoff. Coco: A platform for comparing continuous optimizers in a black-box setting. *Optimization Methods and Software*, 36(1):114–144, 2021.

[80] Nikolaus Hansen, Steffen Finck, Raymond Ros, and Anne Auger. *Real-parameter black-box optimization benchmarking 2009: Noiseless functions definitions*. PhD thesis, INRIA, 2009.

[81] Holger H Hoos and Thomas Stützle. Satlib: An online resource for research on sat. *Sat*, 2000:283–292, 2000.

[82] Frank Hutter, Holger H Hoos, and Kevin Leyton-Brown. Sequential model-based optimization for general algorithm configuration. In *Proc. of International Conference on Learning and Intelligent Optimization (LION'11)*, pages 507–523. Springer, 2011.

[83] Frank Hutter, Holger H. Hoos, Kevin Leyton-Brown, and Thomas Stützle. ParamILS: An automatic algorithm configuration framework. *Journal of Artificial Intelligence Research*, 36:267–306, 2009.

[84] Hsien-Kuei Hwang, Alois Panholzer, Nicolas Rolin, Tsung-Hsi Tsai, and Wei-Mei Chen. Probabilistic analysis of the $(1 + 1)$-evolutionary algorithm. *Evolutionary Computation*, 26(2):299–345, 2018.

[85] Hyun-Sook Yoon and Byung-Ro Moon. An empirical study on the synergy of multiple crossover operators. *IEEE Transactions on Evolutionary Computation*, 6(2):212–223, April 2002.

[86] Thomas Jansen. *Analyzing Evolutionary Algorithms—The Computer Science Perspective*. Springer, 2013.

[87] Thomas Jansen, Kenneth A. De Jong, and Ingo Wegener. On the choice of the offspring population size in evolutionary algorithms. *Evolutionary Computation*, 13:413–440, 2005.

[88] Thomas Jansen and Ingo Wegener. The analysis of evolutionary algorithms–a proof that crossover really can help. *Algorithmica*, 34:47–66, 2002.

[89] Thomas Jansen and Ingo Wegener. Real royal road functions—where crossover provably is essential. *Discrete Applied Mathematics*, 149(1-3):111–125, 2005.

[90] Thomas Jansen and Ingo Wegener. On the analysis of a dynamic evolutionary algorithm. *Journal of Discrete Algorithms*, 4:181–199, 2006.

[91] Thomas Jansen and Christine Zarges. Analysis of evolutionary algorithms: from computational complexity analysis to algorithm engineering. In *Proc. of Foundations of Genetic Algorithms (FOGA'11)*, pages 1–14. ACM, 2011.

[92] G. Karafotias, M. Hoogendoorn, and A.E. Eiben. Parameter control in evolutionary algorithms: Trends and challenges. *IEEE Transactions on Evolutionary Computation*, 19:167–187, 2015.

[93] Giorgos Karafotias, Mark Hoogendoorn, and Ágoston E Eiben. Parameter control in evolutionary algorithms: Trends and challenges. *IEEE Transactions on Evolutionary Computation*, 19(2):167–187, 2014.

[94] Stuart Kauffman and Simon Levin. Towards a general theory of adaptive walks on rugged landscapes. *Journal of Theoretical Biology*, 128:11–45, 1987.

[95] Pascal Kerschke, Holger H Hoos, Frank Neumann, and Heike Trautmann. Automated algorithm selection: Survey and perspectives. *Evolutionary Computation*, 27(1):3–45, 2019.

[96] Scott Kirkpatrick, C. D. Gelatt, and Mario P. Vecchi. Optimization by simulated annealing. *Science*, 220(4598):671–680, 1983.

[97] Lars Kotthoff, Chris Thornton, Holger H Hoos, Frank Hutter, and Kevin Leyton-Brown. Auto-weka: Automatic model selection and hyperparameter optimization in weka. In *Proc. of Automated Machine Learning*, pages 81–95. Springer, 2019.

[98] Timo Kötzing, Dirk Sudholt, and Madeleine Theile. How crossover helps in pseudo-boolean optimization. In *Proc. of Genetic and Evolutionary Computation Conference (GECCO'11)*, pages 989–996. ACM, 2011.

