

Nadia Nedjah, Leandro dos Santos Coelho, and Luiza de Macedo de Mourelle (Eds.)

Multi-Objective Swarm Intelligent Systems

Studies in Computational Intelligence, Volume 261

Editor-in-Chief

Prof. Janusz Kacprzyk
Systems Research Institute
Polish Academy of Sciences
ul. Newelska 6
01-447 Warsaw
Poland
E-mail: kacprzyk@ibspan.waw.pl

Further volumes of this series can be found on our homepage: springer.com

Vol. 241. János Fodor and Janusz Kacprzyk (Eds.)
Aspects of Soft Computing, Intelligent Robotics and Control, 2009
ISBN 978-3-642-03632-3

Vol. 242. Carlos Artemio Coello Coello, Satchidananda Dehuri, and Susmita Ghosh (Eds.)
Swarm Intelligence for Multi-objective Problems in Data Mining, 2009
ISBN 978-3-642-03624-8

Vol. 243. Imre J. Rudas, János Fodor, and Janusz Kacprzyk (Eds.)
Towards Intelligent Engineering and Information Technology, 2009
ISBN 978-3-642-03736-8

Vol. 244. Ngoc Thanh Nguyen, Radosław Piotr Katarzyniak, and Adam Janiak (Eds.)
New Challenges in Computational Collective Intelligence, 2009
ISBN 978-3-642-03957-7

Vol. 245. Oleg Okun and Giorgio Valentini (Eds.)
Applications of Supervised and Unsupervised Ensemble Methods, 2009
ISBN 978-3-642-03998-0

Vol. 246. Thanasis Daradoumis, Santi Caballé, Joan Manuel Marqués, and Fatos Xhafa (Eds.)
Intelligent Collaborative e-Learning Systems and Applications, 2009
ISBN 978-3-642-04000-9

Vol. 247. Monica Bianchini, Marco Maggini, Franco Scarselli, and Lakhmi C. Jain (Eds.)
Innovations in Neural Information Paradigms and Applications, 2009
ISBN 978-3-642-04002-3

Vol. 248. Chee Peng Lim, Lakhmi C. Jain, and Satchidananda Dehuri (Eds.)
Innovations in Swarm Intelligence, 2009
ISBN 978-3-642-04224-9

Vol. 249. Wesam Ashour Barbakh, Ying Wu, and Colin Fyfe
Non-Standard Parameter Adaptation for Exploratory Data Analysis, 2009
ISBN 978-3-642-04004-7

Vol. 250. Raymond Chiong and Sandeep Dhakal (Eds.)
Natural Intelligence for Scheduling, Planning and Packing Problems, 2009
ISBN 978-3-642-04038-2

Vol. 251. Zbigniew W. Ras and William Ribarsky (Eds.)
Advances in Information and Intelligent Systems, 2009
ISBN 978-3-642-04140-2

Vol. 252. Ngoc Thanh Nguyen and Edward Szczerbicki (Eds.)
Intelligent Systems for Knowledge Management, 2009
ISBN 978-3-642-04169-3

Vol. 253. Roger Lee and Naohiro Ishii (Eds.)
Software Engineering Research, Management and Applications 2009, 2009
ISBN 978-3-642-05440-2

Vol. 254. Kyandoghere Kyamakya, Wolfgang A. Halang, Herwig Unger, Jean Chamberlain Chedjou, Nikolai F. Rulkov, and Zhong Li (Eds.)
Recent Advances in Nonlinear Dynamics and Synchronization, 2009
ISBN 978-3-642-04226-3

Vol. 255. Catarina Silva and Bernardete Ribeiro
Inductive Inference for Large Scale Text Classification, 2009
ISBN 978-3-642-04532-5

Vol. 256. Patricia Melin, Janusz Kacprzyk, and Witold Pedrycz (Eds.)
Bio-inspired Hybrid Intelligent Systems for Image Analysis and Pattern Recognition, 2009
ISBN 978-3-642-04515-8

Vol. 257. Oscar Castillo, Witold Pedrycz, and Janusz Kacprzyk (Eds.)
Evolutionary Design of Intelligent Systems in Modeling, Simulation and Control, 2009
ISBN 978-3-642-04513-4

