Evolutionary algorithms for solving power system optimization problems

Biswas, Partha Pratim

2019

Biswas, P. P. (2019). Evolutionary algorithms for solving power system optimization problems. Doctoral thesis, Nanyang Technological University, Singapore.

<https://hdl.handle.net/10356/105518>

<https://doi.org/10.32657/10220/47833>

**NANYANG
TECHNOLOGICAL
UNIVERSITY**

SINGAPORE

**EVOLUTIONARY ALGORITHMS FOR SOLVING POWER
SYSTEM OPTIMIZATION PROBLEMS**

PARTHA PRATIM BISWAS

SCHOOL OF ELECTRICAL AND ELECTRONIC ENGINEERING

2019

EVOLUTIONARY ALGORITHMS FOR SOLVING POWER SYSTEM OPTIMIZATION PROBLEMS

PARTHA PRATIM BISWAS

School of Electrical and Electronic Engineering

A thesis submitted to the Nanyang Technological University
in partial fulfilment of the requirement for the degree of
Doctor of Philosophy

2019

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

13/03/2019
.....
Date

.....
Partha Pratim Biswas

Supervisor Declaration Statement

I have reviewed the content and presentation style of this thesis and declare it is free of plagiarism and of sufficient grammatical clarity to be examined. To the best of my knowledge, the research and writing are those of the candidate except as acknowledged in the Author Attribution Statement. I confirm that the investigations were conducted in accord with the ethics policies and integrity standards of Nanyang Technological University and that the research data are presented honestly and without prejudice.

13 Mar 2019

Date

.....
Ponnuthurai N. Suganthan

Authorship Attribution Statement

This thesis contains material from 8(eight) paper(s) published in the following peer-reviewed journal(s) / from papers accepted at conferences in which I am listed as an author.

Some sections of **Chapter 2** are published as Partha P. Biswas, and P. N. Suganthan. "Multiobjective Evolutionary Optimization." *Wiley Encyclopedia of Electrical and Electronics Engineering* (2018): 1-15. DOI: 10.1002/047134608X.W8380.

The contributions of the co-authors are as follows:

- Assoc. Prof. P. N. Suganthan provided the initial direction and proofread the manuscript.

Some parts of **Chapter 3 section 3.1** are published as Partha P. Biswas, P. N. Suganthan, R. Mallipeddi, and Gehan AJ Amaratunga. "Optimal power flow solutions using differential evolution algorithm integrated with effective constraint handling techniques." *Engineering Applications of Artificial Intelligence* 68 (2018): 81-100. DOI: 10.1016/j.engappai.2017.10.019.

The contributions of the co-authors are as follows:

- The chapter involves a lot of experiments and case studies. Assoc. Prof. R. Mallipeddi helped with computational resources in running some simulations.
- Assoc. Prof. P. N. Suganthan and Prof. Gehan AJ Amaratunga assisted in proofreading the manuscript.

Chapter 3 section 3.3 is published as Partha P. Biswas, P. N. Suganthan, and Gehan AJ Amaratunga. "Optimal power flow solutions incorporating stochastic wind and solar power." *Energy Conversion and Management* 148 (2017): 1194-1207. DOI: 10.1016/j.enconman.2017.06.071.

The contributions of the co-authors are as follows:

- Assoc. Prof. P. N. Suganthan provided the direction on constrained single-objective optimization problems.

- Prof. Gehan AJ Amaratunga proofread the manuscript.

Chapter 4 is published as Partha P. Biswas, P. N. Suganthan, R. Mallipeddi, and Gehan AJ Amaratunga. "Optimal reactive power dispatch with uncertainties in load demand and renewable energy sources adopting scenario-based approach." *Applied Soft Computing* 75 (2019): 616-632. DOI: 10.1016/j.asoc.2018.11.042.

The contributions of the co-authors are as follows:

- Assoc. Prof. R. Mallipeddi helped with computational resources in running some simulations.
- Assoc. Prof. P. N. Suganthan and Prof. Gehan AJ Amaratunga assisted in proofreading the manuscript.

Chapter 5 is published as Partha P. Biswas, P. N. Suganthan, B. Y. Qu, and Gehan AJ Amaratunga. "Multiobjective economic-environmental power dispatch with stochastic wind-solar-small hydro power." *Energy* 150 (2018): 1039-1057. DOI: 10.1016/j.energy.2018.03.002.

