
References

1. E.H.L. Aarts, A.E. Eiben, and K.M. van Hee. A general theory of genetic algorithms. Technical Report 89/08, Eindhoven University of Technology, 1989.
2. E.H.L. Aarts and J. Korst. *Simulated Annealing and Boltzmann Machines*. Wiley, Chichester, UK, 1989.
3. E.H.L. Aarts and J.K. Lenstra, editors. *Local Search in Combinatorial Optimization*. Discrete Mathematics and Optimization. Wiley, Chichester, UK, June 1997.
4. D. Adams. *The Hitchhiker's Guide to the Galaxy*. Guild Publishing, London, 1986.
5. E. Alba and B. Dorronsoro. *Cellular Genetic Algorithms*. Computational Intelligence and Complexity. Springer, 2008.
6. L. Altenberg. The schema theorem and Price's theorem. In Whitley and Vose [462], pages 23–50.
7. D. Andre and J.R. Koza. Parallel genetic programming: A scalable implementation using the transputer network architecture. In P.J. Angeline and K.E. Kinnear, editors, *Advances in Genetic Programming 2*, pages 317–338. MIT Press, Cambridge, MA, 1996.
8. P.J. Angeline. Adaptive and self-adaptive evolutionary computations. In *Computational Intelligence*, pages 152–161. IEEE Press, 1995.
9. P.J. Angeline. Subtree crossover: Building block engine or macromutation? In Koza et al. [256], pages 9–17.
10. P.J. Angeline. Competitive fitness evaluation. In Bäck et al. [28], chapter 3, pages 12–14.
11. J. Arabas, Z. Michalewicz, and J. Mulawka. GAVaPS – a genetic algorithm with varying population size. In ICEC-94 [229], pages 73–78.
12. D. Ashlock. *Evolutionary Computation for Modeling and Optimization*. Springer, 2006.
13. Anne Auger, Steffen Finck, Nikolaus Hansen, and Raymond Ros. BBOB 2010: Comparison Tables of All Algorithms on All Noiseless Functions. Technical Report RT-388, INRIA, September 2010.
14. R. Axelrod. *The Evolution of Cooperation*. Basic Books, New York, 1984.
15. R. Axelrod. The evolution of strategies in the iterated prisoner's dilemma. In L. Davis, editor, *Genetic Algorithms and Simulated Annealing*. Pitman, London, 1987.

16. J. Bacardit, M. Stout, J.D. Hirst, K. Sastry, X. Llor, and N. Krasnogor. Automated alphabet reduction method with evolutionary algorithms for protein structure prediction. In Bosman et al. [65], pages 346–353.
17. T. Bäck. The interaction of mutation rate, selection and self-adaptation within a genetic algorithm. In Männer and Manderick [282], pages 85–94.
18. T. Bäck. Self adaptation in genetic algorithms. In Varela and Bourguine [440], pages 263–271.
19. T. Bäck. Selective pressure in evolutionary algorithms: A characterization of selection mechanisms. In ICEC-94 [229], pages 57–62.
20. T. Bäck. Generalised convergence models for tournament and (μ, λ) selection. In Eshelman [156], pages 2–8.
21. T. Bäck. Order statistics for convergence velocity analysis of simplified evolutionary algorithms. In Whitley and Vose [462], pages 91–102.
22. T. Bäck. *Evolutionary Algorithms in Theory and Practice*. Oxford University Press, Oxford, UK, 1996.
23. T. Bäck, editor. *Proceedings of the 7th International Conference on Genetic Algorithms*. Morgan Kaufmann, San Francisco, 1997.
24. T. Bäck. Self-adaptation. In Bäck et al. [28], chapter 21, pages 188–211.
25. T. Bäck, A.E. Eiben, and N.A.L. van der Vaart. An empirical study on GAs “without parameters”. In Schoenauer et al. [368], pages 315–324.
26. T. Bäck, D.B. Fogel, and Z. Michalewicz, editors. *Handbook of Evolutionary Computation*. Institute of Physics Publishing, Bristol, and Oxford University Press, New York, 1997.
27. T. Bäck, D.B. Fogel, and Z. Michalewicz, editors. *Evolutionary Computation 1: Basic Algorithms and Operators*. Institute of Physics Publishing, Bristol, 2000.
28. T. Bäck, D.B. Fogel, and Z. Michalewicz, editors. *Evolutionary Computation 2: Advanced Algorithms and Operators*. Institute of Physics Publishing, Bristol, 2000.
29. T. Bäck and Z. Michalewicz. Test landscapes. In Bäck et al. [26], chapter B2.7, pages 14–20.
30. T. Bäck and H.-P. Schwefel. An overview of evolutionary algorithms for parameter optimization. *Evolutionary Computation*, 1(1):1–23, 1993.
31. T. Bäck, D. Vermeulen, and A.E. Eiben. Effects of tax and evolution in an artificial society. In H.J. Caulfield, S.H. Chen, H.D. Cheng, R. Duro, V. Honavar, E.E. Kerre, M. Lu, M.G. Romay, T.K. Shih, D. Ventura, P. Wang, and Y. Yang, editors, *Proceedings of the Sixth Joint Conference on Information Sciences, (JCIS 2002)*, pages 1151–1156. JCIS/Association for Intelligent Machinery, 2002.
32. J.E. Baker. Reducing bias and inefficiency in the selection algorithm. In Grefenstette [198], pages 14–21.
33. P. Balaprakash, M. Birattari, and T. Stützle. Improvement strategies for the F-Race algorithm: Sampling design and iterative refinement. In T. Bartz-Beielstein, M. Blesa Aguilera, C. Blum, B. Naujoks, A. Roli, G. Rudolph, and M. Sampels, editors, *Hybrid Metaheuristics*, volume 4771 of *Lecture Notes in Computer Science*, pages 108–122. Springer, 2007.
34. J.M. Baldwin. A new factor in evolution. *American Naturalist*, 30, 1896.

35. Shummet Baluja. Population-based incremental learning: A method for integrating genetic search based function optimization and competitive learning. Technical report, Carnegie Mellon University, Pittsburgh, PA, USA, 1994.
36. W. Banzhaf, J. Daida, A.E. Eiben, M.H. Garzon, V. Honavar, M. Jakiela, and R.E. Smith, editors. *Proceedings of the Genetic and Evolutionary Computation Conference (GECCO-1999)*. Morgan Kaufmann, San Francisco, 1999.
37. W. Banzhaf, P. Nordin, R.E. Keller, and F.D. Francone. *Genetic Programming: An Introduction*. Morgan Kaufmann, San Francisco, 1998.
38. W. Banzhaf and C. Reeves, editors. *Foundations of Genetic Algorithms 5*. Morgan Kaufmann, San Francisco, 1999.
39. N.A. Baricelli. Numerical testing of evolution theories, part 1. *Acta Biotheor.*, 16:69–98, 1962.
40. Abu S. S. M. Barkat Ullah, Ruhul Sarker, David Cornforth, and Chris Lokan. AMA: a new approach for solving constrained real-valued optimization problems. *Soft Computing*, 13(8-9):741–762, August 2009.
41. T. Bartz-Beielstein. *New Experimentalism Applied to Evolutionary Computation*. PhD thesis, Universität Dortmund, 2005.
42. T. Bartz-Beielstein, K.E. Parsopoulos, and M.N. Vrahatis. Analysis of Particle Swarm Optimization Using Computational Statistics. In Chalkis, editor, *Proceedings of the International Conference of Numerical Analysis and Applied Mathematics (ICNAAM 2004)*, pages 34–37. Wiley, 2004.
43. T. Bartz-Beielstein and M. Preuss. Considerations of Budget Allocation for Sequential Parameter Optimization (SPO). In L. Paquete et al., editors, *Workshop on Empirical Methods for the Analysis of Algorithms, Proceedings*, pages 35–40, Reykjavik, Iceland, 2006. Online Proceedings.
44. J.C. Bean. Genetic algorithms and random keys for sequencing and optimisation. *ORSA Journal of Computing*, 6(2):154–160, 1994.
45. J.C. Bean and A.B. Hadj-Alouane. A dual genetic algorithm for bounded integer problems. Technical Report 92-53, University of Michigan, 1992.
46. R.K. Belew and L.B. Booker, editors. *Proceedings of the 4th International Conference on Genetic Algorithms*. Morgan Kaufmann, San Francisco, 1991.
47. P. Bentley. From coffee tables to hospitals: Generic evolutionary design. In Bentley [48], pages 405–423.
48. P.J. Bentley, editor. *Evolutionary Design by Computers*. Morgan Kaufmann, San Francisco, 1999.
49. P.J. Bentley and D.W. Corne, editors. *Creative Evolutionary Systems*. Morgan Kaufmann, San Francisco, 2002.
50. P.J. Bentley and D.W. Corne. An introduction to creative evolutionary systems. In Bentley and Corne [49], pages 1–75.
51. A.D. Bethke. *Genetic Algorithms as Function Optimizers*. PhD thesis, University of Michigan, 1981.
52. H.-G. Beyer. *The Theory of Evolution Strategies*. Springer, 2001.
53. H.-G. Beyer and D.V. Arnold. Theory of evolution strategies: A tutorial. In Kallel et al. [240], pages 109–134.
54. H.-G. Beyer and H.-P. Schwefel. Evolution strategies: A comprehensive introduction. *Natural Computing*, 1(1):3–52, 2002.
55. M. Birattari. *Tuning Metaheuristics*. Springer, 2005.
56. M. Birattari, Z. Yuan, P. Balaprakash, and T. Stützle. F-Race and iterated F-Race: An overview. In T. Bartz-Beielstein, M. Chiarandini, L. Paquete, and