Vol. 258. Leonardo Franco, David A. Elizondo, and José M. Jerez (Eds.)
Constructive Neural Networks, 2009
ISBN 978-3-642-04511-0

Vol. 259. Kasthurirangan Gopalakrishnan, Halil Ceylan, and Nii O. Attoh-Okin (Eds.)
Intelligent and Soft Computing in Infrastructure Systems Engineering, 2009
ISBN 978-3-642-04585-1

Vol. 260. Edward Szczerbicki and Ngoc Thanh Nguyen (Eds.)
Smart Information and Knowledge Management, 2009
ISBN 978-3-642-04583-7

Vol. 261. Nadia Nedjah, Leandro dos Santos Coelho, and Luiza de Macedo de Moura (Eds.)
Multi-Objective Swarm Intelligent Systems, 2009
ISBN 978-3-642-05164-7

Nadia Nedjah, Leandro dos Santos Coelho, and
Luiza de Macedo de Mourelle (Eds.)

Multi-Objective Swarm Intelligent Systems

Theory & Experiences

Nadia Nedjah
Universidade do Estado do Rio de Janeiro
Faculdade de Engenharia
sala 5022-D
Rua São Francisco Xavier 524
20550-900, MARACANÃ-RJ
Brazil
E-mail: nadia@eng.uerj.br

Luiza de Macedo Mourelle
Universidade do Estado do Rio de Janeiro
Faculdade de Engenharia
sala 5022-D
Rua São Francisco Xavier 524
20550-900, MARACANÃ-RJ
Brazil
E-mail: ldmm@eng.uerj.br

Leandro dos Santos Coelho
Universidade Federal do Paraná
Departamento de Engenharia Elétrica
Pós-Graduação em Engenharia Elétrica
Centro Politécnico
81531-980, Curitiba-PR, Brazil
and
Pontifícia Universidade
Católica do Paraná
Centro de Ciências
Exatas de Tecnologia
Pós-Graduação em Engenharia
de Produção e Sistemas (PPGEPS)
Rua Imaculada Conceição 1155
80215-901, Curitiba-PR, Brazil
E-mail: leandro.coelho@pucpr.br

ISBN 978-3-642-05164-7

e-ISBN 978-3-642-05165-4

DOI 10.1007/978-3-642-05165-4

Studies in Computational Intelligence

ISSN 1860-949X

Library of Congress Control Number: 2009940420

© 2010 Springer-Verlag Berlin Heidelberg

This work is subject to copyright. All rights are reserved, whether the whole or part of the material is concerned, specifically the rights of translation, reprinting, reuse of illustrations, recitation, broadcasting, reproduction on microfilm or in any other way, and storage in data banks. Duplication of this publication or parts thereof is permitted only under the provisions of the German Copyright Law of September 9, 1965, in its current version, and permission for use must always be obtained from Springer. Violations are liable to prosecution under the German Copyright Law.

The use of general descriptive names, registered names, trademarks, etc. in this publication does not imply, even in the absence of a specific statement, that such names are exempt from the relevant protective laws and regulations and therefore free for general use.

Typeset & Cover Design: Scientific Publishing Services Pvt. Ltd., Chennai, India.

Printed in acid-free paper

9 8 7 6 5 4 3 2 1

springer.com

Preface

Recently, a new class of heuristic techniques, the swarm intelligence has emerged. In this context, more recently, biologists and computer scientists in the field of “artificial life” have been turning to insects for ideas that can be used for heuristics. Many aspects of the collective activities of social insects, such as foraging of ants, birds flocking and fish schooling are self-organizing, meaning that complex group behavior emerges from the interactions of individuals who exhibit simple behaviors by themselves.

Swarm intelligence is an innovative computational way to solving hard problems. This discipline is mostly inspired by the behavior of ant colonies, bird flocks and fish schools and other biological creatures. In general, this is done by mimicking the behavior of these swarms.

Swarm intelligence is an emerging research area with similar population and evolution characteristics to those of genetic algorithms. However, it differentiates in emphasizing the cooperative behavior among group members. Swarm intelligence is used to solve optimization and cooperative problems among intelligent agents, mainly in artificial network training, cooperative and/or decentralized control, operational research, power systems, electro-magnetics device design, mobile robotics, and others. The most well-known representatives of swarm intelligence in optimization problems are: the food-searching behavior of ants, particle swarm optimization, and bacterial colonies.

