Bibliography

[1] P. Amato and M. Farina. An alife-inspired evolutionary algorithm for dynamic multiobjective optimization problems. In F. Hoffmann, M. Köppen, F. Klawonn, and R. Roy, editors, *Soft Computing: Methodologies and Applications*, volume 32 of *Advances in Soft Computing*, pages 113–125. Springer Berlin/Heidelberg, 2005.

[2] Z. Avdagić, S. Konjicija, and S. Omanović. Evolutionary approach to solving non-stationary dynamic multi-objective problems. In A. Abraham, A-E. Hassanien, P. Siarry, and A. Engelbrecht, editors, *Foundations of Computational Intelligence Volume 3*, volume 203 of *Studies in Computational Intelligence*, pages 267–289. Springer Berlin/Heidelberg, 2009.

[3] C.R.B. Azevedo and A.F.R. Araujo. Generalized immigration schemes for dynamic evolutionary multiobjective optimization. In *Proceedings of Congress on Evolutionary Computation*, pages 2033–2040, june 2011.

[4] A. Banks, J. Vincent, and C. Anyakoha. A review of particle swarm optimization. part i: background and development. *Natural Computing*, 6(4):467–484, 2007.

[5] A. Banks, J. Vincent, and C. Anyakoha. A review of particle swarm optimization. part ii: hybridisation, combinatorial, multicriteria and constrained optimization, and indicative applications. *Natural Computing*, 7(1):109–124, 2008.

[6] T. Bartz-Beielstein, P. Limbourg, J. Mehnen, K. Schmitt, K.E. Parsopoulos, and M.N. Vrahatis. Particle swarm optimizers for pareto optimization with enhanced archiving techniques. In *Proceedings of the Congress on Evolutionary Computation*, volume 3, pages 1780–1787, dec. 2003.

[7] N. Beume, C.M. Fonseca, M. Lopez-Ibanez, L. Paquete, and J. Vahrenhold. On the complexity of computing the hypervolume indicator. *IEEE Transactions on Evolutionary Computation*, 13(5):1075–1082, oct. 2009.

[8] N. Beume and G. Rudolph. Faster s-metric calculation by considering dominated hypervolume as klee's measure problem. In *Proceedings of Computational Intelligence*, pages 233–238. IASTED/ACTA Press, 2007.

[9] H-G. Beyer and H-P. Schwefel. Evolution strategies – a comprehensive introduction. *Natural Computing*, 1(1):3–52, 2002.

[10] Z. Bingul. Adaptive genetic algorithms applied to dynamic multiobjective problems. *Applied Soft Computing*, 7:791–799, 2007.

[11] J. Branke. Gecco tutorial: Optimization in dynamic environments. Available online at: `http://www.cs.york.ac.uk/rts/docs/GECCO_2004/Workshop%20proceedings/gecco04/TUT026.pdf`, 2004. Last accessed on: 12 May 2011.

[12] J. Branke, E. Salihoğlu, and Ş. Uyar. Towards an analysis of dynamic environments. In *Proceedings of the Conference on Genetic and Evolutionary Computation*, pages 1433–1440, New York, NY, USA, 2005. ACM.

[13] J. Branke and H. Schmeck. *Advances in evolutionary computing: theory and applications*, chapter Designing evolutionary algorithms for dynamic optimization problems, pages 239–262. Natural Computing Series. Springer, 2003.

[14] F.M. Burnet. *The clonal selection theory of acquired immunity*. Cambridge University Press, Cambridge, U.K., 1959.

[15] M. Cámara, J. Ortega, and F. de Toro. The parallel single front genetic algorithm (psfga) in dynamic multi-objective optimization. In F. Sandoval, A. Prieto, J. Cabestany, and M. Gra na, editors, *Computational and Ambient Intelligence*, volume 4507 of *Lecture Notes in Computer Science*, pages 300–307. Springer Berlin/Heidelberg, 2007.

[16] M. Cámara, J. Ortega, and F. de Toro. A single front genetic algorithm for parallel multi-objective optimization in dynamic environments. *Neurocomputing*, 72(16-18):3570–3579, 2009. Financial Engineering; Computational and Ambient Intelligence (IWANN 2007).

[17] M. Cámara, J. Ortega, and F. de Toro. Approaching dynamic multi-objective optimization problems by using parallel evolutionary algorithms. In C. Coello Coello, C. Dhaenens, and L. Jourdan, editors, *Advances in Multi-Objective Nature Inspired Computing*, volume 272 of *Studies in Computational Intelligence*, pages 63–86. Springer Berlin/Heidelberg, 2010.

[18] M. Cámara, J. Ortega, and F.J. de Toro. Parallel processing for multi-objective optimization in dynamic environments. *International Parallel and Distributed Processing Symposium*, 0:243–250, 2007.

[19] M. Cámara, J. Ortega, and F.J. de Toro. A single front genetic algorithm for parallel multi-objective optimization in dynamic environments. *Neurocomputing*, 72(16–18):3570–3579, 2007.

[20] M. Cámara, J. Ortega, and F.J. de Toro. A diversity enhanced signle front multi-objective algorithm for dynamic optimization problems. In *Proceedings of the International Conference on Metaheuristics and Nature Inspired Computing*, 2008.

[21] A. Carlisle and G. Dozier. An off-the-shelf pso. In *Proceedings of Particle Swarm Optimization Workshop*, Indianapolis, Indiana, U.S.A., 2001.

[22] A. Carlisle and G. Dozier. Tracking changing extrema with adaptive particle swarm optimizer. In *Proceedings of World Automation Congress*, volume 13, pages 265–270, Orlando, Florida, U.S.A., June 2002.

[23] H. Chen, M. Li, and X. Chen. Using diversity as an additional-objective in dynamic multi-objective optimization algorithms. *Electronic Commerce and Security, International Symposium*, 1:484–487, 2009.

[24] CHPC. Sun hybrid system. http://www.chpc.ac.za/sun. Last accessed online on: 20 December 2011.

[25] W. Chu, X. Gao, and S. Sorooshian. Handling boundary constraints for particle swarm optimization in high-dimensional search space. *Information Sciences*, 2010. In Press.

[26] M. Clerc. *Particle swarm optimization*. ISTE Ltd, 2006.

[27] M. Clerc and J. Kennedy. The particle swarm - explosion, stability, and convergence in a multidimensional complex space. *IEEE Transactions on Evolutionary Computation*, 6(1):58–73, feb 2002.

[28] H.G. Cobb. An investigation into the use of hypermutation as an adaptive operator in genetic algorithms having continuous, time-dependent nonstationary environments. Technical report, Naval Research Laboratory: Navy Center for Applied Research in Articial Intelligence, Washington, DC, U.S.A., 11 December 1990.