- M. Preuss, editors, *Experimental Methods for the Analysis of Optimization Algorithms*, pages 311–336. Springer, 2010.
57. S. Blackmore. *The Meme Machine*. Oxford University Press, Oxford, UK, 1999.
 58. T. Blickle and L. Thiele. A comparison of selection schemes used in genetic algorithms. Technical Report TIK Report 11, December 1995, Computer Engineering and Communication Networks Lab, Swiss Federal Institute of Technology, 1995.
 59. J.S. De Bonet, C. Isbell, and P. Viola. Mimic: Finding optima by estimating probability densities. *Advances in Neural Information Processing Systems*, 9:424–431, 1997.
 60. J. Bongard, V. Zykov, and H. Lipson. Resilient machines through continuous self-modeling. *Science*, 314:1118–1121, 2006.
 61. J.C. Bongard. Evolutionary robotics. *Communications of the ACM*, 56(8), 2013.
 62. L.B. Booker. *Intelligent Behaviour as an adaptation to the task environment*. PhD thesis, University of Michigan, 1982.
 63. Y. Borenstein and A. Moraglio, editors. *Theory and Principled Methods for the Design of Metaheuristics*. Natural Computing Series. Springer, 2014.
 64. P. Bosman and D. Thierens. Expanding from discrete to continuous estimation of distribution algorithms: The idea. In Schoenauer et al. [368], pages 767–776.
 65. Peter A. N. Bosman, Tina Yu, and Anikó Ekárt, editors. *GECCO '07: Proceedings of the 2007 GECCO conference on Genetic and evolutionary computation*, New York, NY, USA, 2007. ACM.
 66. M.F. Bramlette. Initialization, mutation and selection methods in genetic algorithms for function optimization. In Belew and Booker [46], pages 100–107.
 67. H.J. Bremermann, M. Rogson, and S. Salaff. Global properties of evolution processes. In H.H. Pattee, E.A. Edlsack, L. Fein, and A.B. Callahan, editors, *Natural Automata and Useful Simulations*, pages 3–41. Spartan Books, Washington DC, 1966.
 68. L. Bull. *Artificial Symbiology*. PhD thesis, University of the West of England, 1995.
 69. L. Bull and T.C. Fogarty. Horizontal gene transfer in endosymbiosis. In C.G. Langton and K. Shimohara, editors, *Proceedings of the 5th International Workshop on Artificial Life: Synthesis and Simulation of Living Systems (ALIFE-96)*, pages 77–84. MIT Press, Cambridge, MA, 1997.
 70. L. Bull, O. Holland, and S. Blackmore. On meme–gene coevolution. *Artificial Life*, 6:227–235, 2000.
 71. E. K. Burke, T. Curtois, M. R. Hyde, G. Kendall, G. Ochoa, S. Petrovic, J.A. Vázquez Rodríguez, and M. Gendreau. Iterated local search vs. hyperheuristics: Towards general-purpose search algorithms. In *IEEE Congress on Evolutionary Computation*, pages 1–8. IEEE Press, 2010.
 72. E.K. Burke, G. Kendall, and E. Soubeiga. A tabu search hyperheuristic for timetabling and rostering. *Journal of Heuristics*, 9(6), 2003.
 73. E.K. Burke and J.P. Newall. A multi-stage evolutionary algorithm for the timetable problem. *IEEE Transactions on Evolutionary Computation*, 3(1):63–74, 1999.
 74. E.K. Burke, J.P. Newall, and R.F. Weare. Initialization strategies and diversity in evolutionary timetabling. *Evolutionary Computation*, 6(1):81–103, 1998.

75. M.V. Butz. *Rule-Based Evolutionary Online Learning Systems*. Studies in Fuzziness and Soft Computing Series. Springer, 2006.
76. P. Caleb-Solly and J.E. Smith. Adaptive surface inspection via interactive evolution. *Image and Vision Computing*, 25(7):1058–1072, 2007.
77. A. Caponio, G.I. Cascella, F. Neri., N. Salvatore., and M. Sumner. A Fast Adaptive Memetic Algorithm for Online and Offline Control Design of PMSM Drives. *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, 37(1):28–41, 2007.
78. U.K. Chakraborty. An analysis of selection in generational and steady state genetic algorithms. In *Proceedings of the National Conference on Molecular Electronics*. NERIST (A.P.) India, 1995.
79. U.K. Chakraborty, K. Deb, and M. Chakraborty. Analysis of selection algorithms: A Markov Chain approach. *Evolutionary Computation*, 4(2):133–167, 1997.
80. P. Cheeseman, B. Kenefsky, and W. M. Taylor. Where the really hard problems are. In *Proceedings of the Twelfth International Joint Conference on Artificial Intelligence, IJCAI-91*, pages 331–337, 1991.
81. K. Chellapilla and D.B. Fogel. Evolving an expert checkers playing program without human expertise. *IEEE Transactions on Evolutionary Computation*, 5(4):422–428, 2001.
82. X. Chen. An Algorithm Development Environment for Problem-Solving. In *(ICCP), 2010 International Conference on Computational Problem-Solving*, pages 85–90, 2010.
83. Y.P. Chen. *Extending the Scalability of Linkage Learning Genetic Algorithms: - Theory & Practice*, volume 190 of *Studies in Fuzziness and Soft Computing*. Springer, 2006.
84. H. Cobb. An investigation into the use of hypermutation as an adaptive operator in a genetic algorithm having continuous, time-dependent nonstationary environments. Memorandum 6760, Naval Research Laboratory, 1990.
85. H.G. Cobb and J.J. Grefenstette. Genetic algorithms for tracking changing environments. In Forrest [176], pages 523–530.
86. C.A. Coello Coello, D.A. Van Veldhuizen, and G.B. Lamont. *Evolutionary Algorithms for Solving Multi-Objective Problems*. Kluwer Academic Publishers, Boston, 2nd edition, 2007. ISBN 0-3064-6762-3.
87. J.P. Cohoon, S.U. Hedge, W.N. Martin, and D. Richards. Punctuated equilibria: A parallel genetic algorithm. In Grefenstette [198], pages 148–154.
88. J.P. Cohoon, W.N. Martin, and D.S. Richards. Genetic algorithms and punctuated equilibria in VLSI. In Schwefel and Männer [374], pages 134–144.
89. P. Cowling, G. Kendall, and E. Soubeiga. A hyperheuristic approach to scheduling a sales summit. *Lecture Notes in Computer Science*, 2079:176–95, 2001.
90. B. Craenen, A.E. Eiben, and J.I. van Hemert. Comparing evolutionary algorithms on binary constraint satisfaction problems. *IEEE Transactions on Evolutionary Computation*, 7(5):424–444, 2003.
91. M. Crepinsek, S. Liu, and M. Mernik. Exploration and exploitation in evolutionary algorithms: A survey. *ACM Computing Surveys*, 45(3):35:1–35:33, July 2013.
92. C. Darwin. *The Origin of Species*. John Murray, 1859.

93. R. Das and D. Whitley. The only challenging problems are deceptive: Global search by solving order-1 hyperplanes. In Belew and Booker [46], pages 166–173.
94. D. Dasgupta and D. McGregor. SGA: A structured genetic algorithm. Technical Report IKBS-8-92, University of Strathclyde, 1992.
95. Y. Davidor. A naturally occurring niche & species phenomenon: The model and first results. In Belew and Booker [46], pages 257–263.
96. Y. Davidor, H.-P. Schwefel, and R. Männer, editors. *Proceedings of the 3rd Conference on Parallel Problem Solving from Nature*, number 866 in Lecture Notes in Computer Science. Springer, 1994.
97. L. Davis. Adapting operator probabilities in genetic algorithms. In Schaffer [365], pages 61–69.
98. L. Davis, editor. *Handbook of Genetic Algorithms*. Van Nostrand Reinhold, 1991.
99. T.E. Davis and J.C. Principe. A Markov chain framework for the simple genetic algorithm. *Evolutionary Computation*, 1(3):269–288, 1993.
100. R. Dawkins. *The Selfish Gene*. Oxford University Press, Oxford, UK, 1976.
101. R. Dawkins. *The Blind Watchmaker*. Longman Scientific and Technical, 1986.
102. K.A. De Jong. *An Analysis of the Behaviour of a Class of Genetic Adaptive Systems*. PhD thesis, University of Michigan, 1975.
103. K.A. De Jong. Genetic algorithms are NOT function optimizers. In Whitley [457], pages 5–18.
104. K.A. De Jong. *Evolutionary Computation: A Unified Approach*. The MIT Press, 2006.
105. K.A. De Jong and J. Sarma. Generation gaps revisited. In Whitley [457], pages 19–28.
106. K.A. De Jong and J. Sarma. On decentralizing selection algorithms. In Eshelman [156], pages 17–23.
107. K.A. De Jong and W.M. Spears. An analysis of the interacting roles of population size and crossover in genetic algorithms. In Schwefel and Männer [374], pages 38–47.
108. K.A. De Jong and W.M. Spears. A formal analysis of the role of multi-point crossover in genetic algorithms. *Annals of Mathematics and Artificial Intelligence*, 5(1):1–26, April 1992.
109. K. Deb. Genetic algorithms in multimodal function optimization. Master’s thesis, University of Alabama, 1989.
110. K. Deb. *Multi-objective Optimization using Evolutionary Algorithms*. Wiley, Chichester, UK, 2001.
111. K. Deb and R.B. Agrawal. Simulated binary crossover for continuous search space. *Complex Systems*, 9:115–148, 1995.
112. K. Deb, S. Agrawal, A. Pratap, and T. Meyarivan. A Fast Elitist Non-Dominated Sorting Genetic Algorithm for Multi-Objective Optimization: NSGA-II. In Schoenauer et al. [368], pages 849–858.
113. K. Deb and H.-G. Beyer. Self-Adaptive Genetic Algorithms with Simulated Binary Crossover. *Evolutionary Computation*, 9(2), June 2001.
114. K. Deb and D.E. Goldberg. An investigation of niche and species formation in genetic function optimization. In Schaffer [365], pages 42–50.
115. E.D. deJong, R.A. Watson, and J.B. Pollack. Reducing bloat and promoting diversity using multi-objective methods. In Spector et al. [415], pages 11–18.