The contributions of the co-authors are as follows:

- Assoc. Prof. P. N. Suganthan provided the direction on constrained multi-objective optimization problems.
- Assistant Prof. B. Y. Qu helped with some coding of an algorithm.
- Prof. Gehan AJ Amaratunga proofread the manuscript.

Some parts of **Chapter 6** are published as Partha P. Biswas, P. N. Suganthan, and Gehan AJ Amaratunga. "Distribution network reconfiguration together with distributed generator and shunt capacitor allocation for loss minimization." In *Evolutionary Computation (CEC), 2018 IEEE Congress on*, pp. 1-7. IEEE 2018. DOI: 10.1109/CEC.2018.8477894.

The contributions of the co-authors are as follows:

- Assoc. Prof. P. N. Suganthan and Prof. Gehan AJ Amaratunga proofread the manuscript.

Chapter 7 section 7.1 is published as Partha P. Biswas, P. N. Suganthan, and Gehan AJ Amaratunga. "Optimal placement of wind turbines in a windfarm using L-SHADE algorithm." *In Evolutionary Computation (CEC), 2017 IEEE Congress on*, pp. 83-88. IEEE 2017. DOI: 10.1109/CEC.2017.7969299.

The contributions of the co-authors are as follows:

- Assoc. Prof. P. N. Suganthan provided details on application and usefulness of the algorithm used in the paper.
- Prof. Gehan AJ Amaratunga proofread the manuscript.

Chapter 7 section 7.2 is published as Partha P. Biswas, P. N. Suganthan, and Gehan AJ Amaratunga. "Decomposition based multi-objective evolutionary algorithm for windfarm layout optimization." *Renewable Energy* 115 (2018): 326-337. DOI: 10.1016/j.renene.2017.08.041.

The contributions of the co-authors are as follows:

- Assoc. Prof. P. N. Suganthan provided direction on application of the multi-objective evolutionary algorithms.
- Prof. Gehan AJ Amaratunga proofread the manuscript.

13/03/2019
Date

.....
Partha Pratim Biswas

Dedicated to my family members for their continuous
support, love and encouragement

Acknowledgements

This thesis would not have been possible without support of many individuals. I am thankful to all of them.

Firstly, I want to express my gratitude to my supervisor and guide Assoc. Prof. Ponnuthurai N. Suganthan for giving me the opportunity to pursue PhD program. I had been working in the industry and honestly had no plan to enroll for the PhD program post my Masters in Power Engineering. His awareness, far-sighted ideas on the application of artificial intelligence in power system motivated me to take up the research work on power system optimization. Thereafter, his systematic guidance and constant inspiration have made submission of this thesis possible within two years of my PhD study.

I am also thankful to my co-authors for their help and support in preparing and proofreading the journal manuscripts. A special mention to Assoc. Prof. Rammohan Mallipeddi who has given directions at various stages in tackling tough comments from the reviewers.

I would also like to mention Prof. Gehan A. Amaratunga who had managed funding for PhD study under Cambridge Centre for Carbon Reduction in Chemical Technology project.

Most importantly, I am highly indebted to my beloved and supportive family members – my wife, my son, my parents and my parents-in-law. I have no hesitation in admitting the fact that I could spend less quality time with my family members in the last couple of years. I was also relieved of most of the household chores and responsibilities of a father so that I could devote more time on research. I sincerely thank you all.

Lastly, I extend my gratitude to my colleagues for their help and cooperation at various stages in my study.