[99] Natalio Krasnogor and Jim Smith. A memetic algorithm with self-adaptive local search: TSP as a case study. In *Proc. of Genetic and Evolutionary Computation Conference (GECCO'00)*, pages 987–994. Morgan Kaufmann, 2000.

[100] Martin S Krejca and Carsten Witt. Theory of estimation-of-distribution algorithms. *Theory of Evolutionary Computation*, pages 405–442, 2020.

[101] William B Langdon and Riccardo Poli. *Foundations of Genetic Programming.* Springer Science & Business Media, 2013.

[102] Gilbert Laporte. The traveling salesman problem: An overview of exact and approximate algorithms. *European Journal of Operational Research*, 59(2):231–247, 1992.

[103] Pedro Larranaga. A review on estimation of distribution algorithms. In *Estimation of Distribution Algorithms*, pages 57–100. Springer, 2002.

[104] Jörg Lässig and Dirk Sudholt. Adaptive population models for offspring populations and parallel evolutionary algorithms. In *Proc. of Foundations of Genetic Algorithms (FOGA'11)*, pages 181–192. ACM, 2011.

[105] Per Kristian Lehre and Pietro S Oliveto. Runtime analysis of population-based evolutionary algorithms: introductory tutorial at gecco 2017. In *Proc. of Genetic and Evolutionary Computation Conference (GECCO'17), Companion Material*, pages 414–434, 2017.

[106] Per Kristian Lehre and Carsten Witt. Black-box search by unbiased variation. *Algorithmica*, 64:623–642, 2012.

[107] Per Kristian Lehre and Xin Yao. Crossover can be constructive when computing unique input–output sequences. *Soft Computing*, 15(9):1675–1687, 2011.

[108] Johannes Lengler and Nicholas Spooner. Fixed budget performance of the (1+1) EA on linear functions. In *Proc. of Foundations of Genetic Algorithms (FOGA'15)*, pages 52–61. ACM, 2015.

[109] Rui Li, Michael TM Emmerich, Jeroen Eggermont, Thomas Bäck, Martin Schütz, Jouke Dijkstra, and Johan HC Reiber. Mixed integer evolution strategies for parameter optimization. *Evolutionary Computation*, 21(1):29–64, 2013.

[110] Andrei Lissovoi, Pietro S. Oliveto, and John Alasdair Warwicker. On the runtime analysis of generalised selection hyper-heuristics for pseudo-Boolean optimisation. In *Proc. of Genetic and Evolutionary Computation Conference (GECCO'17)*, pages 849–856. ACM, 2017.

[111] Manuel López-Ibáñez, Jérémie Dubois-Lacoste, Leslie Pérez Cáceres, Mauro Birattari, and Thomas Stützle. The Irace package: Iterated racing for automatic algorithm configuration. *Operations Research Perspectives*, 3:43–58, 2016.

[112] Manuel López-Ibánez and Thomas Stützle. Automatically improving the anytime behaviour of optimisation algorithms. *European Journal of Operational Research*, 235(3):569–582, 2014.

[113] Andrew Lucas. Ising formulations of many np problems. *Frontiers in Physics*, 2:5, 2014.

[114] Fernando H Magnago and Ali Abur. Fault location using wavelets. *IEEE transactions on Power Delivery*, 13(4):1475–1480, 1998.

[115] Vincent Mellor. Numerical simulations of the ising model on the union jack lattice. *arXiv preprint arXiv:1101.5015*, 2011.

[116] Burkhard Militzer, Michele Zamparelli, and Dieter Beule. Evolutionary search for low autocorrelated binary sequences. *IEEE Transactions on Evolutionary Computation*, 2(1):34–39, 1998.

[117] Vladimir Mironovich and Maxim Buzdalov. Evaluation of heavy-tailed mutation operator on maximum flow test generation problem. In *Proc. of Genetic and Evolutionary Computation Conference (GECCO'17), Companion Material*, pages 1423–1426. ACM, 2017.

[118] Melanie Mitchell, John H. Holland, and Stephanie Forrest. When will a genetic algorithm outperform hill climbing? In *Proc. of Neural Information Processing Systems Conference (NIPS'93)*, volume 6, pages 51–58. Morgan Kaufmann, 1993.