116. D. Dennett. *Darwin's Dangerous Idea*. Penguin, London, 1995.
117. C.M. Dinu, P. Dimitrov, B. Weel, and A. E. Eiben. Self-adapting fitness evaluation times for on-line evolution of simulated robots. In *GECCO '13: Proc of the 15th conference on Genetic and Evolutionary Computation*, pages 191–198. ACM Press, 2013.
118. B. Doerr, E. Happ, and C. Klein. Crossover can provably be useful in evolutionary computation. *Theor. Comput. Sci.*, 425:17–33, March 2012.
119. S. Doncieux, J.-B. Mouret, N. Bredeche, and V. Padois. Evolutionary robotics: Exploring new horizons. In S. Doncieux, N. Bredeche, and J.-B. Mouret, editors, *New Horizons in Evolutionary Robotics*, volume 341 of *Studies in Computational Intelligence*, chapter 2, pages 3–25. Springer, 2011.
120. S. Droste, T. Jansen, and I. Wegener. Upper and lower bounds for randomized search heuristics in black-box optimization. *Theory of Computing Systems*, 39(4):525–544, 2006.
121. A. E. Eiben. Grand challenges for evolutionary robotics. *Frontiers in Robotics and AI*, 1(4), 2014.
122. A. E. Eiben. In Vivo Veritas: towards the Evolution of Things. In T. Bartz-Beielstein, J. Branke, B. Filipič, and J. Smith, editors, *Parallel Problem Solving from Nature – PPSN XIII*, volume 8672 of *LNCS*, pages 24–39. Springer, 2014.
123. A. E. Eiben, E. Haasdijk, and N. Bredeche. Embodied, on-line, on-board evolution for autonomous robotics. In P. Levi and S. Kernbach, editors, *Symbiotic Multi-Robot Organisms: Reliability, Adaptability, Evolution*, chapter 5.2, pages 361–382. Springer, 2010.
124. A. E. Eiben and M. Jelasity. A critical note on Experimental Research Methodology in Experimental research methodology in EC. In *Proceedings of the 2002 Congress on Evolutionary Computation (CEC 2002)*, pages 582–587. IEEE Press, Piscataway, NJ, 2002.
125. A. E. Eiben and S. K. Smit. Evolutionary algorithm parameters and methods to tune them. In Y. Hamadi, E. Monfroy, and F. Saubion, editors, *Autonomous Search*, pages 15–36. Springer, 2012.
126. A.E. Eiben. Multiparent recombination. In Bäck et al. [27], chapter 33.7, pages 289–307.
127. A.E. Eiben. Evolutionary algorithms and constraint satisfaction: Definitions, survey, methodology, and research directions. In Kallel et al. [240], pages 13–58.
128. A.E. Eiben. Multiparent recombination in evolutionary computing. In Ghosh and Tsutsui [184], pages 175–192.
129. A.E. Eiben, E.H.L. Aarts, and K.M. Van Hee. Global convergence of genetic algorithms: a Markov chain analysis. In Schwefel and Männer [374], pages 4–12.
130. A.E. Eiben and T. Bäck. An empirical investigation of multi-parent recombination operators in evolution strategies. *Evolutionary Computation*, 5(3):347–365, 1997.
131. A.E. Eiben, T. Bäck, M. Schoenauer, and H.-P. Schwefel, editors. *Proceedings of the 5th Conference on Parallel Problem Solving from Nature*, number 1498 in *Lecture Notes in Computer Science*. Springer, 1998.
132. A.E. Eiben, N. Bredeche, M. Hoogendoorn, J. Stradner, J. Timmis, A.M. Tyrrell, and A. Winfield. The triangle of life: Evolving robots in real-time and real-space. In P. Lio, O. Miglino, G. Nicosia, S. Nolfi, and M. Pavone, editors, *Proc. 12th European Conference on the Synthesis and Simulation of Living Systems*, pages 1056–1063. MIT Press, 2013.

133. A.E. Eiben, R. Hinterding, and Z. Michalewicz. Parameter Control in Evolutionary Algorithms. *IEEE Transactions on Evolutionary Computation*, 3(2):124–141, 1999.
134. A.E. Eiben, B. Jansen, Z. Michalewicz, and B. Paechter. Solving CSPs using self-adaptive constraint weights: how to prevent EAs from cheating. In Whitley et al. [453], pages 128–134.
135. A.E. Eiben and M. Jelasity. A Critical Note on Experimental Research Methodology in EC. In *Proceedings of the 2002 IEEE Congress on Evolutionary Computation (CEC 2002)*, pages 582–587. IEEE Press, 2002.
136. A.E. Eiben, S. Kernbach, and E. Haasdijk. Embodied artificial evolution – artificial evolutionary systems in the 21st century. *Evolutionary Intelligence*, 5(4):261–272, 2012.
137. A.E. Eiben and Z. Michalewicz, editors. *Evolutionary Computation*. IOS Press, 1998.
138. A.E. Eiben, R. Nabuurs, and I. Booi. The Escher evolver: Evolution to the people. In Bentley and Corne [49], pages 425–439.
139. A.E. Eiben, P.-E. Raué, and Zs. Ruttkay. Repairing, adding constraints and learning as a means of improving GA performance on CSPs. In J.C. Bioch and S.H. Nienhuys-Cheng, editors, *Proceedings of the 4th Belgian-Dutch Conference on Machine Learning*, number 94-05 in EUR-CS, pages 112–123. Erasmus University Press, 1994.
140. A.E. Eiben and G. Rudolph. Theory of evolutionary algorithms: a bird’s eye view. *Theoretical Computer Science*, 229(1–2):3–9, 1999.
141. A.E. Eiben and Zs. Ruttkay. Constraint-satisfaction problems. In T. Baeck, D.B. Fogel, and Z. Michalewicz, editors, *Evolutionary Computation 2: Advanced Algorithms and Operators*, pages 75–86. Institute of Physics Publishing, 2000.
142. A.E. Eiben and A. Schippers. On evolutionary exploration and exploitation. *Fundamenta Informaticae*, 35(1-4):35–50, 1998.
143. A.E. Eiben and C.A. Schippers. Multi-parent’s niche: n-ary crossovers on NK-landscapes. In Voigt et al. [445], pages 319–328.
144. A.E. Eiben, M.C. Schut, and A.R. de Wilde. Is self-adaptation of selection pressure and population size possible? A case study. In Thomas Philip Runarsson, Hans-Georg Beyer, Edmund K. Burke, Juan J. Merelo Guervós, L. Darrell Whitley, and Xin Yao, editors, *PPSN*, volume 4193 of *Lecture Notes in Computer Science*, pages 900–909. Springer, 2006.
145. A.E. Eiben and S. K. Smit. Parameter tuning for configuring and analyzing evolutionary algorithms. *Swarm and Evolutionary Computation*, 1(1):19–31, 2011.
146. A.E. Eiben and J.E. Smith. *Introduction to Evolutionary Computing*. Springer, Berlin Heidelberg, 2003.
147. A.E. Eiben and J.E. Smith. From evolutionary computation to the evolution of things. *Nature*, 2015. In press.
148. A.E. Eiben, I.G. Sprinkhuizen-Kuyper, and B.A. Thijssen. Competing crossovers in an adaptive GA framework. In *Proceedings of the 1998 IEEE Congress on Evolutionary Computation (CEC 1998)*, pages 787–792. IEEE Press, 1998.
149. A.E. Eiben and J.K. van der Hauw. Solving 3-SAT with adaptive genetic algorithms. In ICEC-97 [231], pages 81–86.

150. A.E. Eiben and J.K. van der Hauw. Graph colouring with adaptive genetic algorithms. *J. Heuristics*, 4:1, 1998.
151. A.E. Eiben and J.I. van Hemert. SAW-ing EAs: Adapting the fitness function for solving constrained problems. In D. Corne, M. Dorigo, and F. Glover, editors, *New Ideas in Optimization*, pages 389–402. McGraw-Hill, 1999.
152. A.E. Eiben, C.H.M. van Kemenade, and J.N. Kok. Orgy in the computer: Multi-parent reproduction in genetic algorithms. In Morán et al. [305], pages 934–945.
153. M.A. El-Beltagy, P.B. Nair, and A.J. Keane. Metamodeling techniques for evolutionary optimization of computationally expensive problems: Promises and limitations. In Banzhaf et al. [36], pages 196–203.
154. N. Eldredge and S.J. Gould. *Models of Paleobiology*, chapter Punctuated Equilibria: an alternative to phyletic gradualism, pages 82–115. Freeman Cooper, San Francisco, 1972.
155. J.M. Epstein and R. Axtell. *Growing Artificial Societies: Social Sciences from Bottom Up*. Brookings Institution Press and The MIT Press, 1996.
156. L.J. Eshelman, editor. *Proceedings of the 6th International Conference on Genetic Algorithms*. Morgan Kaufmann, San Francisco, 1995.
157. L.J. Eshelman, R.A. Caruana, and J.D. Schaffer. Biases in the crossover landscape. In Schaffer [365], pages 10–19.
158. L.J. Eshelman and J.D. Schaffer. Preventing premature convergence in genetic algorithms by preventing incest. In Belew and Booker [46], pages 115–122.
159. L.J. Eshelman and J.D. Schaffer. Crossover’s niche. In Forrest [176], pages 9–14.
160. L.J. Eshelman and J.D. Schaffer. Real-coded genetic algorithms and interval schemata. In Whitley [457], pages 187–202.
161. L.J. Eshelman and J.D. Schaffer. Productive recombination and propagating and preserving schemata. In Whitley and Vose [462], pages 299–313.
162. Álvaro Fialho. *Adaptive Operator Selection for Optimization*. PhD thesis, Université Paris-Sud XI, Orsay, France, December 2010.
163. D. Floreano, P. Husbands, and S. Nolfi. Evolutionary robotics. In B. Siciliano and O. Khatib, editors, *Springer Handbook of Robotics*, pages 1423–1451. Springer, 2008.
164. T.C. Fogarty, F. Vavak, and P. Cheng. Use of the genetic algorithm for load balancing of sugar beet presses. In Eshelman [156], pages 617–624.
165. D.B. Fogel. *Evolving Artificial Intelligence*. PhD thesis, University of California, 1992.
166. D.B. Fogel. *Evolutionary Computation*. IEEE Press, 1995.
167. D.B. Fogel, editor. *Evolutionary Computation: the Fossil Record*. IEEE Press, Piscataway, NJ, 1998.
168. D.B. Fogel. *Blondie24: Playing at the Edge of AI*. Morgan Kaufmann, San Francisco, 2002.
169. D.B. Fogel. Better than Samuel: Evolving a nearly expert checkers player. In Ghosh and Tsutsui [184], pages 989–1004.
170. D.B. Fogel and J.W. Atmar. Comparing genetic operators with Gaussian mutations in simulated evolutionary processes using linear systems. *Biological Cybernetics*, 63(2):111–114, 1990.
171. D.B. Fogel and L.C. Stayton. On the effectiveness of crossover in simulated evolutionary optimization. *BioSystems*, 32(3):171–182, 1994.