[29] C. Coello Coello and G.T. Pulido. A micro-genetic algorithm for multiobjective optimization. In E. Zitzler, L. Thiele, K. Deb, C. Coello Coello, and D. Corne, editors, *Evolutionary multi-criterion optimization*, volume 1993 of *Lecture Notes in Computer Science*, pages 126–140. Springer Berlin/Heidelberg, 2001.

[30] C.A. Coello Coello. Evolutionary multiobjective optimization. Available online at: `http://www.lania.mx/~ccoello/`. Last accessed on: 23 May 2011.

[31] C.A. Coello Coello. *Computational Intelligence: Principles and Practice*, chapter 20 years of evolutionary multi-objective optimization: what has been done and what remains to be done, pages 73–88. IEEE Computational Intelligence Society, 2006.

[32] C.A. Coello Coello. Evolutionary multi-objective optimization: a historical view of the field. *IEEE Computational Intelligence Magazine*, 1(1):28–36, feb 2006.

[33] C.A. Coello Coello and M.S. Lechuga. Mopso: a proposal for multiple objective particle swarm optimization. In *Proceedings of Congress on Evolutionary Computation*, volume 2, pages 1051–1056, 2002.

[34] C.A. Coello Coello, G.T. Pulido, and M.S. Lechuga. Handling multiple objectives with particle swarm optimization. *IEEE Transactions on Evolutionary Computation*, 8(3):256–279, june 2004.

[35] C.A. Coello Coello, D.A. van Veldhuizen, and G.B. Lamont. *Evolutionary algorithms for solving multi-objective problems*. Kluwer Academic Publishers/Plenum Publishers, 2002.

[36] Y. Collette and P. Siarry. *Multiobjective optimization*. Decision Engineering. Springer-Verlag, 2003.

[37] C. Cruz, J. González, and D. Pelta. Optimization in dynamic environments: a survey on problems, methods and measures. *Soft Computing - A Fusion of Foundations, Methodologies and Applications*, pages 1–22, 2010.

[38] K. Deb. Multi-objective genetic algorithms: problem difficulties and construction of test problems. *Evolutionary Computation*, (3):205–230, 1999.

[39] K. Deb. *Multi-objective optimization using evolutionary algorithms*. John Wiley & Sons, Ltd, 2001.

[40] K. Deb. *Multi-objective optimization using evolutionary algorithms*. John Wiley & Sons, Ltd, 2004.

[41] K. Deb. Single and multi-objective dynamic optimization: two tales from an evolutionary perspective. Technical Report 2011004, Kalyanmoy Deb Kanpur Genetic Algorithms Laboratory (KanGAL), February 2011.

[42] K. Deb, S. Agarwal, A. Pratap, and T. Meyarivan. A fast and elitist multiobjective genetic algorithm: Nsga-ii. Technical Report 200001, Kanpur, India, 2000.

[43] K. Deb and R.B. Agrawal. Simulated binary crossover for continuous search space. *Complex Systems*, 9:115–148, 1995.

[44] K. Deb, A. Anand, and D. Joshi. A computationally efficient evolutionary algorithm for real-parameter optimization. *Evolutionary Computation*, 10(4):371–395, 2002.

[45] K. Deb and D.E. Goldberg. An investigation of niche and species formation in genetic function optimization. In *Proceedings of the International Conference on Genetic Algorithms*. Morgan Kaufmann Publishers, june.

[46] K. Deb, U.B. Rao N., and S. Karthik. Dynamic multi-objective optimization and decision-making using modied nsga-ii: a case study on hydro-thermal power scheduling. In *Proceedings of International Conference on Evolutionary Multi-criterion optimization*, pages 803–817, Matsushima, Japan, 2007.

[47] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan. A fast and elitist multiobjective genetic algorithm: Nsga-ii. *IEEE Transactions on Evolutionary Computation*, 6(2):182–197, apr 2002.

[48] K. Deb, A. Sinha, and S. Kukkonen. Multi-objective test problems, linkages, and evolutionary methodologies. In *Proceedings of the Conference on Genetic and Evolutionary Computation*, pages 1141–1148, New York, NY, USA, 2006. ACM.

[49] K. Deb, L. Thiele, M. Laumanns, and E. Zitzler. Scalable multi-objective optimization test problems. In *Proceedings of Congress on Evolutionary Computation*, pages 825–830, Honolulu, 12-17 May 2002.

[50] J. Duhain. Empirical analysis of particle swarm optimization on dynamic environments. Master's thesis, University of Pretoria. To be published.

[51] R. Eberhart, P. Simpson, and R. Dobbins. *Computational Intelligence PC Tools*. Academic Press Professional, first edition, 1996. page 217.

[52] R.C. Eberhart and Y. Shi. Particle swarm optimization: developments, applications and resources. In *Proceedings of Congress on Evolutionary Computation*, volume 1, pages 81–86, 2001.

[53] R.C. Eberhart and Y. Shi. Tracking and optimizing dynamic systems with particle swarms. In *Proceedings of Congress on Evolutionary Computation*, pages 94–100, May 2001.

[54] T. Elsayed. Genetic algorithms tutorial. Last access online: 11 April 2011.

[55] A.P. Engelbrecht. *Fundamentals of Computational Swarm Intelligence*. John Wiley and Sons, Ltd, 2005.

[56] A.P. Engelbrecht. Fruitless wandering: Where are my particles?, 2012. Proceedings of World Congress on Computational Intelligence: Congress on Evolutionary Compuation. To be published.

[57] M. Farina. A minimal cost hybrid strategy for pareto optimal front approximation. *Evolutionary Optimization*, 3(1):41–52, 2001.

[58] M. Farina, K. Deb, and P. Amato. Dynamic multiobjective optimization problems: test cases, approximations, and applications. *IEEE Transactions on Evolutionary Computation*, 8(5):425–442, October 2004.

[59] L.J. Fogel. *On the organization of intellect*. PhD thesis, University of California, 1964.

[60] C.M. Fonseca and P.J. Fleming. Genetic algorithms for multiobjective optimization: formulation, discussion and generalization. In *Proceedings of the International Conference in Genetic Algorithms*, pages 416–423, San Franciso, U.S.A., 1993.

[61] C.M. Fonseca, M. López-Ibá nez, L. Paquete, and A.P. Guerreiro. Computation of the hypervolume indicator. Version 1.3. Last accessed on 4 February 2012.

[62] C.M. Fonseca, L. Paquete, and M. Lopez-Ibanez. An improved dimension-sweep algorithm for the hypervolume indicator. In *Proceedings of Congress on Evolutionary Computation*, pages 1157–1163, july 2006.

[63] F.v.d.Bergh. *An analysis of particle swarm optimizers*. PhD thesis, Department of Computer Science University of Pretoria, 2002.