Real-world engineering problems often require concurrent optimization of several design objectives, which are conflicting in most of the cases. Such an optimization is generally called multi-objective or multi-criterion optimization. In this context, the development of improvements for swarm intelligence methods to multi-objective problems is an emergent research area.

In Chapter 1, which is entitled *Multi-objective Gaussian Particle Swarm Approach Applied to Multi-Loop PI Controller Tuning of a Quadruple-Tank System*, the authors propose a multi-objective particle swarm optimization approach inspired from some previous related work. The approach updates the velocity vector using the Gaussian distribution, called MGPSO, to solve

the multi-objective optimization of the multi-loop Proportional-Integral control tuning.

In Chapter 2, which is entitled *A Non-Ordered Rule Induction Algorithm Through Multi-Objective Particle Swarm Optimization: Issues and Applications*, the authors propose a new approach, called MOPSO-N, validate its efficiency. They also describe the application of MOPSO-N in the Software Engineering domain.

In Chapter 3, which is entitled *Use of Multiobjective Evolutionary Algorithms in Water Resources Engineering*, the authors investigate the efficiency of multi-objective particle swarm optimization in Water Resources Engineering.

In Chapter 4, which is entitled *Micro-MOPSO: A Multi-Objective Particle Swarm Optimizer that Uses a Very Small Population Size*, the author presents a multi-objective evolutionary algorithm (MOEA) based on the heuristic called “particle swarm optimization” (PSO). This multi-objective particle swarm optimizer (MOPSO) is characterized for using a very small population size, which allows it to require a very low number of objective function evaluations (only 3000 per run) to produce reasonably good approximations of the Pareto front of problems of moderate dimensionality.

In Chapter 5, which is entitled *Dynamic Multi-objective Optimisation using PSO*, the author introduces the usage of the vector evaluated particle swarm optimiser (VEPSO) to solve DMOOPs, wherein every objective is solved by one swarm and the swarms share knowledge amongst each other about the objective that it is solving.

In Chapter 6, which is entitled *Meta-PSO for Multi-Objective EM Problems*, the authors investigate some variations over the standard PSO algorithm, referred to as Meta-PSO, aiming at enhancing the global search capability, and, therefore, improving the algorithm convergence.

In Chapter 7, which is entitled *Multi-Objective Wavelet-Based Pixel-Level Image Fusion Using Multi-Objective Constriction Particle Swarm Optimization*, the authors present a new methodology of multi-objective pixel-level image fusion based on discrete wavelet transform and design an algorithm of multi-objective constriction particle swarm optimization (MOCPSO).

In Chapter 8, which is entitled *Multi-objective Damage Identification Using Particle Swarm Optimization Techniques*, the authors present a particle swarm optimization-based strategies for multi-objective structural damage identification. Different variations of the conventional PSO based on evolutionary concepts are implemented for detecting the damage of a structure in a multi-objective framework.

The editors are very much grateful to the authors of this volume and to the reviewers for their tremendous service by critically reviewing the chapters. The editors would like also to thank Prof. Janusz Kacprzyk, the editor-in-chief of the Studies in Computational Intelligence Book Series and Dr. Thomas Ditzinger, Springer Verlag, Germany for the editorial assistance and excellent cooperative collaboration to produce this important scientific work.

We hope that the reader will share our excitement to present this volume on **Multi-Objective Swarm Intelligent Systems** and will find it useful.