Abstract

The scope of optimization in power system is ample. In general, optimization helps efficient and economical operation of the electrical system. It is worthwhile to note that power system problems are mostly non-linear and non-convex, and they often require optimization of two or more conflicting objectives. The problem can also be a mix of discrete and continuous variables that are needed to be handled by the optimization algorithms. During earlier days, classical numerical optimization methods were in use. The classical methods are known to perform well for convex and continuous optimization problems as these methods usually employ a gradient based search that has the tendency to converge to local optima. Revolution in numerical optimization introduced several evolutionary algorithms (EAs) and techniques in the last three decades. Most of these methods can successfully overcome the problem of premature convergence and explore the search space in pursuit of the global optimum. The field of evolutionary algorithms being dynamic, the classical power system optimization problems can be revisited to check whether performance of the network can be enhanced with the application of new algorithms. Furthermore, renewable energy sources are becoming integral parts of the modern smart grid, a fact that opens up avenues for formulation of new optimization problems incorporating many more components. The primary scope of this research is in applying the state-of-the-art variants of differential evolution (DE) algorithm for single-objective optimization and selected evolutionary algorithms for multi-objective optimization problems in power system. This thesis includes a detailed survey of the algorithm success history based adaptive differential evolution (SHADE) and its variant the linear population size reduction technique of SHADE (L-SHADE) for single-objective optimization; decomposition based multi-objective evolutionary algorithm (MOEA/D) and summation based multi-objective differential evolution (SMODE) for multi-objective optimization. Furthermore, operational and security constraints are also common in the electrical network. Static penalty function method has been the easiest and simplest way to deal with the constraints in power system problems. In this thesis, we present a review of three constraint handling (CH) techniques for EAs - superiority of feasible solutions (SF), epsilon (ϵ) constraint (EC) handling and stochastic ranking (SR) methods. The constraint handling techniques have been successfully implemented in conjunction with the EAs and applied to the existing and newly proposed formulations of constrained optimization problems in power system such as optimal power flow (OPF), economic-environmental dispatch (EED) and optimal reactive

power dispatch (ORPD). In addition, studies on optimal siting of wind turbines in a windfarm and loss minimization in a distribution network are also presented in relevant chapters. The final chapter of the thesis concludes with potential future works on optimization in smart grid.

Abbreviations

CH	Constraint handling
CI	Computational intelligence
DE	Differential evolution
DED	Dynamic economic dispatch
DFIG	Doubly-fed induction generator
DG	Distributed generation or generator
EA	Evolutionary algorithm
EC	Epsilon (ϵ) constraint handling technique
ED	Economic dispatch
EED	Economic-environmental dispatch
FACTS	Flexible alternating current transmission system
HAPF	Hybrid active power filter
IEEE	Institute of electrical and electronics engineers
ISO	Independent system operator
L-SHADE	Linear population size reduction technique of success history based adaptive differential evolution
MOEA	Multi-objective evolutionary algorithm
MOEA/D	Multi-objective evolutionary algorithm based on decomposition
MOEED	Multi-objective economic-environmental dispatch
MOOPF	Multi-objective optimal power flow
MOP	Multi-objective optimization problem
OPF	Optimal power flow
ORPD	Optimal reactive power dispatch
PDF	Probability density function
p.u.	Per unit
PV	Photovoltaic
RDN	Radial distribution network
SC	Shunt capacitor
SF	Superiority of feasible solutions
SHADE	Success history based adaptive differential evolution
SMODE	Summation based multi-objective differential evolution
SP	Self-adaptive penalty
SR	Stochastic ranking method of constraint handling
THD	Total harmonic distortion
UC	Unit commitment
WT	Wind turbine

Contents

<i>ACKNOWLEDGEMENTS</i>	II
<i>ABSTRACT</i>	III
<i>ABBREVIATIONS</i>	V
<i>LIST OF FIGURES</i>	IX
<i>LIST OF TABLES</i>	XIII
1. INTRODUCTION	1
1.1. Motivation and objective	1
1.2. Major contributions of the thesis	2
1.3. Outline of the thesis	4
2. EVOLUTIONARY ALGORITHMS AND POWER SYSTEM OPTIMIZATION PROBLEMS	6
2.1. Evolutionary algorithms (EAs)	6
2.1.1 Evolutionary algorithms (EAs) for single-objective optimization	6
2.1.1.1 SHADE algorithm	7
2.1.1.2 L-SHADE algorithm	9
2.1.2 Multi-objective evolutionary algorithms (MOEAs)	9
2.1.2.1 Decomposition based multi-objective evolutionary algorithm (MOEA/D) ..	11
2.1.2.2 Summation based multi-objective differential evolution (SMODE)	15
2.1.3 Constraint handling (CH) techniques	17
2.1.3.1 Superiority of feasible solutions (SF)	18
2.1.3.2 Epsilon (ϵ) constraint (EC) handling technique	18
2.1.3.3 Stochastic ranking (SR) method for constraint handling	19
2.1.4 Integration of CH techniques with evolutionary algorithms (EAs)	20
2.1.4.1 Integration of CH techniques with SHADE algorithm	20
2.1.4.2 Integration of CH technique SF with MOEA/D	22
2.1.4.3 Integration of CH technique SF with SMODE	26
2.2. Power system optimization problems	29
2.2.1 Optimal power flow (OPF)	29