172. L.J. Fogel, P.J. Angeline, and T. Bäck, editors. *Proceedings of the 5th Annual Conference on Evolutionary Programming*. MIT Press, Cambridge, MA, 1996.
173. L.J. Fogel, A.J. Owens, and M.J. Walsh. Artificial intelligence through a simulation of evolution. In A. Callahan, M. Maxfield, and L.J. Fogel, editors, *Biophysics and Cybernetic Systems*, pages 131–156. Spartan, Washington DC, 1965.
174. L.J. Fogel, A.J. Owens, and M.J. Walsh. *Artificial Intelligence through Simulated Evolution*. Wiley, Chichester, UK, 1966.
175. C.M. Fonseca and P.J. Fleming. Genetic algorithms for multiobjective optimization: formulation, discussion and generalization. In Forrest [176], pages 416–423.
176. S. Forrest, editor. *Proceedings of the 5th International Conference on Genetic Algorithms*. Morgan Kaufmann, San Francisco, 1993.
177. S. Forrest and M. Mitchell. Relative building block fitness and the building block hypothesis. In Whitley [457], pages 109–126.
178. B. Freisleben and P. Merz. A genetic local search algorithm for solving the symmetric and asymmetric travelling salesman problem. In ICEC-96 [230], pages 616–621.
179. A.A. Freitas. *Data Mining and Knowledge Discovery with Evolutionary Algorithms*. Springer, 2002.
180. M. Garey and D. Johnson. *Computers and Intractability. A Guide to the Theory of NP-Completeness*. Freeman, San Francisco, 1979.
181. C. Gathercole and P. Ross. Dynamic training subset selection for supervised learning in genetic programming. In Davidor et al. [96], pages 312–321. Lecture Notes in Computer Science 866.
182. D.K. Gehlhaar and D.B. Fogel. Tuning evolutionary programming for conformationally flexible molecular docking. In Fogel et al. [172], pages 419–429.
183. I. Gent and T. Walsh. Phase transitions from real computational problems. In *Proceedings of the 8th International Symposium on Artificial Intelligence*, pages 356–364, 1995.
184. A. Ghosh and S. Tsutsui, editors. *Advances in Evolutionary Computation: Theory and Applications*. Springer, 2003.
185. F. Glover. Tabu search: 1. *ORSA Journal on Computing*, 1(3):190–206, Summer 1989.
186. F. Glover. Tabu search and adaptive memory programming — advances, applications, and challenges. In R.S. Barr, R.V. Helgason, and J.L. Kennington, editors, *Interfaces in Computer Science and Operations Research*, pages 1–75. Kluwer Academic Publishers, Norwell, MA, 1996.
187. D.E. Goldberg. Genetic algorithms and Walsh functions: I. A gentle introduction. *Complex Systems*, 3(2):129–152, April 1989.
188. D.E. Goldberg. Genetic algorithms and Walsh functions: II. Deception and its analysis. *Complex Systems*, 3(2):153–171, April 1989.
189. D.E. Goldberg. *Genetic Algorithms in Search, Optimization and Machine Learning*. Addison-Wesley, 1989.
190. D.E. Goldberg and K. Deb. A comparative analysis of selection schemes used in genetic algorithms. In Rawlins [351], pages 69–93.
191. D.E. Goldberg, B. Korb, and K. Deb. Messy genetic algorithms: Motivation, analysis, and first results. *Complex Systems*, 3(5):493–530, October 1989.
192. D.E. Goldberg and R. Lingle. Alleles, loci, and the traveling salesman problem. In Grefenstette [197], pages 154–159.

193. D.E. Goldberg and J. Richardson. Genetic algorithms with sharing for multimodal function optimization. In Grefenstette [198], pages 41–49.
194. D.E. Goldberg and R.E. Smith. Nonstationary function optimization using genetic algorithms with dominance and diploidy. In Grefenstette [198], pages 59–68.
195. M. Gorges-Schleuter. ASPARAGOS: An asynchronous parallel genetic optimization strategy. In Schaffer [365], pages 422–427.
196. J. Gottlieb and G.R. Raidl. The effects of locality on the dynamics of decoder-based evolutionary search. In Whitley et al. [453], pages 283–290.
197. J.J. Grefenstette, editor. *Proceedings of the 1st International Conference on Genetic Algorithms and Their Applications*. Lawrence Erlbaum, Hillsdale, New Jersey, 1985.
198. J.J. Grefenstette, editor. *Proceedings of the 2nd International Conference on Genetic Algorithms and Their Applications*. Lawrence Erlbaum, Hillsdale, New Jersey, 1987.
199. J.J. Grefenstette. Genetic algorithms for changing environments. In Männer and Manderick [282], pages 137–144.
200. J.J. Grefenstette. Deception considered harmful. In Whitley [457], pages 75–91.
201. J.J. Grefenstette, R. Gopal, B. Rosmaita, and D. van Guch. Genetic algorithm for the TSP. In Grefenstette [197], pages 160–168.
202. J.J. Grefenstette. Optimisation of Control Parameters for Genetic Algorithms. *IEEE Transactions on Systems, Man and Cybernetics*, 16(1):122–128, 1986.
203. J.J. Merelo Guervos, P. Adamidis, H.-G. Beyer, J.-L. Fernandez-Villacanas, and H.-P. Schwefel, editors. *Proceedings of the 7th Conference on Parallel Problem Solving from Nature*, number 2439 in Lecture Notes in Computer Science. Springer, 2002.
204. E. Haasdijk, N. Bredeche, and A. E. Eiben. Combining environment-driven adaptation and task-driven optimisation in evolutionary robotics. *PLoS ONE*, 9(6):e98466, 2014.
205. A.B. Hadj-Alouane and J.C. Bean. A genetic algorithm for the multiple-choice integer program. Technical Report 92-50, University of Michigan, 1992.
206. N. Hansen. The CMA evolution strategy: A comparing review. In J.A. Lozano and P. Larranaga, editors, *Towards a New Evolutionary Computation: Advances in Estimation of Distribution Algorithms*, pages 75–102. Springer, 2006.
207. N. Hansen and A. Ostermeier. Completely derandomized self-adaptation in evolution strategies. *Evolutionary Computation*, 9(2):159–195, 2001.
208. P. Hansen and N. Mladenović. An introduction to variable neighborhood search. In S. Voß, S. Martello, I.H. Osman, and C. Roucairol, editors, *Metaheuristics: Advances and Trends in Local Search Paradigms for Optimization. Proceedings of MIC 97 Conference*. Kluwer Academic Publishers, Dordrecht, The Netherlands, 1998.
209. G. Harik and D.E. Goldberg. Learning linkage. In R.K. Belew and M.D. Vose, editors, *Foundations of Genetic Algorithms 4*, pages 247–262. Morgan Kaufmann, San Francisco, 1996.
210. E. Hart, P. Ross, and J. Nelson. Solving a real-world problem using an evolving heuristically driven schedule builder. *Evolutionary Computation*, 6(1):61–81, 1998.
211. W.E. Hart. *Adaptive Global Optimization with Local Search*. PhD thesis, University of California, San Diego, 1994.

212. M.S. Hillier and F.S. Hillier. Conventional optimization techniques. In Sarker et al. [363], chapter 1, pages 3–25.
213. W.D. Hillis. Co-evolving parasites improve simulated evolution as an optimization procedure. In C.G. Langton, C. Taylor, J.D. Farmer, and S. Rasmussen, editors, *Proceedings of the Workshop on Artificial Life (ALIFE '90)*, pages 313–324, Redwood City, CA, USA, 1992. Addison-Wesley.
214. R. Hinterding, Z. Michalewicz, and A.E. Eiben. Adaptation in evolutionary computation: A survey. In ICEC-97 [231].
215. G.E. Hinton and S.J. Nowlan. How learning can guide evolution. *Complex Systems*, 1:495–502, 1987.
216. P.G. Hoel, S.C. Port, and C.J. Stone. *Introduction to Stochastic Processes*. Houghton Mifflin, 1972.
217. F. Hoffmeister and T. Bäck. Genetic self-learning. In Varela and Bourguine [440], pages 227–235.
218. J.H. Holland. Genetic algorithms and the optimal allocation of trials. *SIAM J. of Computing*, 2:88–105, 1973.
219. J.H. Holland. Adaptation. In Rosen and Snell, editors, *Progress in Theoretical Biology: 4*. Plenum, 1976.
220. J.H. Holland. *Adaption in Natural and Artificial Systems*. MIT Press, Cambridge, MA, 1992. 1st edition: 1975, The University of Michigan Press, Ann Arbor.
221. J.N. Hooker. Testing heuristics: We have it all wrong. *Journal of Heuristics*, 1:33–42, 1995.
222. W. Hordijk and B. Manderick. The usefulness of recombination. In Morán et al. [305], pages 908–919.
223. J. Horn, N. Nafpliotis, and D.E. Goldberg. A niched Pareto genetic algorithm for multiobjective optimization. In ICEC-94 [229], pages 82–87.
224. C.R. Houck, J.A. Joines, M.G. Kay, and J.R. Wilson. Empirical investigation of the benefits of partial Lamarckianism. *Evolutionary Computation*, 5(1):31–60, 1997.
225. P. Husbands. Distributed co-evolutionary genetic algorithms for multi-criteria and multi-constraint optimisation. In T.C. Fogarty, editor, *Evolutionary Computing: Proceedings of the AISB workshop*, LNCS 865, pages 150–165. Springer, 1994.
226. F. Hutter, T. Bartz-Beielstein, H.H. Hoos, K. Leyton-Brown, and K.P. Murphy. Sequential model-based parameter optimisation: an experimental investigation of automated and interactive approaches. In T. Bartz-Beielstein, M. Chiarandini, L. Paquete, and M. Preuss, editors, *Empirical Methods for the Analysis of Optimization Algorithms*, chapter 15, pages 361–411. Springer, 2010.
227. F. Hutter, H.H. Hoos, K. Leyton-Brown, and T. Stützle. ParamILS: an automatic algorithm configuration framework. *Journal of Artificial Intelligence Research*, 36:267–306, October 2009.
228. H. Iba, H. de Garis, and T. Sato. Genetic programming using a minimum description length principle. In Kinnear [249], pages 265–284.
229. *Proceedings of the First IEEE Conference on Evolutionary Computation*. IEEE Press, Piscataway, NJ, 1994.
230. *Proceedings of the 1996 IEEE Conference on Evolutionary Computation*. IEEE Press, Piscataway, NJ, 1996.
231. *Proceedings of the 1997 IEEE Conference on Evolutionary Computation*. IEEE Press, Piscataway, NJ, 1997.