August 2009

Nadia Nedjah

State University of Rio de Janeiro, Brazil

Leandro dos S. Coelho

Federal University of Paraná, Brazil and

Pontifical Catholic University of Paraná, Brazil

Luiza M. Mourelle

State University of Rio de Janeiro, Brazil

Contents

1	Multiobjective Gaussian Particle Swarm Approach Applied to Multi-loop PI Controller Tuning of a Quadruple-Tank System	1
	<i>Leandro dos Santos Coelho, Helon Vicente Hultmann Ayala, Nadia Nedjah, Luiza de Macedo Mourelle</i>	
1.1	Introduction	2
1.2	Description of Quadruple-Tank Process.....	3
1.3	Fundamentals of Multi-objective Optimization and PSO	5
1.3.1	Multi-objective Optimization	6
1.3.2	Classical PSO and MOPSO Approaches	7
1.3.3	The Proposed MGPSO Approach	9
1.4	Simulation Results.....	9
1.5	Summary.....	14
	References	14
2	A Non-ordered Rule Induction Algorithm through Multi-Objective Particle Swarm Optimization: Issues and Applications	17
	<i>André B. de Carvalho, Aurora Pozo, Silvia Vergilio</i>	
2.1	Introduction	17
2.2	Rule Learning Concepts	20
2.3	Performance Assessment of Stochastic Multi-Objective Optimizers	23
2.3.1	Performance Assessment	26
2.4	Multi-Objective Particle Swarm Optimization	27
2.5	Rule Learning with MOPSO	29
2.6	MOPSO Evaluation	31
2.6.1	AUC Comparison	32
2.6.2	Pareto Front Analysis	33

2.7	Predicting Faults	35
2.7.1	Dataset	36
2.7.2	Evaluation Measures	36
2.7.3	Algorithms	37
2.7.4	AUC Comparison	37
2.7.5	Influence of C-K Suite Metrics in Fault-Proneness ...	37
2.8	Related Works	39
2.9	Conclusions	40
	References	41
3	Use of Multiobjective Evolutionary Algorithms in Water Resources Engineering	45
	<i>Francisco Venícius Fernandes Barros, Eduardo Sávio Passos Rodrigues Martins, Luiz Sérgio Vasconcelos Nascimento, Dirceu Silveira Reis Jr.</i>	
3.1	Introduction	45
3.2	Literature Review	47
3.3	Evolutionary Algorithm	48
3.3.1	Uni-objective Optimization	49
3.3.2	Multiobjective Approach Using Pareto Dominance Criterion	54
3.4	Evaluation of the Algorithms with Test Functions	58
3.4.1	Test Functions and Theirs Theoretical Minima	58
3.5	Use of Multiobjective Evolutionary Algorithms in Calibration of Hydrologic Models	62
3.5.1	Hydrologic Model	63
3.5.2	Discussion of the Results	66
3.6	Use of Multiobjective Evolutionary Algorithms in Reservoirs' System Operation	71
3.6.1	Background	71
3.6.2	The Reservoir System	72
3.6.3	The Current Operating Policy	74
3.6.4	Derivation of a New Operating Policy	75
3.7	Summary	78
	References	80
4	Micro-MOPSO: A Multi-Objective Particle Swarm Optimizer That Uses a Very Small Population Size	83
	<i>Juan Carlos Fuentes Cabrera, Carlos A. Coello Coello</i>	
4.1	Introduction	83
4.2	Basic Concepts	84
4.3	Particle Swarm Optimization	85
4.4	Related Work	86
4.5	The Micro-MOPSO	88
4.5.1	Leader Selection	90

4.5.2	Reinitialization Process	92
4.5.3	Mutation Operator	92
4.6	Experiments and Results	93
4.6.1	Performance Measures	93
4.6.2	Experiments	97
4.6.3	Results	98
4.7	Conclusions and Future Work	100
	References	101
5	Dynamic Multi-objective Optimisation Using PSO	105
	<i>Mardé Greeff, Andries P. Engelbrecht</i>	
5.1	Introduction	105
5.2	Background	107
5.3	Vector Evaluated Particle Swarm Optimisation	109
5.3.1	VEPSO for Dynamic Multi-objective Optimisation	110
5.4	Experiments	110
5.4.1	Benchmark Functions	111
5.4.2	Performance Metrics	112
5.4.3	Statistical Analysis	113
5.5	Results	114
5.5.1	Overall Performance	114
5.5.2	Population Size	117
5.5.3	Response Strategies	120
5.6	Summary	121
	References	121
6	Meta-PSO for Multi-Objective EM Problems	125
	<i>Marco Mussetta, Paola Pirinoli, Stefano Selleri, Riccardo E. Zich</i>	
6.1	Introduction	125
6.2	Basic PSO Algorithm	130
6.3	Undifferentiated Meta-PSO	132
6.3.1	Meta-PSO	132
6.3.2	Modified Meta-PSO	133
6.3.3	Stabilized Modified Meta-PSO	134
6.4	Differentiated Meta-PSO Algorithms	134
6.4.1	Absolute Leader Meta-PSO	134
6.4.2	Democratic Leader Meta-PSO	135
6.5	Algorithm Tuning	136
6.6	Meta-PSO for Multi-Objective Optimization	139
6.7	Dual Band Linear Array Design	143
6.8	Conclusions	148
	References	149