[64] Gheorghe and Păun. Computing with membranes. *Journal of Computer and System Sciences*, 61(1):108–143, 2000.

[65] C-K. Goh, Y.S. Ong, K.C. Tan, and E.J. Teoh. An investigation on evolutionary gradient search for multi-objective optimization. In *Proceedings of World*

Congress on Computational Intelligence: Congress on Evolutionary Computation, pages 3741–3746, Hong Kong, june 2008.

[66] C-K. Goh and K. Tan. A coevolutionary paradigm for dynamic multi-objective optimization. In *Evolutionary Multi-objective Optimization in Uncertain Environments*, volume 186 of *Studies in Computational Intelligence*, pages 153–185. Springer Berlin/Heidelberg, 2009.

[67] C-K. Goh and K.C. Tan. A competitive-cooperative coevolutionary paradigm for dynamic multiobjective optimization. *IEEE Transactions on Evolutionary Computation*, 13(1):103–127, February 2009.

[68] D.E. Goldberg. *Genetic Algorithms in search, optimization and machine learning.* Addison-Wesly, 1989.

[69] D.E. Goldberg and K. Deb. *Foundations of genetic algorithms*, chapter A comparison of selection schemes used in genetic algorithms, pages 69–93. Morgan Kaufmann, 1991.

[70] D.E. Goldberg and J. Richardson. Genetic algorithm with sharing for multimodal function optimization. In *Proceedings of the International Conference on Genetic Algorithms and their Applications*, pages 41–49, Hillsdale, New Jersey, 1987. Lawrence Erlbaum.

[71] M. Greeff and A. Engelbrecht. Dynamic multi-objective optimisation using pso. In Nadia Nedjah, Leandro dos Santos Coelho, and Luiza de Macedo Mourelle, editors, *Multi-Objective Swarm Intelligent Systems*, volume 261 of *Studies in Computational Intelligence*, pages 105–123. Springer Berlin/Heidelberg, 2010.

[72] M. Greeff and A.P. Engelbrecht. Solving dynamic multi-objective problems with vector evaluated particle swarm optimisation. In *Proceedings of World Congress on Computational Intelligence (WCCI): Congress on Evoluationary Computation*, pages 2917–2924, Hong Kong, june 2008.

[73] J. Grobler and A.P. Engelbrecht. Hybridizing pso and de for improved vector evaluated multi-objective optimization. In *Proceedings of Congress on Evolutionary Computation*, pages 1255–1262, may 2009.

[74] S-U. Guan, Q. Chen, and W. Mo. Evolving dynamic multi-objective optimization problems with objective replacement. *Artificial Intelligence Review*, 23:267–293, 2005.

[75] M.P. Hansen and A. Jaszkiewicz. Evaluating the quality of approximations to the non-dominated set. Technical Report IMM-REP-1998-7, Technical University of Denmark, 22 March 1998.

[76] I. Hatzakis and D. Wallace. Dynamic multi-objective optimization with evolutionary algorithms: a forward-looking approach. In *Proceedings of the Conference on Genetic and Evolutionary Computation*, pages 1201–1208, New York, NY, USA, 2006. ACM.

[77] M. Helbig and A.P. Engelbrecht. *Metaheuristics for dynamic optimization*, chapter Dynamic multi-objective optimisation using PSO. Springer Verlag. To be published.

[78] M. Helbig and A.P. Engelbrecht. Archive management for dynamic multi-objective optimisation problems using vector evaluated particle swarm optimisation. In *Proceedings of Congress on Evolutionary Computation*, pages 2047–2054, New Orleans, U.S.A., june 2011.

[79] S. Helwig and R. Wanka. Particle swarm optimization in high-dimensional bounded search spaces. In *Proceedings of Swarm Intelligence Symposium*, pages 198–205, apr 2007.

[80] A.G. Hernández-Díaz, L.V. Santana-Quintero, C.A. Coello Coello, and J. Molina. Pareto-adaptive ϵ-dominance. *Evolutionary Computation*, 15(4):493–517, 2007.

[81] F. Herrera, M. Lozano, and J.L. Verdegay. Tackling real-coded genetic algorithms: operators and tools for behavioural analysis. *Artificial Intelligence Review*, 12(4):265–319, 1998.

[82] J.H. Holland. *Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control, and artificial intelligence.* University of Michigan Press, Oxford, UK, 1975.

[83] J. Horn, N. Nafpliotis, and D.E. Goldberg. A niched pareto genetic algorithm for multiobjective optimization. In *Proceedings of World Congress on Computational Intelligence: Congress on Evolutionary Computation*, volume 1, pages 82–87, jun 1994.

[84] L. Huang, I.H. Suh, and A. Abraham. Dynamic multi-objective optimization based on membrane computing for control of time-varying unstable plants. *Information Sciences*, 181(11):2370– 2391, 2011.

[85] S. Huband, P. Hingston, L. Barone, and L. While. A review of multiobjective test problems and a scalable test problem toolkit. *IEEE Transactions on Evolutionary Computation*, 10(5):477–506, oct. 2006.

[86] E.J. Hughes. Multiple single objective pareto sampling. In *Proceedings of the Congress on Evolutionary Computation*, volume 4, pages 2678–2684, dec. 2003.

[87] A. Isaacs, V. Puttige, T. Ray, W. Smith, and S. Anavatti. Development of a memetic algorithm for dynamic multi-objective optimization and its applications for online neural network modeling of uavs. In *Proceedings of World Congress on Computational Intelligence: International Joint Conference on Neural Networks*, pages 548 –554, june 2008.

[88] A. Isaacs, T. Ray, and W. Smith. Memetic algorithm for dynamic bi-objective optimization problems. In *Proceedings of Congress on Evolutionary Computation*, pages 1707–1713, Trondheim, Norway, may 2009.

[89] Y. Jin and J. Branke. Evolutionary optimization in uncertain environments - a survey. *IEEE Transactions on Evolutionary Computation*, 9(3):303–317, June 2005.

[90] Y. Jin and B. Sendhoff. Constructing dynamic optimization test problems using the multi-objective optimization concept. In G. Raidl et al., editors, *Applications*

of Evolutionary Computing, volume 3005 of *Lecture Notes in Computer Science*, pages 525–536. Springer Berlin/Heidelberg, 2004.

[91] K. De Jong. Evolving in a changing world. In *Proceedings of International Symposium on Foundations of Intelligent Systems*, Lecture Notes in Computer Science, pages 512–519. Springer Berlin/Heidelberg, 1999.

[92] K.A. De Jong. *Analysis of the behaviour of a class of genetic adaptive systems*. PhD thesis, University of Michigan, Computer and Communication Sciences Department, University of Michigan, aug 1975.