232. A. Jain and D.B. Fogel. Case studies in applying fitness distributions in evolutionary algorithms. II. Comparing the improvements from crossover and gaussian mutation on simple neural networks. In X. Yao and D.B. Fogel, editors, *Proc. of the 2000 IEEE Symposium on Combinations of Evolutionary Computation and Neural Networks*, pages 91–97. IEEE Press, Piscataway, NJ, 2000.
233. N. Jakobi, P. Husbands, and I. Harvey. Noise and the reality gap: The use of noise and the reality gap: The use of simulation in evolutionary robotics. In *Proc. of the Third European Conference on Artificial Life*, number 929 in LNCS, pages 704–720. Springer, 1995.
234. T. Jansen. *Analyzing Evolutionary Algorithms. The Computer Science Perspective*. Natural Computing Series. Springer, 2013.
235. Y. Jin. A comprehensive survey of fitness approximation in evolutionary computation. *Soft Computing*, 9(1):3–12, 2005.
236. Y. Jin. Surrogate-assisted evolutionary computation: Recent advances and future challenges. *Swarm and Evolutionary Computation*, 1(2):61–70, 2011.
237. J.A. Joines and C.R. Houck. On the use of non-stationary penalty functions to solve nonlinear constrained optimisation problems with GA's. In ICEC-94 [229], pages 579–584.
238. T. Jones. *Evolutionary Algorithms, Fitness Landscapes and Search*. PhD thesis, University of New Mexico, Albuquerque, NM, 1995.
239. L. Kallel, B. Naudts, and C. Reeves. Properties of fitness functions and search landscapes. In Kallel et al. [240], pages 175–206.
240. L. Kallel, B. Naudts, and A. Rogers, editors. *Theoretical Aspects of Evolutionary Computing*. Springer, 2001.
241. G. Karafotias, M. Hoogendoorn, and A.E. Eiben. Trends and challenges in evolutionary algorithms parameter control. *IEEE Transactions on Evolutionary Computation*, 19(2):167–187, 2015.
242. G. Karafotias, S.K. Smit, and A.E. Eiben. A generic approach to parameter control. In C. Di Chio et al., editor, *Applications of Evolutionary Computing, EvoStar 2012*, volume 7248 of LNCS, pages 361–370. Springer, 2012.
243. H. Kargupta. The gene expression messy genetic algorithm. In ICEC-96 [230], pages 814–819.
244. S.A. Kauffman. *Origins of Order: Self-Organization and Selection in Evolution*. Oxford University Press, New York, NY, 1993.
245. A.J. Keane and S.M. Brown. The design of a satellite boom with enhanced vibration performance using genetic algorithm techniques. In I.C. Parmee, editor, *Proceedings of the Conference on Adaptive Computing in Engineering Design and Control 96*, pages 107–113. P.E.D.C., Plymouth, 1996.
246. G. Kendall, P. Cowling, and E. Soubeiga. Choice function and random hyperheuristics. In *Proceedings of Fourth Asia-Pacific Conference on Simulated Evolution and Learning (SEAL)*, pages 667–671, 2002.
247. J. Kennedy and R. Eberhart. Particle swarm optimization. In *Proceedings of the 1995 IEEE International Conference on Neural Networks*, volume 4, pages 1942–1948, November 1995.
248. J. Kennedy and R.C. Eberhart. *Swarm Intelligence*. Morgan Kaufmann, 2001.
249. K.E. Kinnear, editor. *Advances in Genetic Programming*. MIT Press, Cambridge, MA, 1994.
250. S. Kirkpatrick, C. Gelatt, and M. Vecchi. Optimization by simulated annealing. *Science*, 220:671–680, 1983.

251. J.D. Knowles and D.W. Corne. Approximating the nondominated front using the Pareto Archived Evolution Strategy. *Evolutionary Computation*, 8(2):149–172, 2000.
252. J.R. Koza. *Genetic Programming*. MIT Press, Cambridge, MA, 1992.
253. J.R. Koza. *Genetic Programming II*. MIT Press, Cambridge, MA, 1994.
254. J.R. Koza. Scalable learning in genetic programming using automatic function definition. In Kinnear [249], pages 99–117.
255. J.R. Koza and F.H. Bennett. Automatic synthesis, placement, and routing of electrical circuits by means of genetic programming. In Spector et al. [416], pages 105–134.
256. J.R. Koza, K. Deb, M. Dorigo, D.B. Fogel, M. Garzon, H. Iba, and R.L. Riolo, editors. *Proceedings of the 2nd Annual Conference on Genetic Programming*. MIT Press, Cambridge, MA, 1997.
257. Oliver Kramer. Evolutionary self-adaptation: a survey of operators and strategy parameters. *Evolutionary Intelligence*, 3(2):51–65, 2010.
258. N. Krasnogor. Coevolution of genes and memes in memetic algorithms. In A.S. Wu, editor, *Proceedings of the 1999 Genetic and Evolutionary Computation Conference Workshop Program*, 1999.
259. N. Krasnogor. *Studies in the Theory and Design Space of Memetic Algorithms*. PhD thesis, University of the West of England, 2002.
260. N. Krasnogor. Self-generating metaheuristics in bioinformatics: The protein structure comparison case. *Genetic Programming and Evolvable Machines. Kluwer academic Publishers*, 5(2):181–201, 2004.
261. N. Krasnogor, B.P. Blackburne, E.K. Burke, and J.D. Hirst. Multimeme algorithms for protein structure prediction. In Guervos et al. [203], pages 769–778.
262. N. Krasnogor and S.M. Gustafson. A study on the use of “self-generation” in memetic algorithms. *Natural Computing*, 3(1):53–76, 2004.
263. N. Krasnogor and J.E. Smith. A memetic algorithm with self-adaptive local search: TSP as a case study. In Whitley et al. [453], pages 987–994.
264. N. Krasnogor and J.E. Smith. Emergence of profitable search strategies based on a simple inheritance mechanism. In Spector et al. [415], pages 432–439.
265. N. Krasnogor and J.E. Smith. A tutorial for competent memetic algorithms: Model, taxonomy and design issues. *IEEE Transactions on Evolutionary Computation*, 9(5):474–488, 2005.
266. T. Krink, P. Rickers, and R. Thomsen. Applying self-organised criticality to evolutionary algorithms. In Schoenauer et al. [368], pages 375–384.
267. M.W.S. Land. *Evolutionary Algorithms with Local Search for Combinatorial Optimization*. PhD thesis, University of California, San Diego, 1998.
268. W.B. Langdon, T. Soule, R. Poli, and J.A. Foster. The evolution of size and shape. In Spector et al. [416], pages 163–190.
269. P.L. Lanzi. Learning classifier systems: then and now. *Evolutionary Intelligence*, 1:63–82, 2008.
270. P.L. Lanzi, W. Stolzmann, and S.W. Wilson, editors. *Learning Classifier Systems: From Foundations to Applications*, volume 1813 of *LNAI*. Springer, 2000.
271. S. Lin and B. Kernighan. An effective heuristic algorithm for the Traveling Salesman Problem. *Operations Research*, 21:498–516, 1973.
272. X. Llorca, R. Reddy, B. Matesic, and R. Bhargava. Towards better than human capability in diagnosing prostate cancer using infrared spectroscopic imaging. In Bosman et al. [65], pages 2098–2105.

273. F.G. Lobo, C.F. Lima, and Z. Michalewicz, editors. *Parameter Setting in Evolutionary Algorithms*. Springer, 2007.
274. R. Lohmann. Application of evolution strategy in parallel populations. In Schwefel and Männer [374], pages 198–208.
275. S. Luke and L. Spector. A comparison of crossover and mutation in genetic programming. In Koza et al. [256], pages 240–248.
276. G. Luque and E. Alba. *Parallel Genetic Algorithms*, volume 367 of *Studies in Computational Intelligence*. Springer, 2011.
277. W.G. Macready and D.H. Wolpert. Bandit problems and the exploration/exploitation tradeoff. *IEEE Transactions on Evolutionary Computation*, 2(1):2–22, April 1998.
278. S.W. Mahfoud. Crowding and preselection revisited. In Männer and Manderick [282], pages 27–36.
279. S.W. Mahfoud. Boltzmann selection. In Bäck et al. [26], pages C2.5:1–4.
280. R. Mallipeddi and P. Suganthan. Differential evolution algorithm with ensemble of parameters and mutation and crossover strategies. In B. Panigrahi, S. Das, P. Suganthan, and S. Dash, editors, *Swarm, Evolutionary, and Memetic Computing*, volume 6466 of *Lecture Notes in Computer Science*, pages 71–78. Springer, 2010.
281. B. Manderick and P. Spiessens. Fine-grained parallel genetic algorithms. In Schaffer [365], pages 428–433.
282. R. Männer and B. Manderick, editors. *Proceedings of the 2nd Conference on Parallel Problem Solving from Nature*. North-Holland, Amsterdam, 1992.
283. O. Maron and A. Moore. The racing algorithm: Model selection for lazy learners. In *Artificial Intelligence Review*, volume 11, pages 193–225. Kluwer Academic Publishers, USA, April 1997.
284. W.N. Martin, J. Lienig, and J.P. Cohoon. Island (migration) models: evolutionary algorithms based on punctuated equilibria. In Bäck et al. [28], chapter 15, pages 101–124.
285. W.N. Martin and W.M. Spears, editors. *Foundations of Genetic Algorithms 6*. Morgan Kaufmann, San Francisco, 2001.
286. J. Maturana, F. Lardeux, and F. Saubion. Autonomous operator management for evolutionary algorithms. *Journal of Heuristics*, 16:881–909, 2010.
287. G. Mayley. Landscapes, learning costs and genetic assimilation. *Evolutionary Computation*, 4(3):213–234, 1996.
288. J. Maynard-Smith. *The Evolution of Sex*. Cambridge University Press, Cambridge, UK, 1978.
289. J. Maynard-Smith and E. Száthmary. *The Major Transitions in Evolution*. W.H. Freeman, 1995.
290. J.T. McClave and T. Sincich. *Statistics*. Prentice Hall, 9th edition, 2003.
291. B. McGinley, J. Maher, C. O’Riordan, and F. Morgan. Maintaining healthy population diversity using adaptive crossover, mutation, and selection. *IEEE Transactions on Evolutionary Computation*, 15(5):692–714, 2011.
292. P. Merz. *Memetic Algorithms for Combinatorial Optimization Problems: Fitness Landscapes and Effective Search Strategies*. PhD thesis, University of Siegen, Germany, 2000.
293. P. Merz and B. Freisleben. Fitness landscapes and memetic algorithm design. In D. Corne, M. Dorigo, and F. Glover, editors, *New Ideas in Optimization*, pages 245–260. McGraw Hill, London, 1999.