7	Multi-Objective Wavelet-Based Pixel-Level Image Fusion Using Multi-Objective Constriction Particle Swarm Optimization	151
	<i>Yifeng Niu, Lincheng Shen, Xiaohua Huo, Guangxia Liang</i>	
7.1	Introduction	152
7.2	Fundamentals of Wavelet Transform	153
7.2.1	Wavelet Transform of 1-D Signals	154
7.2.2	Wavelet Transform of 2-D Images	155
7.3	Multi-Objective Pixel-Level Image Fusion Based on Discrete Wavelet Transform	157
7.4	Evaluation Metrics of Image Fusion	158
7.4.1	Image Feature Metrics	159
7.4.2	Image Similarity Metrics	159
7.4.3	Mutual Information Metrics	160
7.5	MOCPSO Algorithm	162
7.5.1	MOCPSO Flow	163
7.5.2	Initialization of Algorithm	163
7.5.3	Update Particle Swarm	164
7.5.4	Adaptive Mutation	164
7.5.5	Repository Control	165
7.5.6	Uniform Design for Parameter Establishment	166
7.5.7	Convergence Analysis of MOCPSO	167
7.6	Experiments and Analysis	168
7.6.1	Uniform Design for MOCPSO Parameters	169
7.6.2	Comparison of MOCPSO and MOPSO	170
7.6.3	Multi-focus Image Fusion	171
7.6.4	Blind Image Fusion	173
7.6.5	Multi-resolution Image Fusion	173
7.6.6	Color Image Fusion	175
7.7	Conclusions	176
	References	177
8	Multi-objective Damage Identification Using Particle Swarm Optimization Techniques	179
	<i>Ricardo Perera, Sheng-En Fang</i>	
8.1	Introduction	179
8.2	Single Objective Damage Identification Problem Formulation	182
8.3	Multi-objective Damage Identification	183
8.3.1	Formulation of the Multi-objective Problem	183
8.3.2	Objective Functions	185
8.4	Overview of Basic Particle Swarm Optimization (PSO)	186
8.5	Multi-objective PSO	187
8.5.1	Initialization and Constraint Handling	188
8.5.2	Archiving	188

8.5.3	Selection of <i>pbest</i> and <i>gbest</i>	189
8.5.4	Use of a Mutation Operator	190
8.6	Benchmarking Experiments	191
8.6.1	Simply Supported Beam	192
8.6.2	Experimental Reinforced Concrete Frame	199
8.7	Conclusions	205
	References	205
Author Index		209
Index		211

List of Figures

1.1	Schematic diagram of quadruple-tank process	4
1.2	Pareto front of MOPSO obtained from the first simulation . . .	10
1.3	Pareto front of MOPSO obtained from the second simulation	11
1.4	Best result in terms of f_1 for the MOPSO	12
1.5	Best result in terms of f_1 for the MGPSO	12
1.6	Best result in terms of f_2 for the MOPSO	12
1.7	Best result in terms of f_2 for the MGPSO	13
1.8	Best result in terms of arithmetic mean of f_1 and f_2 for the MOPSO	13
1.9	Best result in terms of arithmetic mean of f_1 and f_2 for the MGPSO	13
2.1	A ROC Graph plotted with a set of classifiers. The continuous line shows the Pareto Front.	23
2.2	Pareto Front of the positive rules for Dataset 2 (<i>ecoli</i>)	25
2.3	Approximation sets of the positive rules for Dataset 2(<i>ecoli</i>) generated by both MOPSO algorithms	25
2.4	Approximation sets for the <i>ecoli</i> dataset, positive rules	34
3.1	Illustration of the Pareto optimal solution concept for a minimization problem with two objectives	55
3.2	Multiobjective Problem 5: Behavior, Optimal Pareto front and solutions in the search space	60
3.3	True Pareto fronts and those identified by the algorithms: MOHBMO, MOPSO and MOSCEM	62
3.4	Watershed representation in the HYMOD model	64
3.5	Schematic representation of the hydrologic model HYMOD	64