[93] J. Kennedy. The particle swarm: social adaptation of knowledge. In *Proceedings of the International Conference on Evolutionary Computation*, pages 303–308, apr 1997.

[94] J. Kennedy and R.C. Eberhart. Particle swarm optimization. In *Proceedings of International Conference on Neural Networks*, volume IV, pages 1942–1948, 1995.

[95] J. Kennedy and R. Mendes. Population structure and particle swarm performance. In *Proceedings of World Congress on Computational Intelligence: Congress on Evolutionary Computation*, volume 2, pages 1671–1676, Honolulu, Hawaii, May 2002.

[96] A.K.M. Khaled, A. Talukder, and M. Kirley. A pareto following variation operator for fast-converging multiobjective evolutionary algorithms. In *Proceedings of World Congress on Computational Intelligence: Congress on Evolutionary Computation*, pages 2270–2277, june 2008.

[97] K. Kim, R.I. McKay, and B-R. Moon. Multiobjective evolutionary algorithms for dynamic social network clustering. In *Proceedings of the Conference on Genetic and Evolutionary Computation*.

[98] J. Knowles and D. Corne. The pareto archived evolution strategy: a new baseline algorithm for pareto multiobjective optimisation. In *Proceedings of the Congress on Evolutionary Computation*, volume 1, pages 98–105, 1999.

[99] J.D. Knowles. *Local-search and hybrid evolutionary algorithms for Pareto optimisation*. PhD thesis, Department of Computer Science The University of Reading, 2002.

[100] W. Koo, C. Goh, and K. Tan. A predictive gradient strategy for multiobjective evolutionary algorithms in a fast changing environment. *Memetic Computing*, 2(2):87–110, 2010.

[101] M. Laumanns, L. Thiele, K. Deb, and E. Zitzler. Combining convergence and diversity in evoluationary multiobjective optimization. *Evoluationary Computation*, 10(3):263–282, 2002.

[102] M.S. Lechuga. *Multi-objective optimisation using sharing in swarm optimisation algorithms*. PhD thesis, University of Birmingham, July 2009.

[103] Y-W. Leung and Y. Wang. U-measure: A quality measure for multiobjective programming. *IEEE Transactions on Systems, Man, and Cybernetics*, 33(3):337–343, 2003.

[104] G. Leyland. *Multi-objective optimization applied to industrial energy problems*. PhD thesis, École Polytechnique Fédérale de Lausanne (EPFL), Lausanne, Switzerland, 2002.

[105] H. Li and Q. Zhang. A multiobjective differential evolution based on decomposition for multiobjective optimization with variable linkages. In T. Runarsson, H-G. Beyer, E. Burke, J. Merelo-Guervós, L. Whitley, and X. Yao, editors, *Parallel problem solving from nature - PPSN IX*, volume 4193 of *Lecture Notes in Computer Science*, pages 583–592. Springer Berlin/Heidelberg, 2006.

[106] H. Li and Q. Zhang. Multiobjective optimization problems with complicated pareto sets, moea/d and nsga-ii. *IEEE Transactions on Evoluationary Computation*, 13(2):284–302, 2009.

[107] X. Li. Better spread and convergence: particle swarm multiobjective optimization using the maximin fitness function. In K. Deb, editor, *Proceedings of Conference on*

Genetic and Evolutionary Computation, volume 3102 of *Lecture Notes in Computer Science*, pages 117–128. Springer Berlin/Heidelberg, 2004.

[108] X. Li, J. Branke, and M. Kirley. On performance metrics and particle swarm methods for dynamic multiobjective optimization problems. In *Proceedings of Congress on Evolutionary Computation*, pages 576–583, sept. 2007.

[109] Kampur Genetic Algorithms Library. Software developed at kangal. Available online at: `http://www.iitk.ac.in/kangal/codes.shtml`. Last accessed on: 12 May 2011.

[110] C-A. Liu. New dynamic multiobjective evolutionary algorithm with core estimation of distribution. *Electrical and Control Engineering, International Conference on*, 0:1345–1348, 2010.

[111] C-A. Liu and Y. Wang. New evolutionary algorithm for dynamic multiobjective optimization problems. In L. Jiao, L. Wang, X-B. Gao, J. Liu, and F. Wu, editors, *Advances in Natural Computation*, volume 4221 of *Lecture Notes in Computer Science*, pages 889–892. Springer Berlin/Heidelberg, 2006.

[112] C-A. Liu and Y. Wang. Dynamic multi-objective optimization evolutionary algorithm. *International Conference on Natural Computation*, 4:456–459, 2007.

[113] R. Liu, W. Zhang, L. Jiao, F. Liu, and J. Ma. A sphere-dominance based preference immune-inspired algorithm for dynamic multi-objective optimization. In *Proceedings of the Conference on Genetic and Evolutionary Computation*, pages 423–430, New York, NY, USA, 2010. ACM.

[114] G. Lizárraga Lizárraga. *On the evaluation of the quality of non-dominated sets.* PhD thesis, Centro de Investigación en Matemáticas, A.C. (CIMAT), April 2009.

[115] K.M. Malan and A.P. Engelbrecht. Algorithm comparisons and the significance of population size. In *Proceedings of the World Congress on Computational Intelligence: Congress on Evolutionary Computation*, pages 914–920, june 2008.

[116] W. Mathyssen and A.P. Engelbrecht.

[117] J. Mehnen, G. Rudolph, and T. Wagner. Evolutionary optimization of dynamic multiobjective functions. Technical Report CI-204/06, Universität Dortmund, Universität Dortmund, Fachbereich Informatik/XI, 44221, Dortmund, Germany, May 2006.

[118] Z. Michalewicz. *Genetic algorithms + data structures = evolution programs*. Springer Berlin/Heidelberg, 1996.

[119] P. Moscato. On evolution, search, optimization, genetic algorithms and martial arts: towards memetic algorithms. Technical report, California Institute of Technology, Pasadena, California, U.S.A., 1999.

[120] J.A. Nelder and R. Mead. A simplex method for function minimization. *Computer Journal*, 7(4):308–313, 1965.

[121] M. Obitko. Introduction to genetic algorithms: biological background. Last accessed online: 11 April 2011.

[122] G. Pampará, A.P. Engelbrecht, and T. Cloete. Cilib: A collaborative framework for computational intelligence algorithms - part i. In *Proceedings of World Congress on Computational Intelligence*, pages 1750–1757, Hong Kong, 1-8 June 2008. Source code available at: http://www.cilib.net. Last accessed on: 6 March 2011.

[123] K.E. Parsopoulos, D.K. Tasoulis, N.G. Pavlidis, V.P. Plagianakos, and M.N. Vrahatis. Vector evaluated differential evolution for multiobjective optimization. In *Proceedings of Congress on Evolutionary Computation*, volume 1, pages 204–211, june 2004.