294. R. Meuth, M.H. Lim, Y.S. Ong, and D.C. Wunsch. A proposition on memes and meta-memes in computing for higher-order learning. *Memetic Computing*, 1(2):85–100, 2009.
295. Z. Michalewicz. *Genetic Algorithms + Data Structures = Evolution Programs*. Springer, 3rd edition, 1996.
296. Z. Michalewicz. *Genetic algorithms + data structures = evolution programs (3rd, extended ed.)*. Springer, New York, NY, USA, 1996.
297. Z. Michalewicz. Decoders. In Bäck et al. [28], chapter 8, pages 49–55.
298. Z. Michalewicz, K. Deb, M. Schmidt, and T. Stidsen. Test-case generator for nonlinear continuous parameter optimization techniques. *IEEE Transactions on Evolutionary Computation*, 4(3):197–215, 2000.
299. Z. Michalewicz and G. Nazhiyath. Genocop III: A coevolutionary algorithm for numerical optimisation problems with nonlinear constraints. In *Proceedings of the 1995 IEEE Conference on Evolutionary Computation*, pages 647–651. IEEE Press, Piscataway, NJ, 1995.
300. Z. Michalewicz and M. Schmidt. Evolutionary algorithms and constrained optimization. In Sarker et al. [363], chapter 3, pages 57–86.
301. Z. Michalewicz and M. Schmidt. TCG-2: A test-case generator for nonlinear parameter optimisation techniques. In Ghosh and Tsutsui [184], pages 193–212.
302. Z. Michalewicz and M. Schoenauer. Evolutionary algorithms for constrained parameter optimisation problems. *Evolutionary Computation*, 4(1):1–32, 1996.
303. J.F. Miller, T. Kalganova, D. Job, and N. Lipnitskaya. The genetic algorithm as a discovery engine: Strange circuits and new principles. In Bentley and Corne [49], pages 443–466.
304. D.J. Montana. Strongly typed genetic programming. *Evolutionary Computation*, 3(2):199–230, 1995.
305. F. Morán, A. Moreno, J. J. Merelo, and P. Chacón, editors. *Advances in Artificial Life. Third International Conference on Artificial Life*, volume 929 of *Lecture Notes in Artificial Intelligence*. Springer, 1995.
306. N. Mori, H. Kita, and Y. Nishikawa. Adaptation to a changing environment by means of the thermodynamical genetic algorithm. In Voigt et al. [445], pages 513–522.
307. A. Moroni, J. Manzolli, F. Von Zuben, and R. Gudwin. Vox populi: Evolutionary computation for music evolution. In Bentley and Corne [49], pages 206–221.
308. P.A. Moscato. On evolution, search, optimization, genetic algorithms and martial arts: Towards memetic algorithms. Technical Report Caltech Concurrent Computation Program Report 826, Caltech, 1989.
309. P.A. Moscato. *Problemas de Otimização NP, Aproximabilidade e Computação Evolutiva: Da Prática à Teoria*. PhD thesis, Universidade Estadual de Campinas, Brazil, 2001.
310. T. Motoki. Calculating the expected loss of diversity of selection schemes. *Evolutionary Computation*, 10(4):397–422, 2002.
311. H. Mühlenbein. Parallel genetic algorithms, population genetics and combinatorial optimization. In Schaffer [365], pages 416–421.
312. M. Munetomo and D.E. Goldberg. Linkage identification by non-monotonicity detection for overlapping functions. *Evolutionary Computation*, 7(4):377–398, 1999.

313. V. Nannen and A. E. Eiben. A method for parameter calibration and relevance estimation in evolutionary algorithms. In M. Keijzer, editor, *Proceedings of the Genetic and Evolutionary Computation Conference (GECCO-2006)*, pages 183–190. Morgan Kaufmann, San Francisco, 2006.
314. V. Nannen and A. E. Eiben. Relevance Estimation and Value Calibration of Evolutionary Algorithm Parameters. In Manuela M. Veloso, editor, *Proceedings of the 20th International Joint Conference on Artificial Intelligence (IJCAI)*, pages 1034–1039. Hyderabad, India, 2007.
315. A.L. Nelson, G.J. Barlow, and L. Doitsidis. Fitness functions in evolutionary robotics: A survey and analysis. *Robotics and Autonomous Systems*, 57(4):345–370, 2009.
316. F. Neri. An Adaptive Multimeme Algorithm for Designing HIV Multidrug Therapies. *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, 4(2):264–278, 2007.
317. F. Neri. Fitness diversity based adaptation in Multimeme Algorithms: A comparative study. In *IEEE Congress on Evolutionary Computation, CEC 2007*, pages 2374–2381, 2007.
318. F. Neumann and C. Witt. *Bioinspired Computation in Combinatorial Optimization: Algorithms and Their Computational Complexity*. Natural Computing Series. Springer, 2010.
319. Q.H. Nguyen, Y.-S. Ong, M.H. Lim, and N. Krasnogor. Adaptive cellular memetic algorithms. *Evolutionary Computation*, 17(2), June 2009.
320. Q.H. Nguyen, Y.S. Ong, and M.H. Lim. A Probabilistic Memetic Framework. *IEEE Transactions on Evolutionary Computation*, 13(3):604–623, 2009.
321. A. Nix and M. Vose. Modelling genetic algorithms with Markov chains. *Annals of Mathematics and Artificial Intelligence*, pages 79–88, 1992.
322. S. Nolfi and D. Floreano. *Evolutionary Robotics: The Biology, Intelligence, and Technology of Self-Organizing Machines*. MIT Press, Cambridge, MA, 2000.
323. P. O’Dowd, A.F. Winfield, and M. Studley. The distributed co-evolution of an embodied simulator and controller for swarm robot behaviours. In *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2011)*, pages 4995–5000. IEEE Press, 2011.
324. C.K. Oei, D.E. Goldberg, and S.J. Chang. Tournament selection, niching, and the preservation of diversity. Technical Report 91011, University of Illinois Genetic Algorithms Laboratory, 1991.
325. I.M. Oliver, D.J. Smith, and J. Holland. A study of permutation crossover operators on the travelling salesman problem. In Grefenstette [198], pages 224–230.
326. Y.S. Ong and A.J. Keane. Meta-lamarckian learning in memetic algorithms. *IEEE Transactions on Evolutionary Computation*, 8(2):99–110, 2004.
327. Y.S. Ong, M.H. Lim, and X. Chen. Memetic Computation—Past, Present & Future [Research Frontier]. *Computational Intelligence Magazine, IEEE*, 5(2):24–31, 2010.
328. Y.S. Ong, M.H. Lim, N. Zhu, and K.W. Wong. Classification of adaptive memetic algorithms: A comparative study. *IEEE Transactions on Systems Man and Cybernetics Part B*, 36(1), 2006.
329. B. Paechter, R.C. Rankin, A. Cumming, and T.C. Fogarty. Timetabling the classes of an entire university with an evolutionary algorithm. In Eiben et al. [131], pages 865–874.

330. C.M. Papadimitriou. *Computational complexity*. Addison-Wesley, Reading, Massachusetts, 1994.
331. C.M. Papadimitriou and K. Steiglitz. *Combinatorial optimization: algorithms and complexity*. Prentice Hall, Englewood Cliffs, NJ, 1982.
332. J. Paredis. The symbiotic evolution of solutions and their representations. In Eshelman [156], pages 359–365.
333. J. Paredis. Coevolutionary algorithms. In Bäck et al. [26].
334. I.C. Parmee. Improving problem definition through interactive evolutionary computing. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing*, 16(3):185–202, 2002.
335. O. Pauplin, P. Caleb-Solly, and J.E. Smith. User-centric image segmentation using an interactive parameter adaptation tool. *Pattern Recognition*, 43(2):519–529, February 2010.
336. M. Pelikan, D.E. Goldberg, and E. Cantù-Paz. BOA: The Bayesian optimization algorithm. In Banzhaf et al. [36], pages 525–532.
337. M. Pelikan and H. Mühlhain. The bivariate marginal distribution algorithm. In R. Roy, T. Furuhashi, and P.K. Chawdhry, editors, *Advances in Soft Computing—Engineering Design and Manufacturing*, pages 521–535. Springer, 1999.
338. C. Pettey. Diffusion (cellular) models. In Bäck et al. [28], chapter 16, pages 125–133.
339. C.B. Pettey, M.R. Leuze, and J.J. Grefenstette. A parallel genetic algorithm. In Grefenstette [198], pages 155–161.
340. R. Poli, J. Kennedy, and T. Blackwell. Particle swarm optimization – an overview. *Swarm Intelligence*, 1(1):33–57, 2007.
341. C. Potta, R. Poli, J. Rowe, and K. De Jong, editors. *Foundations of Genetic Algorithms 7*. Morgan Kaufmann, San Francisco, 2003.
342. M.A. Potter and K.A. De Jong. A cooperative coevolutionary approach to function optimisation. In Davidor et al. [96], pages 248–257.
343. K.V. Price, R.N. Storn, and J.A. Lampinen. *Differential Evolution: A Practical Approach to Global Optimization*. Natural Computing Series. Springer, 2005.
344. P. Prosser. An empirical study of phase transitions in binary constraint satisfaction problems. *Artificial Intelligence*, 81:81–109, 1996.
345. A. Prügel-Bennet and J. Shapiro. An analysis of genetic algorithms using statistical mechanics. *Phys. Review Letters*, 72(9):1305–1309, 1994.
346. A. Prügel-Bennett. Modelling evolving populations. *J. Theoretical Biology*, 185(1):81–95, March 1997.
347. A. Prügel-Bennett. Modelling finite populations. In Potta et al. [341].
348. A. Prügel-Bennett and A. Rogers. Modelling genetic algorithm dynamics. In L. Kallel, B. Naudts, and A. Rogers, editors, *Theoretical Aspects of Evolutionary Computing*, pages 59–85. Springer, 2001.
349. A. K. Qin, V. L. Huang, and P. N. Suganthan. Differential evolution algorithm with strategy adaptation for global numerical optimization. *Trans. Evol. Comp.*, 13:398–417, April 2009.
350. N. Radcliffe. Forma analysis and random respectful recombination. In Belew and Booker [46], pages 222–229.
351. G. Rawlins, editor. *Foundations of Genetic Algorithms*. Morgan Kaufmann, San Francisco, 1991.