3.6	Optimum solutions identified by the algorithms MOHBMO, MOSCEM and MOPSO for functions of_1 and of_2 : Set of optimal parameters	65
3.7	Optimum solutions identified by the algorithms MOHBMO, MOSCEM and MOPSO for functions of_1 and of_2 : Identified Pareto fronts	66
3.8	Observed hydrograph and optimal hydrographs associated to Pareto front points	67
3.9	Calibration and validation results for gauge station 34750000	68
3.10	Calibration and validation results for gauge station 36125000	69
3.11	Calibration and validation results for gauge station 35760000	70
3.12	Current reservoirs' system used for water supply of the metropolitan region of Fortaleza	73
3.13	Composite of 10 Pareto fronts obtained by MOHBMO and MOPSO	77
4.1	An example in which the auxiliary archive exceeds its maximum allowable limit	91
4.2	Graphical comparison of the Pareto fronts for ZDT1	94
4.3	Graphical comparison of the Pareto fronts for ZDT2	95
4.4	Graphical comparison of the Pareto fronts for ZDT3	96
4.5	Graphical comparison of the Pareto fronts for ZDT4	97
4.6	Graphical comparison of the Pareto fronts for ZDT6	98
4.7	Graphical comparison of the Pareto fronts for Kursawe's test function	99
4.8	Graphical comparison of the Pareto fronts for Viennet's test function	100
5.1	Solutions for Function FDA1 using ring topology on the top and random topology on the bottom	115
5.2	Solutions for Function FDA2 using ring topology on the top and random topology on the bottom	116
5.3	Solutions for Function FDA4 using ring topology on the top and random topology on the bottom	118
5.4	Solutions for Function FDA5 using ring topology on the top and random topology on the bottom	119
6.1	Dominance relation and Pareto front for a set of solutions in a multi-objective space	128
6.2	PSO basic layout	131
6.3	Meta-PSO basic layout	133
6.4	Modified Meta-PSO basic layout	133

6.5	Differentiated Meta-PSO basic layout. Forces over the generic particle are: (a) pull toward personal best $\mathbf{P}_{1,j}$; (b) pull toward swarm best $\mathbf{S}_1$. For what concerns the Leader, he is subject also to (c) pull toward global best $\mathbf{G}$ (belonging to swarm 2).	135
6.6	Best agent behavior over 50 independent trials for PSO and SM ² PSO	137
6.7	Domain of multi-objective problem defined in (6.14) and distribution of dominant solutions	140
6.8	Domain of multi-objective problem defined in (6.15) and distribution of dominant solutions	141
6.9	Dominant solutions for function (6.14) found.	142
6.10	Dominant solutions for function (6.15) found.	143
6.11	Dominant solutions of multi-objective optimization of the dual band linear array: comparison	145
6.12	Dominant solutions of multi-objective optimization of the dual band linear array: results	145
6.13	Resulting radiation pattern for the optimized beam scanning linear array in no tilt configuration	147
6.14	Resulting radiation pattern for the optimized beam scanning linear array in maximum tilt configuration	148
7.1	Haar wavelet $\psi(x)$	154
7.2	Illustration of discrete wavelet transform	157
7.3	Illustration of multi-objective pixel-level image fusion based on DWT	157
7.4	Relationship among entropy and mutual information for three variables	161
7.5	Illustration of MOCPSO algorithm	163
7.6	Results of multi-objective multi-focus image fusion	172
7.7	Results of multi-objective blind image fusion	173
7.8	Results of multi-objective multi-resolution image fusion	174
7.9	Results of multi-objective color image fusion	175
8.1	Flowchart of MOEPSO for solving damage identification problems	187
8.2	Finite element mesh and damage scenario for the beam	192
8.3	Pareto fronts for the six versions of the PSO algorithm: Beam. (a) 30 runs; (b) 100 runs	193
8.4	Pareto fronts for the three versions of the PSO algorithm based on FS: Beam. (a) 30 runs; (b) 100 runs	194
8.5	Pareto fronts for the three versions of the PSO algorithm based on RW: Beam. (a) 30 runs; (b) 100 runs	195
8.6	Comparison of Pareto fronts among SPGA, NPGA and MOEPSO-M-FS.	198