[124] K.E. Parsopoulos, D.K. Tasoulis, and M.N. Vrahatis. Multiobjective optimization using parallel vector evaluated particle swarm optimization. In *Proceedings of IASTED International Conference on Artificial Intelligence and Applications*, Innsbruck Austria, 2004.

[125] K.E. Parsopoulos and M.N. Vrahatis. Recent approaches to global optimization problems through particle swarm optimization. *Natural Computing*, 1(2-3):235–306, 2002.

[126] R. Poli, J. Kennedy, and T. Blackwell. Particle swarm optimization: An overview. *Swarm Intelligence*, 1(1):33–57, 2007.

[127] T. Ray, A. Isaacs, and W. Smith. A memetic algorithm for dynamic multiobjective optimization. In C-K. Goh, Y-S. Ong, and K. Tan, editors, *Multi-Objective memetic algorithms*, volume 171 of *Studies in Computational Intelligence*, pages 353–367. Springer Berlin/Heidelberg, 2009.

[128] R.E. Rosenthal. Principles of multiobjective optimization. *Decision Sciences*, 16:132–152, 1985.

[129] R. Roy and J. Mehnen. Dynamic multi-objective optimisation for machining gradient materials. *CIRP Annals - Manufacturing Technology*, (57):429–432, 2008.

[130] D.K. Saxena, T. Ray, K. Deb, and A.Tiwari. Constrained many-objective optimization: a way forward. In *Proceedings of Congress on Evolutionary Computation*, pages 545–552, may 2009.

[131] J.D. Schaffer. Multiple objective optimization with vector evaluated genetic algorithms. In *Proceedings of the International Conference on Genetic Algorithms*, pages 93–100, Hillsdale, NJ, USA, 1985. L. Erlbaum Associates Inc.

[132] J.R. Schott. Fault tolerance design using single and multi-criteria genetic algorithms. Master's thesis, Department of Aeronautics and Astronautics Massachusetts Institute of Technology, 1995.

[133] D. Schuhmacher, B-T. Vo, and B-N. Vo. A consistent metric for performance evaluation of multi-object filters. *IEEE Transactions on Signal Processing*, 56(8):3447–3457, aug 2008.

[134] H-P. Schwefel. Numerische optimierung von computer-modellen mittels der evolutionsstrategie. *Interdisciplinary systems research*, 26, 1977. Birkhäuser, Basel.

[135] R. Shang, L. Jiao, M. Gong, and B. Lu. Clonal selection algorithm for dynamic multiobjective optimization. In Y. Hao, J. Liu, Y. Wang, Y-M. Cheung, H. Yin,

L. Jiao, J. Ma, and Y-C. Jiao, editors, *Computational Intelligence and Security*, volume 3801 of *Lecture Notes in Computer Science*, pages 846–851. Springer Berlin/Heidelberg, 2005.

[136] Y. Shi and R.C. Eberhart. A modified particle swarm optimizer. In *Proceedings of Congress on Evolutionary Computation*, pages 69–73, May 1998.

[137] M. Sierra and C. Coello Coello. Improving pso-based multi-objective optimization using crowding, mutation and ϵ-dominance. In Carlos Coello Coello, Arturo Hernndez Aguirre, and Eckart Zitzler, editors, *Evolutionary multi-criterion optimization*, volume 3410 of *Lecture Notes in Computer Science*, pages 505–519. Springer Berlin Heidelberg, 2005.

[138] M. Cámara Sola. *Parallel processing for dynamic multi-objective optimization*. PhD thesis, Universidad de Granada, Dept. of Computer Architecture and Computer Technology, Universidad de Granada, Spain, April 2010.

[139] W.M. Spears. *The role of mutation and recombination in evolutionary algorithms*. PhD thesis, George Mason University, Fairfax, Virginia, 1998.

[140] M. Srinivas and L.M. Patnaik. Genetic algorithms: a survey. *Computer*, 27(6):17–26, jun 1994.

[141] N. Srinivas and K. Deb. Muiltiobjective optimization using nondominated sorting in genetic algorithms. *Evolutionary Computation*, 2(3):221–248, 1994.

[142] R. Storn and K. Price. Differential evolution - a simple and efficient heuristic for global optimization over continuous spaces. *Journal of Global Optimization*, 11(4):341–359, 1997.

[143] G. Sywerda. Uniform crossover in genetic algorithms. In *Proceedings of International Conference on Genetic algorithms*, pages 2–9, San Francisco, CA, USA, 1989. Morgan Kaufmann Publishers Inc.

[144] A.K.M. Talukder and A. Khaled. Towards high speed multiobjective evolutionary optimizers. In *Proceedings of the Genetic and Evolutionary Computation Conference*, pages 1791–1794, New York, NY, USA, 2008. ACM.

[145] A.K.M. Talukder, A. Khaled, M. Kirley, and R. Buyya. A pareto following variation operator for fast-converging multiobjective evolutionary algorithms. In *Proceedings of the annual conference on Genetic and evolutionary computation*, pages 721–728, New York, NY, USA, 2008. ACM.

[146] K. Tan and C. Goh. Handling uncertainties in evolutionary multi-objective optimization. In Jacek Zurada, Gary Yen, and Jun Wang, editors, *Computational Intelligence: Research Frontiers*, volume 5050 of *Lecture Notes in Computer Science*, pages 262–292. Springer Berlin/Heidelberg, 2008. 10.1007/978-3-540-68860-0_13.

[147] K.C. Tan, Y.H. Chew, T.H. Lee, and Y.J. Yang. A cooperative coevolutionary algorithm for multiobjective optimization. In *Proceedings of the International Conference on Systems, Man and Cybernetics*, volume 1, pages 390–395, oct 2003.

[148] K.C. Tan, Y.J. Yang, and C.K. Goh. A distributed cooperative coevolutionary algorithm for multiobjective optimization. *IEEE Transactions on Evolutionary Computation*, 10(5):527–549, oct 2006.

[149] M. Tang, Z. Huang, and G. Chen. The construction of dynamic multi-objective optimization test functions. In *Proceedings of International Conference on Advances in Computation and Intelligence*, pages 72–79, Berlin, Heidelberg, 2007. Springer-Verlag.

[150] E. Tantar, A-A. Tantar, and P. Bouvry. On dynamic multi-objective optimization, classification and performance measures. In *Proceedings of Congress on Evolutionary Computation*, pages 2759–2766, june 2011.

[151] D.A. van Veldhuizen. *Multiobjective evolutionary algorithms: classification, analyses, and new innovations*. PhD thesis, Graduate School of Engineering Air University, 1999.

[152] F. v.d.Bergh and A.P. Engelbrecht. A study of particle swarm optimization particle trajectories. *Information Sciences*, 176(8):937–971, 2006.