[119] H. Mühlenbein and G. Paaß. From recombination of genes to the estimation of distributions i. binary parameters. In *Proc. of Parallel Problem Solving from Nature (PPSN'96)*, pages 178–187. Springer, 1996.

[120] Heinz Mühlenbein. The equation for response to selection and its use for prediction. *Evolutionary Computation*, 5:303–346, 1997.

[121] Tadahiko Murata and Hisao Ishibuchi. Positive and negative combination effects of crossover and mutation operators in sequencing problems. In *Proc. of Congress on Evolutionary Computation (CEC'16)*, pages 170–175. IEEE, 1996.

[122] Samadhi Nallaperuma, Frank Neumann, and Dirk Sudholt. Expected fitness gains of randomized search heuristics for the traveling salesperson problem. *Evolutionary Computation*, 25(4):673–705, 2017.

[123] Frank Neumann, Pietro Simone Oliveto, Günter Rudolph, and Dirk Sudholt. On the effectiveness of crossover for migration in parallel evolutionary algorithms. In *Proc. of Genetic and Evolutionary Computation Conference (GECCO'11)*, pages 1587–1594. ACM, 2011.

[124] Frank Neumann and Carsten Witt. *Bioinspired Computation in Combinatorial Optimization – Algorithms and Their Computational Complexity*. Springer, 2010.

[125] Tom Packebusch and Stephan Mertens. Low autocorrelation binary sequences. *Journal of Physics A: Mathematical and Theoretical*, 49(16):165001, 2016.

[126] IA Pasha, PS Moharir, and N Sudarshan Rao. Bi-alphabetic pulse compression radar signal design. *Sadhana*, 25(5):481–488, 2000.

[127] Leslie Pérez Cáceres, Manuel López-Ibáñez, Holger Hoos, and Thomas Stützle. An experimental study of adaptive capping in irace. In *Proc. of International Conference on Learning and Intelligent Optimization (LION'17)*, pages 235–250. Springer, 2017.

[128] Eduardo Carvalho Pinto and Carola Doerr. Discussion of a more practice-aware runtime analysis for evolutionary algorithms. In *Proc. of Artificial Evolution (EA'17)*, pages 298–305. Springer, 2017.

[129] Yasha Pushak and Holger Hoos. Algorithm configuration landscapes. In *Prof. of Parallel Problem Solving from Nature (PPSN'18)*, pages 271–283. Springer, 2018.

[130] Masoud Rabbani, M Aramoon Bajestani, and G Baharian Khoshkhou. A multi-objective particle swarm optimization for project selection problem. *Expert Systems with Applications*, 37(1):315–321, 2010.

[131] Jeremy Rapin and Olivier Teytaud. Nevergrad - A gradient-free optimization platform. https://GitHub.com/FacebookResearch/Nevergrad, 2018.

[132] Gerhard Reinelt. Tsplib-a traveling salesman problem library. *ORSA Journal on Computing*, 3(4):376–384, 1991.

[133] Anna Rodionova, Kirill Antonov, Arina Buzdalova, and Carola Doerr. Offspring population size matters when comparing evolutionary algorithms with self-adjusting mutation rates. In *Proc. of Genetic and Evolutionary Computation Conference (GECCO'19)*, pages 855–863. ACM, 2019.

[134] Grzegorz Rozenberg, Thomas Bäck, and Joost N. Kok, editors. *Handbook of Natural Computing: Theory, Experiments, and Applications*. Springer, 2012.

[135] Shokri Z Selim and K1 Alsultan. A simulated annealing algorithm for the clustering problem. *Pattern Recognition*, 24(10):1003–1008, 1991.

[136] Bart Selman, Hector J. Levesque, and David G. Mitchell. A new method for solving hard satisfiability problems. In *Proc. of National Conference on Artificial Intelligence (AAAI'92)*, pages 440–446. AAAI, 1992.

[137] Bobak Shahriari, Kevin Swersky, Ziyu Wang, Ryan P Adams, and Nando De Freitas. Taking the human out of the loop: A review of bayesian optimization. *Proceedings of the IEEE*, 104(1):148–175, 2015.