8.7	Comparison of damage predictions among MOEPSO-M-FS, SPGA and NPGA for the beam	198
8.8	Reinforced concrete frame experimentally tested	199
8.9	Pareto fronts for the six versions of the PSO algorithm: Frame. (a) 30 runs; (b) 100 runs	200
8.10	Pareto fronts for the three versions of the PSO algorithm based on FS: Frame. (a) 30 runs; (b) 100 runs	201
8.11	Pareto fronts for the three versions of the PSO algorithm based on RW: Frame. (a) 30 runs; (b) 100 runs	202
8.12	Comparison of Pareto fronts between SPGA and MOEPSO-M-FS	204
8.13	Comparison of damage predictions among MOEPSO-M-FS and SPGA for the beam part of the frame	204

List of Tables

1.1	Parameters values adopted for the quadruple-tank process ...	5
1.2	Results of MOPSO and MGPSO in multi-loop PI tuning for the quadruple-tank process	11
2.1	A Contingency Table	21
2.2	Description of the experimental data sets	32
2.3	Experiments Results: Mean AUC	33
2.4	Design Metrics	36
2.5	Metrics Description	36
2.6	AUC values for KC1 dataset	37
2.7	Best Learned Rules Through MOPSO-N	38
3.1	Test functions in the uni- and multiobjective optimization ...	59
3.2	Pump stations' capacity	73
3.3	Current operating policy	75
3.4	Operating policy obtained by MOHBMO with minimum pumping cost	78
4.1	Comparison of results between our micro-MOPSO and the NSGA-II	99
5.1	p -values of Statistical Tests	114
5.2	Spacing and Hypervolume Metric Values for Function FDA1	115
5.3	Spacing and Hypervolume Metric Values for Function FDA1	116
5.4	Spacing and Hypervolume Metric Values for Function FDA2	117
5.5	Spacing and Hypervolume Metric Values for Function FDA2	117
5.6	Spacing and Hypervolume Metric Values for Function FDA4	117

5.7	Spacing and Hypervolume Metric Values for Function FDA4.....	118
5.8	Spacing and Hypervolume Metric Values for Function FDA5.....	120
5.9	Spacing and Hypervolume Metric Values for Function FDA5.....	120
5.10	Overall Result Comparison	120
6.1	Optimal weights.....	138
6.2	Performances with different cost functions	138
6.3	Number of dominant solutions for function (6.14) found	141
6.4	Number of dominant solutions for function (6.15) found	142
6.5	Radiation pattern requirements	144
6.6	Optimized distribution of excitation and position of each element for the linear array.	147
7.1	σ values for different number of factors and different number of levels.....	167
7.2	Evaluation criteria of different combinations	170
7.3	Results of Objective Distance of different algorithms	171
7.4	Results of Inverse Objective Distance of different algorithms.....	171
7.5	Results of Spacing of different algorithms.....	171
7.6	Results of Error Ratio of different algorithms	171
7.7	Computational time (in seconds) of different algorithms	172
7.8	Evaluation metrics of multi-objective multi-focus image fusion.....	173
7.9	Evaluation metrics of multi-objective blind image fusion.....	174
7.10	Evaluation metrics of multi-objective multi-resolution image fusion	174
7.11	Evaluation metrics of multi-objective color image fusion	176
8.1	Average density values and Pareto front sizes: Beam (30 runs)	194
8.2	Average density values and Pareto front sizes: Beam (100 runs)	195
8.3	C metrics to measure the coverage of two sets of solutions: Beam. X': First column; X'': First line (30 runs).....	196
8.4	C metrics to measure the coverage of two sets of solutions: Beam. X': First column; X'': First line (100 runs).....	196
8.5	Parameters settings of SPGA and NPGA algorithms	197
8.6	Average density values and Pareto front sizes: Frame (30 runs)	201
8.7	Average density values and Pareto front sizes: Frame (100 runs)	202

8.8	C metrics to measure the coverage of two sets of solutions: Frame. X' : First column; X'' : First line (30 runs)	203
8.9	C metrics to measure the coverage of two sets of solutions: Frame. X' : First column; X'' : First line (100 runs)	203