[153] Y. Wang and C. Dang. An evolutionary algorithm for dynamic multi-objective optimization. *Applied Mathematics and Computation*, 25:6–18, 2008.

[154] Y. Wang and B. Li. Fh-moea: multi-objective evolutionary algorithm based-on fast hyper-volume contribution approach. *Journal of University of Science and Technology*, 38:802–809, 2008.

[155] Y. Wang and B. Li. Investigation of memory-based multi-objective optimization evolutionary algorithm in dynamic environment. In *Proceedings of Congress on Evolutionary Computation*, pages 630–637, Trondheim, Norway, may 2009.

[156] Y. Wang and B. Li. Multi-strategy ensemble evolutionary algorithm for dynamic multi-objective optimization. *Memetic Computing*, 2(1):3–24, 2010.

[157] K. Weicker. Performance measures for dynamic environments. In J. Guervós, P. Adamidis, H-G. Beyer, H-P. Schwefel, and J-L. Fernández-Villaca nas, editors, *Parallel Problem Solving from Nature*, volume 2439 of *Lecture Notes in Computer Science*, pages 64–73. Springer Berlin/Heidelberg, 2002.

[158] A.H. Wright. *Foundations of genetic algorithms*, volume 1, chapter Genetic algorithms for real parameter optimization, pages 205–218. Elsevier Science & Technology Books, june 1991.

[159] X. Yao. An overview of evolutionary computation, 1995. Invited tutorial at International Conference for Young Computer Scientists (ICYCS), Beijing, China. Available online at: `http://0-citeseerx.ist.psu.edu.innopac.up.ac.za/viewdoc/download?doi=10.1.1.56.9127&rep=rep1&type=pdf`. Last accessed on: 30 September 2011.

[160] S-Y. Zeng, G. Chen, L. Zheng, H. Shi, H. de Garis, L. Ding, and L. Kang. A dynamic multi-objective evolutionary algorithm based on an orthogonal design. In *Proceedings of Congress on Evolutionary Computation*, pages 573–580, Vancouver, Canada, 16-21 July 2006.

[161] Q. Zhang, A. Zhou, and Y. Jin. Rm-meda: A regularity model-based multiobjective estimation of distribution algorithm. *IEEE Transactions on Evolutionary Computation*, 12(1):41–63, feb. 2008.

[162] W.-J. Zhang, X.-F. Xie, and D.-C. Bi. Handling boundary constraints for numerical optimization by particle swarm flying in periodic search space. In *Congress on Evolutionary Computation*, volume 2, pages 2307–2311, June 2004.

[163] Z. Zhang. Multiobjective optimization immune algorithm in dynamic environments and its application to greenhouse control. *Applied Soft Computing*, 8:959–971, 2007.

[164] Z. Zhang and S. Qian. Artificial immune system in dynamic environments solving time-varying non-linear constrained multi-objective problems. *Soft Computing - A Fusion of Foundations, Methodologies and Applications*, 15:1333–1349, 2011.

[165] B. Zheng. A new dynamic multi-objective optimization evolutionary algorithm. In *Proceedings of Third International Conference on Natural Computation*, volume 5, pages 565–570, aug. 2007.

[166] A. Zhou, Y. Jin, Q. Zhang, B. Sendhoff, and E. Tsang. Prediction-based population re-initialization for evolutionary dynamic multi-objective optimization. In Shigeru Obayashi, Kalyanmoy Deb, Carlo Poloni, Tomoyuki Hiroyasu, and Tadahiko Murata, editors, *Evolutionary Multi-Criterion Optimization*, volume 4403 of *Lecture Notes in Computer Science*, pages 832–846. Springer Berlin/Heidelberg, 2007.

[167] E. Zitzler. *Evolutionary algorithms for multiobjective optimization: methods and applications*. PhD thesis, Swiss Federal Institute of Technology (ETH) Zurich Switzerland, 1999.

[168] E. Zitzler, D. Brockhoff, and L. Thiele. The hypervolume indicator revisited: on the design of pareto-compliant indicators via weighted integration. In S. Obayashi, K. Deb, C. Poloni, T. Hiroyasu, and T. Murata, editors, *Evolutionary Multi-Criterion Optimization*, volume 4403 of *Lecture Notes in Computer Science*, pages 862–876. Springer Berlin/Heidelberg, 2007.

[169] E. Zitzler, K. Deb, and L. Thiele. Comparison of multiobjective evolutionary algorithms: empirical results. *Evolutionary Computation*, 8(2):173–195, 2000.

[170] E. Zitzler, M. Laumanns, and L. Thiele. SPEA2: Improving the strength Pareto evolutionary algorithm. TIK Report 103, Computer Engineering and Networks Laboratory (TIK), ETH Zurich, Zurich, Switzerland, 2001.

[171] E. Zitzler and L. Thiele. Multiobjective optimization using evolutionary algorithms a comparative case study. 1498:292–301, 1998.

[172] E. Zitzler and L. Thiele. Multiobjective evolutionary algorithms: a comparative case study and the strength pareto approach. *IEEE Transactions on Evolutionary Computation*, 3(4):257–271, nov 1999.

[173] E. Zitzler, L. Thiele, M. Laumanns, C.M. Fonseca, and V. Grunert da Fonseca. Performance assessment of multiobjective optimizers: an analysis and review. *IEEE Transactions on Evolutionary Computation*, 7(2):117–132, April 2003.

UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA

Appendix A

List of Symbols

Δ	spacing metric of Deb
d_i	Euclidean distance in the objective space between solution i of approximated POF and the nearest member of the sampled points of the true POF
d_k^e	distance between the extreme solutions of the approximated POF and the sampled solutions of the true POF
$\prec$	domination relational operator
$\preceq$	weak domination relational operator
$\prec_\epsilon$	ϵ-domination relational operator
F	feasible space, $F \subseteq S$
f_k	objective function
$\mathbf{f}(\mathbf{x}, \mathbf{w}(t))$	dynamic objective function vector
$f(\mathbf{x}, \mathbf{w}(t))$	dynamic objective function
$\mathbf{f}_{ref}$	reference vector for hypervolume calculation
$\mathbf{f}$	objective function vector

g	inequality constraint
γ	path between two solutions in objective space
$\mathbf{g}$	inequality constraint vector
h	equality constraint
$\mathbf{h}$	equality constraint vector
F	neighbourhood of points, $N \subseteq F$
ND	number of non-dominated solutions
n_g	number of inequality constraints
n_h	number of equality constraints
n_k	number of objective functions
n_t	severity of change
n_x	number of decision variables
O_{space}	objective space
O_C	complete outperformance
O_S	strong outperformance
O_W	weak outperformance
O	outperforms
$PF^*(t)$	Pareto-optimal front at time t
PF^*	Pareto-optimal front
PF^*_ϵ	ϵ-approximate Pareto-optimal front
P^*	Pareto-optimal set