2.2.2	Optimal reactive power dispatch.....	33
2.2.3	Economic-environmental dispatch.....	35
2.2.4	Distribution network loss minimization.....	36
2.2.5	Optimal siting of wind turbines in a windfarm	38
3.	OPTIMAL POWER FLOW STUDY	40
3.1.	Single-objective optimal power flow study	40
3.1.1	Mathematical formulation of optimal power flow	41
3.1.2	Objective functions of OPF	43
3.1.3	Case studies, results and comparisons of single-objective OPF cases	49
3.1.4	Conclusion: single-objective OPF study	66
3.2.	Multi-objective optimal power flow study	68
3.2.1	Objectives, case studies for MOOPF and input for MOEA/D-SF	69
3.2.3	Conclusion: multi-objective OPF study	90
3.3.	Optimal power flow study with stochastic wind and solar power	92
3.3.1	Mathematical models of OPF incorporating stochastic wind and solar power	93
3.3.2	Stochastic wind / solar power and uncertainty models	99
3.3.3	Case studies and results for OPF with stochastic wind and solar power	104
3.3.4	Conclusion: OPF study with stochastic wind and solar power	115
4.	OPTIMAL REACTIVE POWER DISPATCH	116
4.1.	Introduction to optimal reactive power dispatch (ORPD)	116
4.2.	Mathematical models for ORPD study	117
4.3.	Scenario generation and reduction techniques of uncertain load demand, wind and solar power.....	120
4.4.	Simulation results, analyses and comparisons for ORPD cases	126
4.5.	Conclusion: optimal reactive power dispatch study	140
5.	ECONOMIC-ENVIRONMENTAL DISPATCH WITH STOCHASTIC WIND-SOLAR-SMALL HYDRO POWER	141
5.1.	Introduction to multi-objective economic environmental dispatch (MOEED)	141
5.2.	Mathematical models for MOEED study	142
5.3.	Calculation of stochastic power of renewable sources	150

5.4.	Simulation results, analyses and comparisons for MOEED study	158
5.5.	Conclusion: MOEED study with stochastic wind-solar-small hydro power	167
6.	DISTRIBUTION NETWORK LOSS MINIMIZATION.....	168
6.1.	Introduction to distribution network loss minimization study	168
6.2.	Mathematical formulation and calculation of power loss in the RDN	169
6.3.	Case studies for RDN loss minimization	172
6.4.	Inputs for L-SHADE algorithm for cases of RDN loss minimization.....	173
6.5.	Results and comparisons of RDN loss minimization cases	174
6.6.	Conclusion: loss minimization in RDN	181
7.	OPTIMAL SITING OF WIND TURBINES IN A WINDFARM	183
7.1.	A single-objective approach to optimal siting of wind turbines in a windfarm.....	183
7.1.1	Windfarm mathematical modeling.....	183
7.1.2	Case studies and objective formulation.....	186
7.1.3	Simulation results and comparisons for single-objective optimization cases	188
7.1.4	Conclusion: a single-objective approach to optimal siting of wind turbines	191
7.2.	A multi-objective approach to optimal siting of wind turbines in a windfarm.....	192
7.2.1	Mathematical models and numerical data	192
7.2.2	Application of MOEA/D algorithm to optimal siting of wind turbines	197
7.2.3	Case studies for multi-objective optimization cases	198
7.2.4	Conclusion: a multi-objective approach to optimal siting of wind turbines	212
8.	SUMMARY, CONCLUSION AND FUTURE WORK	213
8.1.	Summary and conclusion	213
8.2.	Future work.....	215
	LIST OF PUBLICATIONS	217
	APPENDIX.....	219
	BIBLIOGRAPHY	232