352. I. Rechenberg. *Evolutionstrategie: Optimierung technischer Systeme nach Prinzipien des biologischen Evolution*. Frommann-Hollboog Verlag, Stuttgart, 1973.
353. C. Reeves and J. Rowe. *Genetic Algorithms: Principles and Perspectives*. Kluwer, Norwell MA, 2002.
354. A. Rogers and A. Prügel-Bennett. Modelling the dynamics of a steady-state genetic algorithm. In Banzhaf and Reeves [38], pages 57–68.
355. J. Romero and P. Machado. *The Art of Artificial Evolution*. Natural Computing Series. Springer, 2008.
356. G. Rudolph. Global optimization by means of distributed evolution strategies. In Schwefel and Männer [374], pages 209–213.
357. G. Rudolph. Convergence properties of canonical genetic algorithms. *IEEE Transactions on Neural Networks*, 5(1):96–101, 1994.
358. G. Rudolph. Convergence of evolutionary algorithms in general search spaces. In ICEC-96 [230], pages 50–54.
359. G. Rudolph. Reflections on bandit problems and selection methods in uncertain environments. In Bäck [23], pages 166–173.
360. G. Rudolph. Takeover times and probabilities of non-generational selection rules. In Whitley et al. [453], pages 903–910.
361. T. Runarson and X. Yao. Constrained evolutionary optimization – the penalty function approach. In Sarker et al. [363], chapter 4, pages 87–113.
362. A. Salman, K. Mehrota, and C. Mohan. Linkage crossover for genetic algorithms. In Banzhaf et al. [36], pages 564–571.
363. R. Sarker, M. Mohammadian, and X. Yao, editors. *Evolutionary Optimization*. Kluwer Academic Publishers, Boston, 2002.
364. J.D. Schaffer. *Multiple Objective Optimization with Vector Evaluated Genetic Algorithms*. PhD thesis, Vanderbilt University, Tennessee, 1984.
365. J.D. Schaffer, editor. *Proceedings of the 3rd International Conference on Genetic Algorithms*. Morgan Kaufmann, San Francisco, 1989.
366. J.D. Schaffer and L.J. Eshelman. On crossover as an evolutionarily viable strategy. In Belew and Booker [46], pages 61–68.
367. D. Schlierkamp-Voosen and H. Mühlenbein. Strategy adaptation by competing subpopulations. In Davidor et al. [96], pages 199–209.
368. M. Schoenauer, K. Deb, G. Rudolph, X. Yao, E. Lutton, J.J. Merelo, and H.-P. Schwefel, editors. *Proceedings of the 6th Conference on Parallel Problem Solving from Nature*, number 1917 in Lecture Notes in Computer Science. Springer, 2000.
369. M. Schoenauer and S. Xanthakis. Constrained GA optimisation. In Forrest [176], pages 573–580.
370. S. Schulenburg and P. Ross. Strength and money: An LCS approach to increasing returns. In P.L. Lanzi, W. Stolzmann, and S.W. Wilson, editors, *Advances in Learning Classifier Systems*, volume 1996 of *LNAI*, pages 114–137. Springer, 2001.
371. M.C. Schut, E. Haasdijk, and A.E. Eiben. What is situated evolution? In *Proceedings of the 2009 IEEE Congress on Evolutionary Computation (CEC 2009)*, pages 3277–3284. IEEE Press, 2009.
372. H.-P. Schwefel. *Numerische Optimierung von Computer-Modellen mittels der Evolutionstrategie*, volume 26 of *ISR*. Birkhaeuser, Basel/Stuttgart, 1977.
373. H.-P. Schwefel. *Evolution and Optimum Seeking*. Wiley, New York, 1995.

374. H.-P. Schwefel and R. Männer, editors. *Proceedings of the 1st Conference on Parallel Problem Solving from Nature*, number 496 in Lecture Notes in Computer Science. Springer, 1991.
375. M Serpell and JE Smith. Self-Adaption of Mutation Operator and Probability for Permutation Representations in Genetic Algorithms. *Evolutionary Computation*, 18(3):1–24, February 2010.
376. S. K. Smit and A. E. Eiben. Beating the ‘world champion’ evolutionary algorithm via REVAC tuning. In *IEEE Congress on Evolutionary Computation*, pages 1–8, Barcelona, Spain, 2010. IEEE Computational Intelligence Society, IEEE Press.
377. S.K. Smit. *Algorithm Design in Experimental Research*. Ph.D Thesis, Vrije Universiteit Amsterdam, 2012.
378. S.K. Smit and A.E. Eiben. Comparing parameter tuning methods for evolutionary algorithms. In *Proceedings of the 2009 IEEE Congress on Evolutionary Computation (CEC 2009)*, pages 399–406. IEEE Press, 2009.
379. A.E. Smith and D.W. Coit. Penalty functions. In Bäck et al. [28], chapter 7, pages 41–48.
380. A.E. Smith and D.M. Tate. Genetic optimisation using a penalty function. In Forrest [176], pages 499–505.
381. J. Smith. Credit assignment in adaptive memetic algorithms. In *Proceedings of GECCO 2007, the ACM-SIGEVO conference on Evolutionary Computation*, pages 1412–1419, 2007.
382. J.E. Smith. *Self-Adaptation in Evolutionary Algorithms*. PhD thesis, University of the West of England, Bristol, UK, 1998.
383. J.E. Smith. Modelling GAs with self-adaptive mutation rates. In Spector et al. [415], pages 599–606.
384. J.E. Smith. Co-evolution of memetic algorithms: Initial investigations. In Guervos et al. [203], pages 537–548.
385. J.E. Smith. On appropriate adaptation levels for the learning of gene linkage. *J. Genetic Programming and Evolvable Machines*, 3(2):129–155, 2002.
386. J.E. Smith. Parameter perturbation mechanisms in binary coded GAs with self-adaptive mutation. In Rowe, Poli, DeJong, and Cotta, editors, *Foundations of Genetic Algorithms 7*, pages 329–346. Morgan Kaufmann, San Francisco, 2003.
387. J.E. Smith. Protein structure prediction with co-evolving memetic algorithms. In *Proceedings of the 2003 Congress on Evolutionary Computation (CEC 2003)*, pages 2346–2353. IEEE Press, Piscataway, NJ, 2003.
388. J.E. Smith. The co-evolution of memetic algorithms for protein structure prediction. In W.E. Hart, N. Krasnogor, and J.E. Smith, editors, *Recent Advances in Memetic Algorithms*, pages 105–128. Springer, 2004.
389. J.E. Smith. Co-evolving memetic algorithms: A review and progress report. *IEEE Transactions in Systems, Man and Cybernetics, part B*, 37(1):6–17, 2007.
390. J.E. Smith. On replacement strategies in steady state evolutionary algorithms. *Evolutionary Computation*, 15(1):29–59, 2007.
391. J.E. Smith. Estimating meme fitness in adaptive memetic algorithms for combinatorial problems. *Evolutionary Computation*, 20(2):165188, 2012.
392. J.E. Smith, M. Bartley, and T.C. Fogarty. Microprocessor design verification by two-phase evolution of variable length tests. In ICEC-97 [231], pages 453–458.
393. J.E. Smith and T.C. Fogarty. An adaptive poly-parental recombination strategy. In T.C. Fogarty, editor, *Evolutionary Computing 2*, pages 48–61. Springer, 1995.

394. J.E. Smith and T.C. Fogarty. Evolving software test data - GAs learn self expression. In T.C. Fogarty, editor, *Evolutionary Computing*, number 1143 in Lecture Notes in Computer Science, pages 137–146, 1996.
395. J.E. Smith and T.C. Fogarty. Recombination strategy adaptation via evolution of gene linkage. In ICEC-96 [230], pages 826–831.
396. J.E. Smith and T.C. Fogarty. Self adaptation of mutation rates in a steady state genetic algorithm. In ICEC-96 [230], pages 318–323.
397. J.E. Smith and T.C. Fogarty. Operator and parameter adaptation in genetic algorithms. *Soft Computing*, 1(2):81–87, 1997.
398. J.E. Smith, T.C. Fogarty, and I.R. Johnson. Genetic feature selection for clustering and classification. In *Proceedings of the IEE Colloquium on Genetic Algorithms in Image Processing and Vision*, volume IEE Digest 1994/193, 1994.
399. J.E. Smith and F. Vavak. Replacement strategies in steady state genetic algorithms: dynamic environments. *J. Computing and Information Technology*, 7(1):49–60, 1999.
400. J.E. Smith and F. Vavak. Replacement strategies in steady state genetic algorithms: static environments. In Banzhaf and Reeves [38], pages 219–234.
401. R.E. Smith, C. Bonacina, P. Kearney, and W. Merlat. Embodiment of evolutionary computation in general agents. *Evolutionary Computation*, 8(4):475–493, 2001.
402. R.E. Smith and D.E. Goldberg. Diploidy and dominance in artificial genetic search. *Complex Systems*, 6:251–285, 1992.
403. R.E. Smith and J.E. Smith. An examination of tuneable, random search landscapes. In Banzhaf and Reeves [38], pages 165–181.
404. R.E. Smith and J.E. Smith. New methods for tuneable, random landscapes. In Martin and Spears [285], pages 47–67.
405. C. Soddu. Recognizability of the idea: the evolutionary process of Argenia. In Bentley and Corne [49], pages 109–127.
406. T. Soule and J.A. Foster. Effects of code growth and parsimony pressure on populations in genetic programming. *Evolutionary Computation*, 6(4):293–309, Winter 1998.
407. T. Soule, J.A. Foster, and J. Dickinson. Code growth in genetic programming. In J.R. Koza, D.E. Goldberg, D.B. Fogel, and R.L. Riolo, editors, *Proceedings of the 1st Annual Conference on Genetic Programming*, pages 215–223. MIT Press, Cambridge, MA, 1996.
408. W.M. Spears. Crossover or mutation. In Whitley [457], pages 220–237.
409. W.M. Spears. Simple subpopulation schemes. In A.V. Sebald and L.J. Fogel, editors, *Proceedings of the 3rd Annual Conference on Evolutionary Programming*, pages 296–307. World Scientific, 1994.
410. W.M. Spears. Adapting crossover in evolutionary algorithms. In J.R. McDonnell, R.G. Reynolds, and D.B. Fogel, editors, *Proceedings of the 4th Annual Conference on Evolutionary Programming*, pages 367–384. MIT Press, Cambridge, MA, 1995.
411. W.M. Spears. *Evolutionary Algorithms: the role of mutation and recombination*. Springer, 2000.
412. W.M. Spears and K.A. De Jong. An analysis of multi point crossover. In Rawlins [351], pages 301–315.
413. W.M. Spears and K.A. De Jong. On the virtues of parameterized uniform crossover. In Belew and Booker [46], pages 230–237.