[138] Irwin I Shapiro, Gordon H Pettengill, Michael E Ash, Melvin L Stone, William B Smith, Richard P Ingalls, and Richard A Brockelman. Fourth test of general relativity: preliminary results. *Physical Review Letters*, 20(22):1265, 1968.

[139] Ofer M. Shir, Carola Doerr, and Thomas Bäck. Compiling a benchmarking test-suite for combinatorial black-box optimization: a position paper. In *Proc. of Genetic and Evolutionary Computation Conference (GECCO'18), Companion Material*, pages 1753–1760. ACM, 2018.

[140] William M Spears. Crossover or mutation? In *Proc. of Foundations of genetic algorithms (FOGA'93)*, pages 221–237. Elsevier, 1993.

[141] Dirk Sudholt. Crossover is provably essential for the Ising model on trees. In *Proc. of Genetic and Evolutionary Computation Conference (GECCO'05)*, pages 1161–1167. ACM, 2005.

[142] Dirk Sudholt. A new method for lower bounds on the running time of evolutionary algorithms. *IEEE Transactions on Evolutionary Computation*, 17:418–435, 2013.

[143] Dirk Sudholt. How crossover speeds up building block assembly in genetic algorithms. *Evolutionary Computation*, 25(2):237–274, 2017.

[144] Dirk Sudholt. The benefits of population diversity in evolutionary algorithms: A survey of rigorous runtime analyses. In Benjamin Doerr and Frank Neumann, editors, *Theory of Evolutionary Computation: Recent Developments in Discrete Optimization*, pages 359–404. Springer, 2020.

[145] Ponnuthurai N Suganthan, Nikolaus Hansen, Jing J Liang, Kalyanmoy Deb, Ying-Ping Chen, Anne Auger, and Santosh Tiwari. Problem definitions and evaluation criteria for the cec 2005 special session on real-parameter optimization. *KanGAL report*, 2005005(2005):2005, 2005.

[146] Ryoji Tanabe. Analyzing adaptive parameter landscapes in parameter adaptation methods for differential evolution. In *Proc. of Genetic and Evolutionary Computation Conference (GECCO 20')*, pages 645–653. ACM, 2020.

[147] Dirk Thierens. On benchmark properties for adaptive operator selection. In *Proc. of Genetic and Evolutionary Computation Conference (GECCO'09)*, pages 2217–2218. ACM, 2009.

[148] Tea Tusar, Dimo Brockhoff, and Nikolaus Hansen. Mixed-integer benchmark problems for single- and bi-objective optimization. In *Proc. of Genetic and Evolutionary Computation Conference (GECCO'19)*, pages 718–726. ACM, 2019.

[149] Tea Tušar, Dimo Brockhoff, Nikolaus Hansen, and Anne Auger. Coco: The bi-objective black box optimization benchmarking (bbob-biobj) test suite. *arXiv preprint arXiv:1604.00359*, 2016.

[150] Sander van Rijn, Hao Wang, Matthijs van Leeuwen, and Thomas Bäck. Evolving the structure of evolution strategies. In *Proc. of Symposium Series on Computational Intelligence (SSCI'16)*, pages 1–8. IEEE, 2016.

[151] Bas van Stein, Hao Wang, and Thomas Bäck. Automatic configuration of deep neural networks with parallel efficient global optimization. In *Proc. of International Joint Conference on Neural Networks (IJCNN'19)*, pages 1–7. IEEE, 2019.

[152] Swetha Varadarajan and Darrell Whitley. The massively parallel *mixing genetic algorithm* for the traveling salesman problem. In *Proc. of Genetic and Evolutionary Computation Conference (GECCO'19)*, pages 872–879. ACM, 2019.

[153] Diederick Vermetten, Hao Wang, Thomas Bäck, and Carola Doerr. Towards dynamic algorithm selection for numerical black-box optimization: investigating bbob as a use case. In *Proc. Genetic and Evolutionary Computation Conference (GECCO'20)*, pages 654–662. ACM, 2020.

[154] Hao Wang, Michael Emmerich, and Thomas Bäck. Cooling strategies for the moment-generating function in bayesian global optimization. In *Proc. Congress on Evolutionary Computation (CEC'18)*, pages 1–8. IEEE, 2018.