PF_g^*	global POF
PF_l^*	local POF
POF^*	approximated POF
n_{POF^*}	number of solutions in approximated POF
POF	true POF
$n_{POF'}$	number of sampled solutions in true POF
POF'	sampled solutions of true POF
S	unrestricted search space
τ	current iteration
τ_t	frequency of change
U	Set of utility functions
$\mathbf{x}$	solution vector
$\mathbf{x}_i$	decision variable
$\mathbf{x}_{min}$	lower bound of the feasible values for decision variable $\mathbf{x}$
$\mathbf{x}_N$	local optima
$\mathbf{x}^*$	global optimum solution
$\mathbf{x}^*(t)$	global optimum solution at time step t
$\mathbf{x}_{max}$	upper bound of the feasible values for decision variable $\mathbf{x}$

Appendix B

List of Acronyms

AIS
: artificial immune system. 172, 173, 191

CCEA
: cooperative-coevolution evolutionary algorithm. 6, 143, 151, 152, 154, 155, 177, 178

CI
: computational intelligence. 28, 124, 126, 144, 156, 169, 191, 192

COEA
: competitive-cooperative evolutionary algorithm. 177

D-QMOO
: dynamic queuing multi-objective optimizer. 187, 188

dCCEA
: dynamic CCEA. 176, 178, 179

dCOEA
: dynamic COEA. 177–179, 327–329, 335–337, 339, 340, 346, 353, 362, 363, 366

DE
: differential evolution. 7, 141, 156, 165, 172, 184

dMO-EGS
: dynamic MO-EGS. 175, 176, 191

dynamic VEPSO. 194

DVEPSO

dynamic Vector Evaluated Particle Swarm Optimisation. 2–7, 121, 126, 143, 162, 192, 194–196, 198–202, 209, 222, 223, 225, 228, 248–251, 260, 261, 270, 288, 298, 322–325, 328, 329, 334–336, 338–340, 346, 352, 353, 362, 363, 365–367, 399

EA

evolutionary algorithm. 2, 28, 143–145, 166, 169, 173, 176, 177, 179, 181, 182, 185, 191, 192

GA

genetic algorithm. 6, 121, 126, 136–138, 141–145, 156, 170, 176, 184

GD

generational distance. 91, 92, 102, 173, 179, 180, 182, 186

gIDG

generalised immigrants-based diversity generator. 185

HV

hypervolume. 98–100, 106, 110, 113, 188, 365

HVD

hypervolume distance. 110

HVR

hypervolume ratio. 99, 100, 189

IDMOEA

individual diversity multi-objective optimization evolutionary algorithm. 174, 175

IGD

inverse generational distance. 92

MA

memetic algorithm. 181, 182

VEDE

vector evaluated differential evolution. 7, 156, 165–167

VEDEPSO

vector evaluated differential evolution particle swarm optimisation. 166, 167

VEGA

vector evaluated genetic algorithm. 7, 144, 156, 158, 164–167

VEPSO

vector evaluated particle swarm optimisation. 5, 7, 156, 158–167, 192, 194–196, 198, 199, 206, 208, 228, 248, 365, 366

Appendix C

Calculating the True POS and POF

This appendix discusses how *POS* and *POF* are determined for DMOOPs. Two examples are provided, namely FDA5 and FDA2 modified by Cámara *et al.* [17] [16] [138] referred to in this section as FDA2$_{Camara}$.

C.1 Example 1: FDA2$_{Camara}$

The FDA2$_{Cámara}$ DMOOP has two objective functions (refer to Section 3.2.1) and is defined as

$$\begin{cases} f_1(\mathbf{x_I}) = x_1 \\ g(\mathbf{x_{II}}) = 1 + \sum_{x_i \in \mathbf{x_{II}}} x_i^2 \\ h(\mathbf{x_{III}}, f_1, g, t) = 1 - \left(\frac{f_1}{g}\right)^{H_2(t)} \\ where: \\ H(t) = z^{-\cos(\pi t/4)}, \;\; t = \frac{1}{n_t}\left\lfloor \frac{\tau}{\tau_t} \right\rfloor \\ H_2(t) = H(t) + \sum_{x_i \in \mathbf{x_{III}}} (x_i - H(t)/2)^2 \\ \mathbf{x_I} \in [0,1]; \;\; \mathbf{x_{II}}, \mathbf{x_{III}} \in [-1,1] \end{cases}$$

The goal when solving FDA2$_{Camara}$ is to minimise the two objective functions, namely f_1 and $f_2 = gh$. Since f_1 only depends on x_1 the true POF depends on f_2. In order to minimise gh, both g and h have to be minimised. h will be minimised if the term $\frac{f_1}{g}^{H_2(t)}$ is maximised (since this term is subtracted from 1). The term $\frac{f_1}{g}^{H_2(t)}$ is maximised if g is minimised (since f_1 is divided by g). g is minimised if the term $\sum_{x_i \in \mathbf{x_{II}}} x_i^2$ is minimised, i.e. if $\sum_{x_i \in \mathbf{x_{II}}} x_i^2$ is zero. Therefore, the optimal values for $x_i \in \mathbf{x_{II}}$ is

$x_i = 0$. If $\sum_{x_i \in \mathbf{x_{II}}} x_i^2 = 0$, $g = 1$. Replacing $g = 1$ into $f_2 = gh$, results in $f_2^* = 1 - f_1^{H_2(t)}$. In order to minise f_2^*, $H_2(t)$ has to be minimised. $H_2(t)$ is minimised if the term $\sum_{x_i \in \mathbf{x_{III}}}(x_i - H(t)/2)^2$ is minimised, which results in $H_2^*(t) = H(t)$. Therefore, the optimal values of $x_i \in \mathbf{x_{III}}$ is $x_i = \frac{H(t)}{2}$. Replacing H_2 in f_2^* with H_2^*, results in $f_2 = 1 - f_1^{H(t)}$.

Therefore, POF is $1 - f_1^{H(t)}$. The decision variable values that lead to POF is POS, namely $x_i = 0$, $\forall x_i \in \mathbf{x_{II}}$ and $x_i = \frac{H(t)}{2}$, $\forall x_i \in \mathbf{x_{III}}$.