414. W.M. Spears and K.A. De Jong. Dining with GAs: Operator lunch theorems. In Banzhaf and Reeves [38], pages 85–101.
415. L. Spector, E. Goodman, A. Wu, W.B. Langdon, H.-M. Voigt, M. Gen, S. Sen, M. Dorigo, S. Pezeshk, M. Garzon, and E. Burke, editors. *Proceedings of the Genetic and Evolutionary Computation Conference (GECCO-2001)*. Morgan Kaufmann, San Francisco, 2001.
416. L. Spector, W.B. Langdon, U.-M. O'Reilly, and P.J. Angeline, editors. *Advances in Genetic Programming 3*. MIT Press, Cambridge, MA, 1999.
417. N. Srinivas and K. Deb. Multiobjective optimization using nondominated sorting in genetic algorithms. *Evolutionary Computation*, 2(3):221–248, Fall 1994.
418. C.R. Stephens and H. Waelbroeck. Schemata evolution and building blocks. *Evolutionary Computation*, 7(2):109–124, 1999.
419. R. Storn and K. Price. Differential evolution - a simple and efficient adaptive scheme for global optimization over continuous spaces. Technical Report TR-95-012, ICSI, Berkeley, March 1995.
420. P.N. Suganthan, N. Hansen, J.J. Liang, K. Deb, Y.-P. Chen, A. Auger, and S. Tiwari. Problem definitions and evaluation criteria for the CEC 2005 special session on real-parameter optimization. Technical report, Nanyang Technological University, 2005.
421. P. Surry and N. Radcliffe. Innoculation to initialise evolutionary search. In T.C. Fogarty, editor, *Evolutionary Computing: Proceedings of the 1996 AISB Workshop*, pages 269–285. Springer, 1996.
422. G. Syswerda. Uniform crossover in genetic algorithms. In Schaffer [365], pages 2–9.
423. G. Syswerda. Schedule optimisation using genetic algorithms. In Davis [98], pages 332–349.
424. G. Taguchi and T. Yokoyama. *Taguchi Methods: Design of Experiments*. ASI Press, 1993.
425. R. Tanese. Parallel genetic algorithm for a hypercube. In Grefenstette [198], pages 177–183.
426. D.M. Tate and A.E. Smith. Unequal area facility layout using genetic search. *IIE transactions*, 27:465–472, 1995.
427. L. Tesfatsion. Preferential partner selection in evolutionary labor markets: A study in agent-based computational economics. In V.W. Porto, N. Saravanan, D. Waagen, and A.E. Eiben, editors, *Proc. 7th Annual Conference on Evolutionary Programming*, number 1477 in LNCS, pages 15–24. Springer, 1998.
428. S.R. Thangiah, R. Vinayagamooty, and A.V. Gubbi. Vehicle routing and time deadlines using genetic and local algorithms. In Forrest [176], pages 506–515.
429. D. Thierens. Adaptive strategies for operator allocation. In Lobo et al. [273], pages 77–90.
430. D. Thierens and D.E. Goldberg. Mixing in genetic algorithms. In Forrest [176], pages 38–45.
431. C.K. Ting, W.M. Zeng, and T.C. Lin. Linkage discovery through data mining. *Computational Intelligence Magazine*, 5:10–13, 2010.
432. Vito Trianni. *Evolutionary Swarm Robotics – Evolving Self-Organising Behaviours in Groups of Autonomous Robots*, volume 108 of *Studies in Computational Intelligence*. Springer, 2008.
433. E.P.K. Tsang. *Foundations of Constraint Satisfaction*. Academic Press, 1993.
434. S. Tsutsui. Multi-parent recombination in genetic algorithms with search space boundary extension by mirroring. In Eiben et al. [131], pages 428–437.

435. P.D. Turney. How to shift bias: lessons from the Baldwin effect. *Evolutionary Computation*, 4(3):271–295, 1996.
436. R. Unger and J. Moult. A genetic algorithm for 3D protein folding simulations. In Forrest [176], pages 581–588.
437. J. I. van Hemert and A. E. Eiben. Mondriaan art by evolution. In Eric Postma and Marc Gyssens, editors, *Proceedings of the Eleventh Belgium/Netherlands Conference on Artificial Intelligence (BNAIC'99)*, pages 291–292, 1999.
438. C.H.M. van Kemenade. Explicit filtering of building blocks for genetic algorithms. In Voigt et al. [445], pages 494–503.
439. E. van Nimwegen, J.P. Crutchfield, and M. Mitchell. Statistical dynamics of the Royal Road genetic algorithm. *Theoretical Computer Science*, 229:41–102, 1999.
440. F.J. Varela and P. Bourguine, editors. *Toward a Practice of Autonomous Systems: Proceedings of the 1st European Conference on Artificial Life*. MIT Press, Cambridge, MA, 1992.
441. F. Vavak and T.C. Fogarty. A comparative study of steady state and generational genetic algorithms for use in nonstationary environments. In T.C. Fogarty, editor, *Evolutionary Computing*, pages 297–304. Springer, 1996.
442. F. Vavak and T.C. Fogarty. Comparison of steady state and generational genetic algorithms for use in nonstationary environments. In ICEC-96 [230], pages 192–195.
443. F. Vavak, T.C. Fogarty, and K. Jukes. A genetic algorithm with variable range of local search for tracking changing environments. In Voigt et al. [445], pages 376–385.
444. F. Vavak, K. Jukes, and T.C. Fogarty. Adaptive combustion balancing in multiple burner boiler using a genetic algorithm with variable range of local search. In Bäck [23], pages 719–726.
445. H.-M. Voigt, W. Ebeling, I. Rechenberg, and H.-P. Schwefel, editors. *Proceedings of the 4th Conference on Parallel Problem Solving from Nature*, number 1141 in Lecture Notes in Computer Science. Springer, 1996.
446. M.D. Vose. *The Simple Genetic Algorithm*. MIT Press, Cambridge, MA, 1999.
447. M.D. Vose and G.E. Liepins. Punctuated equilibria in genetic search. *Complex Systems*, 5(1):31, 1991.
448. M. Waibel, L. Keller, and D. Floreano. Genetic Team Composition and Level of Selection in the Evolution of Cooperation. *IEEE transactions on Evolutionary Computation*, 13(3):648–660, 2009.
449. J. Walker, S. Garrett, and M. Wilson. Evolving controllers for real robots: A survey of the literature. *Adaptive Behavior*, 11(3):179–203, 2003.
450. L. Wang, K.C. Tan, and C.M. Chew. *Evolutionary Robotics: from Algorithms to Implementations*, volume 28 of *World Scientific Series in Robotics and Intelligent Systems*. World Scientific, 2006.
451. P.M. White and C.C. Pettey. Double selection vs. single selection in diffusion model GAs. In Bäck [23], pages 174–180.
452. D. Whitley. Permutations. In Bäck et al. [27], chapter 33.3, pages 274–284.
453. D. Whitley, D. Goldberg, E. Cantu-Paz, L. Spector, I. Parmee, and H.-G. Beyer, editors. *Proceedings of the Genetic and Evolutionary Computation Conference (GECCO-2000)*. Morgan Kaufmann, San Francisco, 2000.
454. D. Whitley, K. Mathias, S. Rana, and J. Dzuber. Building better test functions. In Eshelman [156], pages 239–246.

455. L.D. Whitley. Fundamental principles of deception in genetic search. In Rawlins [351], pages 221–241.
456. L.D. Whitley. Cellular genetic algorithms. In Forrest [176], pages 658–658.
457. L.D. Whitley, editor. *Foundations of Genetic Algorithms - 2*. Morgan Kaufmann, San Francisco, 1993.
458. L.D. Whitley, S. Gordon, and K.E. Mathias. Lamarckian evolution, the Baldwin effect, and function optimisation. In Davidor et al. [96], pages 6–15.
459. L.D. Whitley and F. Gruau. Adding learning to the cellular development of neural networks: evolution and the Baldwin effect. *Evolutionary Computation*, 1:213–233, 1993.
460. L.D. Whitley and J. Kauth. Genitor: A different genetic algorithm. In *Proceedings of the Rocky Mountain Conference on Artificial Intelligence*, pages 118–130, 1988.
461. L.D. Whitley, K.E. Mathias, and P. Fitzhorn. Delta coding: An iterative search strategy for genetic algorithms,. In Belew and Booker [46], pages 77–84.
462. L.D. Whitley and M.D. Vose, editors. *Foundations of Genetic Algorithms 3*. Morgan Kaufmann, San Francisco, 1995.
463. W. Wickramasinghe, M. van Steen, and A. E. Eiben. Peer-to-peer evolutionary algorithms with adaptive autonomous selection. In D. Thierens et al., editor, *GECCO '07: Proc of the 9th conference on Genetic and Evolutionary Computation*, pages 1460–1467. ACM Press, 2007.
464. S.W. Wilson. ZCS: A zeroth level classifier system. *Evolutionary Computation*, 2(1):1–18, 1994.
465. S.W. Wilson. Classifier fitness based on accuracy. *Evolutionary Computation*, 3(2):149–175, 1995.
466. A.F.T. Winfield and J. Timmis. Evolvable robot hardware. In *Evolvable Hardware: from Practice to Applications*, Natural Computing Series, page in press. Springer, 2015.
467. D.H. Wolpert and W.G. Macready. No Free Lunch theorems for optimisation. *IEEE Transactions on Evolutionary Computation*, 1(1):67–82, 1997.
468. S. Wright. The roles of mutation, inbreeding, crossbreeding, and selection in evolution. In *Proc. of 6th Int. Congr. on Genetics*, volume 1, pages 356–366. Ithaca, NY, 1932.
469. X. Yao and Y. Liu. Fast evolutionary programming. In Fogel et al. [172].
470. X. Yao, Y. Liu, and G. Lin. Evolutionary programming made faster. *IEEE Transactions on Evolutionary Computing*, 3(2):82–102, 1999.
471. B. Yuan and M. Gallagher. Combining Meta-EAs and Racing for Difficult EA Parameter Tuning Tasks. In Lobo et al. [273], pages 121–142.
472. J. Zar. *Biostatistical Analysis*. Prentice Hall, 4th edition, 1999.
473. Zhi-hui Zhan and Jun Zhang. Adaptive particle swarm optimization. In M. Dorigo, M. Birattari, C. Blum, M. Clerc, T. Stützle, and A. Winfield, editors, *Ant Colony Optimization and Swarm Intelligence*, volume 5217 of *Lecture Notes in Computer Science*, pages 227–234. Springer, 2008.
474. Qingfu Zhang and Hui Li. MOEA/D: A Multiobjective Evolutionary Algorithm Based on Decomposition. *IEEE Transactions on Evolutionary Computation*, 11(6):712–731, 2007.
475. E. Zitzler, M. Laumanns, and L. Thiele. SPEA2: Improving the strength Pareto evolutionary algorithm for multiobjective optimization. In K.C. Giannakoglou, D.T.. Tsahalis, J. Périaux, K.D. Papailiou, and T.C. Fogarty, editors, *Evolutionary Methods for Design Optimization and Control with Applications to Industrial Problems*, pages 95–100, Athens, Greece, 2001. International Center for Numerical Methods in Engineering (Cmine).

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