[155] Hao Wang, Bas van Stein, Michael Emmerich, and Thomas Bäck. A new acquisition function for bayesian optimization based on the moment-generating function. In *Proc. of International Conference on Systems, Man, and Cybernetics (SMC'17)*, pages 507–512. IEEE, 2017.

[156] Hao Wang, Diederick Vermetten, Furong Ye, Carola Doerr, and Thomas Bäck. IOHanalyzer: Detailed performance analyses for iterative optimization heuristic. *ACM Transactions on Evolutionary Learning and Optimization*, 2022.

[157] Richard A. Watson and Thomas Jansen. A building-block royal road where crossover is provably essential. In *Proc. of Genetic and Evolutionary Computation Conference (GECCO'07)*, pages 1452–1459. ACM, 2007.

[158] Thomas Weise. Optimization benchmarking, 2016. Available at http://optimizationbenchmarking.github.io/.

[159] Thomas Weise. The W-Model, a tunable black-box discrete optimization benchmarking (BB-DOB) problem, implemented for the BB-DOB@GECCO workshop, 2018. Data is available at https://github.com/thomasWeise/BBDOB_W_Model.

[160] Thomas Weise and Zijun Wu. Difficult features of combinatorial optimization problems and the tunable w-model benchmark problem for simulating them. In *Proc. of Genetic and Evolutionary Computation Conference (GECCO'18), Companion Material*, pages 1769–1776. ACM, 2018.

[161] Darrell Whitley. A genetic algorithm tutorial. *Statistics and Computing*, 4(2):65–85, 1994.

[162] Darrell Whitley, Swetha Varadarajan, Rachel Hirsch, and Anirban Mukhopadhyay. Exploration and exploitation without mutation: Solving the jump function in $\theta(n)$ time. In *Proc. of Parallel Problem Solving from Nature (PPSN'18)*, pages 55–66. Springer, 2018.

[163] Carsten Witt. Tight bounds on the optimization time of a randomized search heuristic on linear functions. *Combinatorics, Probability & Computing*, 22:294–318, 2013.

[164] Bing Xue, Mengjie Zhang, Will N Browne, and Xin Yao. A survey on evolutionary computation approaches to feature selection. *IEEE Transactions on Evolutionary Computation*, 20(4):606–626, 2015.

[165] Furong Ye, Carola Doerr, and Thomas Bäck. Interpolating local and global search by controlling the variance of standard bit mutation. In *Proc. of Congress on Evolutionary Computation (CEC'19)*, pages 2292–2299. IEEE, 2019.

[166] Furong Ye, Carola Doerr, and Thomas Bäck. Data Sets for the study "Leveraging Benchmarking Data for Informed One-Shot Dynamic Algorithm Selection". https://doi.org/10.5281/zenodo.4501275, February 2021.

[167] Furong Ye, Carola Doerr, and Thomas Bäck. Leveraging benchmarking data for informed one-shot dynamic algorithm selection. In *Proc. of Genetic and Evolutionary Computation Conference (GECCO'21), Companion Material*, pages 245–246. ACM, 2021.

[168] Furong Ye, Carola Doerr, Hao Wang, and Thomas Bäck. Automated configuration of genetic algorithms by tuning for anytime performance. *IEEE Transactions on Evolutionary Computation*, 2022.

[169] Furong Ye, Carola Doerr, Hao Wang, and Thomas Bäck. Data sets for the study "Automated Configuration of Genetic Algorithms by Tuning for Anytime Performance". https://doi.org/10.5281/zenodo.4823492, May 2021.

[170] Furong Ye, Hao Wang, Carola Doerr, and Thomas Bäck. Benchmarking a $(\mu+\lambda)$ genetic algorithm with configurable crossover probability. In *Proc. of Parallel Problem Solving from Nature (PPSN'20)*, pages 699–713. Springer, 2020.

[171] Furong Ye, Hao Wang, Carola Doerr, and Thomas Bäck. Experimental Data Sets for the study "Benchmarking a $(\mu+\lambda)$ Genetic Algorithm with Configurable Crossover Probability". https://doi.org/10.5281/zenodo.3753086, April 2020.

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