C.2 Example 2: FDA5

FDA5 is a three-objective DMOOP [58] (refer to Section 3.2.1), defined as

$$\text{FDA5} = \begin{cases} Minimize: \mathbf{f}(\mathbf{x}, t) = (f_1(\mathbf{x}, g(\mathbf{x_{II}}, t)), \ldots, \\ \qquad\qquad f_k(\mathbf{x}, g(\mathbf{x_{II}}, t))) \\ f_1(\mathbf{x}, g, t) = (1 + g(\mathbf{x_{II}}, t)) \prod_{i=1}^{M-1} \cos\left(\frac{y_i \pi}{2}\right) \\ f_k(\mathbf{x}, g, t) = (1 + g(\mathbf{x_{II}}, t)) \left(\prod_{i=1}^{M-1} \cos\left(\frac{y_i \pi}{2}\right)\right) \\ \sin\left(\frac{y_{M-k+1}\pi}{2}\right), \forall k = 1, \ldots, M-1 \\ \vdots \\ f_m(\mathbf{x}, g, t) = (1 + g(\mathbf{x_{II}}, t)) \prod_{i=1}^{M-1} \sin\left(\frac{y_1 \pi}{2}\right) \\ where: \\ g(\mathbf{x_{II}}, t) = G(t) + \sum_{x_i \in \mathbf{x_{II}}} (x_i - G(t))^2 \\ G(t) = |sin(0.5\pi t)|, \ \ t = \frac{1}{n_t} \left\lfloor \frac{\tau}{\tau_t} \right\rfloor \\ y_i = x_i^{F(t)}, \ \ \forall i = 1, \ldots, (M-1) \\ F(t) = 1 + 100 \sin^4(0.5\pi t) \\ \mathbf{x_{II}} = (x_M, \ldots, x_n) \\ x_i \in [0, 1], \ \forall i = 1, \ldots, n \end{cases} \tag{C.1}$$

In order to minimise FDA5, each objective function has to be minimised. Therefore, g has to be minimised, i.e. the term $\sum_{x_i \in \mathbf{x_{II}}} (x_i - G(t))^2$ has to be minimised. This results in $g = G(t)$ and POF of $\sum_{i=1}^{m} f_i^2 = (1 + G(t))^2$ (refer to [49]). The decision variable values that minimises g is $x_i = G(t)$, $\forall x_i \in \mathbf{x_{II}}$, resulting in POS of $x_i = G(t)$, $\forall x_i \in \mathbf{x_{II}}$.

UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA

Appendix D

Additional Data and Figures for Conducted Experiments

This appendix provides additional data and figures of experiments discussed in Chapters 9, 10 and 11. Section D.1 presents performance measure values, p-values and figures with regards to the data of the experiments that were conducted to investigate the influence of various guide update approaches on the performance of DVEPSO (refer to Chapter 9). The performance measure values and p-values of the sensitivity analysis discussed in Chapter 10 are presented in Section D.2. Finally, Section D.3 presents the performance measure values and p-values of the DMOAs discussed in Chapter 11.

Due to space limitations, the tables and figures can be found on the included CD. Below a list is provided of the data that is available on the CD, as well as the file that contains the specific data.

D.1 Guide Update Approaches

The following additional data is provided on the CD:

- Tables containing performance measure values that were obtained by the various guide update approaches (guide-update-approaches-performance-measure-values.pdf)
- Figures of the wins and losses values obtained by the guide update approaches for each performance measure and DMOOP (guide-update-approaches-wins-and-

losses.pdf)

- Tables presenting the p-values of the Mann-Whitney U tests that were performed on the data obtained by the guide update approaches (guide-update-approaches-pvalues.pdf)

D.2 Sensitivity Analysis

The following additional data is provided on the CD with regards to various approaches used to manage boundary constraint violations:

- Tables containing performance measure values that were obtained by the boundary constraint management approaches (boundary-performance-measure-values.pdf)
- Tables presenting the p-values of the Mann-Whitney U tests that were performed on the data obtained by the boundary constraint violation management approaches (boundary-pvalues.pdf)

Additional data with regards to knowledge sharing approaches that can be found on the CD are:

- Tables containing performance measure values that were obtained by the knowledge sharing strategies (knowledge-performance-measure-values.pdf)
- Tables presenting the p-values of the Mann-Whitney U tests that were performed on the data obtained by the knowledge sharing approaches (knowledge-pvalues.pdf)

The following additional data is provided on the CD with regards to responses after a change in the environment occurs:

- Tables containing performance measure values that were obtained by the responses applied to particles of the sub-swarms (response-particles-performance-measure-values.pdf) and responses applied to the archive (response-archive-performance-measure-values.pdf)
- Tables presenting the p-values of the Mann-Whitney U tests that were performed on the data obtained by the responses applied to the particles (response-particles-pvalues.pdf) and responses applied to the archive (response-archive-pvalues.pdf)

D.3 Comparison of Dynamic Multi-objective Optimisation Algorithms

Additional data with regards to the comparison of DMOAs solving DMOOPs that can be found on the CD are:

- Tables containing performance measure values that were obtained by the DMOAs (comparison-performance-measure-values.pdf)
- Tables presenting the p-values of the Mann-Whitney U tests that were performed on the data obtained by the DMOAs (comparison-pvalues.pdf)

Appendix E

List of Publications

This appendix lists the publications that were derived from the research conducted for this thesis.

Journal Articles

M. Helbig and A.P. Engelbrecht. Dynamic multi-objective optimisation problems. Submitted for review.

M. Helbig and A.P. Engelbrecht. Performance measures for dynamic multi-objective optimisation algorithms. Submitted for review.

Conference Papers

M. Greeff and A.P. Engelbrecht. Solving dynamic multi-objective problems with vector evaluated particle swarm optimisation. In *Proc. of IEEE World Congress on Computational Intelligence: IEEE Congress on Evoluationary Computation*, pages 2917–2924, Hong Kong, June 2008.

M. Helbig and A.P. Engelbrecht. Archive management for dynamic multi-objective optimisation problems using vector evaluated particle swarm optimisation. In *Proc. of the*

IEEE Congress on Evolutionary Computation, pages 2047–2054, New Orleans, U.S.A., June 2011.

M. Helbig and A.P. Engelbrecht. Analyses of Guide Update Approaches for Vector Evaluated Particle Swarm Optimisation on Dynamic Multi-Objective Optimisation Problems. In *Proc. of IEEE World Congress on Computational Intelligence: IEEE Congress on Evoluationary Computation*, pages 2621–2628, Brisbane, June, 2012.

Book Chapters

M. Greeff and A.P. Engelbrecht. Dynamic multi-objective optimisation using PSO. In Nadia Nedjah, Leandro dos Santos Coelho, and Luiza de Macedo Mourelle, editors, *Multi-Objective Swarm Intelligent Systems*, volume 261 of Studies in Computational Intelligence, pages 105–123, Springer Berlin/Heidelberg, 2010.

M. Greeff and A.P. Engelbrecht. Dynamic multi-objective optimisation using PSO. In *Metaheuristics for Dynamic Optimization*, Springer, To be published.