List of Figures

Fig. 1.1. Outline of the thesis	5
Fig. 2.1. Illustration of decision-making process in buying a flight ticket	10
Fig. 2.2. Weight vectors for a bi-objective optimization problem.....	12
Fig. 2.3. Graphical illustration for a subproblem of a bi-objective function in MOEA/D.....	12
Fig. 2.4. SMODE – selection of points in preferential and backup sets	16
Fig. 2.5. Flowchart for implementation of SHADE-XX (XX: SF/EC/SR)	22
Fig. 2.6. Flowchart for implementation of algorithm MOEA/D-SF.....	25
Fig. 2.7. Flowchart for implementation of algorithm SMODE-SF	28
Fig. 3.1. Cost curves of a generator with single fuel and multi-fuel options.....	46
Fig. 3.2. Cost curves of a generator with and without valve-point loading effect.....	48
Fig. 3.3. IEEE 30-bus system – load bus voltage profiles for the best solutions in all cases	55
Fig. 3.4. Comparative convergence among 3-CH techniques for Case 1 of IEEE 30-bus system	57
Fig. 3.5. Comparative convergence among 3-CH techniques for Case 2 of IEEE 30-bus system	57
Fig. 3.6. Comparative convergence among 3-CH techniques for Case 3 of IEEE 30-bus system	58
Fig. 3.7. Comparative convergence among 3-CH techniques for Case 4 of IEEE 30-bus system	58
Fig. 3.8. Comparative convergence among 3-CH techniques for Case 5 of IEEE 30-bus system	59
Fig. 3.9. Comparative convergence among 3-CH techniques for Case 6 of IEEE 30-bus system	59
Fig. 3.10. IEEE 57-bus system – load bus voltage profiles for the best solutions of Cases 7, 8 & 9	62
Fig. 3.11. Comparative convergence among 3-CH techniques for Case 7 of IEEE 57-bus system	63
Fig. 3.12. Comparative convergence among 3-CH techniques for Case 8 of IEEE 57-bus system	64
Fig. 3.13. Comparative convergence among 3-CH techniques for Case 9 of IEEE 57-bus system	64
Fig. 3.14. IEEE 118-bus system – load bus voltage profiles for the best solutions of Cases 10 & 11	65
Fig. 3.15. Convergence curves of Case 10 and Case 11 (SHADE-EC) for IEEE 118-bus system.....	66
Fig. 3.16. Violation of constraint on load bus voltage for some solutions in MOOPF Case 9 with penalty function approach	74
Fig. 3.17. IEEE 30-bus system – generator reactive power values for the best solutions in MOOPF cases ...	78
Fig. 3.18. IEEE 30-bus system – load bus voltage profiles for the worst VD values in MOOPF cases	79
Fig. 3.19. The best Pareto fronts with MOEA/D-SF and MOEA/D-penalty for MOOPF Case 1	82
Fig. 3.20. The best Pareto front with MOEA/D-SF for MOOPF Case 2.....	83
Fig. 3.21. The best Pareto fronts with MOEA/D-SF and MOEA/D-penalty for MOOPF Case 3.....	83
Fig. 3.22. The best Pareto front with MOEA/D-SF for MOOPF Case 4.....	84
Fig. 3.23. The best Pareto front with MOEA/D-SF for MOOPF Case 5.....	84
Fig. 3.24. Parallel coordinates plot of the best PF solutions with MOEA/D-SF for MOOPF Case 6	85
Fig. 3.25. IEEE 57-bus system – generator reactive power values for the best solutions in MOOPF cases ...	86
Fig. 3.26. IEEE 57-bus system – load bus voltage profiles for the worst VD values in MOOPF cases.....	86

Fig. 3.27. The best Pareto fronts with MOEA/D-SF and MOEA/D-penalty for MOOPF Case 7.....	88
Fig. 3.28. The best Pareto front with MOEA/D-SF for MOOPF Case 8.....	89
Fig. 3.29. The best Pareto fronts with MOEA/D-SF and MOEA/D-penalty for MOOPF Case 9.....	89
Fig. 3.30. Parallel coordinates plot of the best PF solutions with MOEA/D-SF for MOOPF Case 10	90
Fig. 3.31. The adapted IEEE 30-bus system for OPF study with stochastic wind and solar power	94
Fig. 3.32. Wind speed distribution (sample size 8000) for wind farm #1 at bus 5	100
Fig. 3.33. Wind speed distribution (sample size 8000) for wind farm #2 at bus 11	100
Fig. 3.34. Solar irradiance distribution (sample size 8000) for the PV plant at bus 13	101
Fig. 3.35. Distribution of available real power (MW) from the PV plant at bus 13	104
Fig. 3.36. Variation of wind power cost vs scheduled power for wind generator <i>WG1</i>	105
Fig. 3.37. Variation of wind power cost vs scheduled power for wind generator <i>WG2</i>	106
Fig. 3.38. Variation of solar power cost vs scheduled power for the PV plant	106
Fig. 3.39. Variation of wind power cost vs Weibull scale parameter (α) for windfarm#1 (bus 5).....	107
Fig. 3.40. Variation of wind power cost vs Weibull scale parameter (α) for windfarm#2 (bus 11).....	107
Fig. 3.41. Variation of PV power cost vs lognormal mean (μ) for the PV plant (bus 13)	108
Fig. 3.42. Convergence of SHADE-SF algorithm for Case 3 and Case 6 of OPF with stochastic sources ...	109
Fig. 3.43. Optimal scheduled real power (MW) vs reserve cost coefficient (<i>KR</i>)	110
Fig. 3.44. Cost curves for change in reserve cost coefficient (<i>KR</i>).....	111
Fig. 3.45. Optimal scheduled real power (MW) vs penalty cost coefficient	112
Fig. 3.46. Cost curves for change in penalty cost coefficient (<i>KP</i>).....	112
Fig. 3.47. Generator bus voltages for Case 4 and Case 5 of OPF with stochastic sources	113
Fig. 3.48. Generator reactive power schedule for Case 4 and Case 5 of OPF with stochastic sources	113
Fig. 3.49. Load bus voltage profiles for Case 3 and Case 6 of OPF with stochastic sources	114
Fig. 4.1. The adapted IEEE 30-bus system with wind and PV units for stochastic ORPD study.....	120
Fig. 4.2. Load demand scenarios (sample size 1000) using normal PDF.....	121
Fig. 4.3. Wind speed scenarios (sample size 1000) for the wind generator (bus 5) using Weibull PDF.....	121
Fig. 4.4. Solar irradiance scenarios (sample size 1000) for the PV (bus 8) using lognormal PDF.....	122
Fig. 4.5. Solar irradiance scenarios (without zero irradiance) for the photovoltaic (PV)	122
Fig. 4.6. Load bus voltage profiles for ORPD case studies of IEEE 30-bus system	129
Fig. 4.7. Convergence curves of SHADE-EC algorithm for ORPD Case 1 and Case 2.....	129
Fig. 4.8. Load bus voltage profiles for ORPD case studies of IEEE 57-bus system	133
Fig. 4.9. Convergence curves of SHADE-EC algorithm for ORPD Case 11 and Case 12.....	133
Fig. 4.10. Optimal settings of generator bus voltages for all scenarios in ORPD Case 21	137
Fig. 4.11. Optimal settings of generator bus voltages for all scenarios in ORPD Case 22.....	138
Fig. 4.12. Load bus voltage profiles under extreme scenarios for ORPD Case 21 and Case 22	139
Fig. 4.13. Minimum and maximum reactive power of generators over all scenarios in ORPD Case 21	139
Fig. 4.14. Minimum and maximum reactive power of generators over all scenarios in ORPD Case 22	139
Fig. 5.1. The adapted IEEE 30-bus system with wind-solar-small hydro units for MOEED study	143

Fig. 5.2. Wind speed distribution (sample size 8000) for the windfarm at bus 5	150
Fig. 5.3. Solar irradiance distribution (sample size 8000) for the PV unit at bus 11	151
Fig. 5.4. Solar irradiance distribution (sample size 8000) for the PV unit at bus 13	152
Fig. 5.5. River flow rate distribution (sample size 8000) for the small-hydro unit at bus 13	152
Fig. 5.6. Available power from solar irradiance for the site of the PV unit at bus 11	155
Fig. 5.7. Distribution of available real power (MW) from the PV unit at bus 11	155
Fig. 5.8. Available solar power (MW) for the site and from the PV unit at bus 13	156
Fig. 5.9. Available hydro power (MW) for the site and from the small-hydro unit at bus 13	157
Fig. 5.10. Available total real power (MW) from the combined PV and small-hydro system at bus 13	157
Fig. 5.11. Comparison of the best and worst Pareto fronts of MOEA/D-SF for MOEED study	160
Fig. 5.12. Comparison of the best and worst Pareto fronts of SMODE-SF for MOEED study	160
Fig. 5.13. Comparison of the best Pareto fronts of two algorithms for MOEED study	161
Fig. 5.14. Comparison of the worst Pareto fronts of two algorithms for MOEED study	161
Fig. 5.15. Generator reactive power schedule for best objectives of the best PF using MOEA/D-SF	165
Fig. 5.16. Generator reactive power schedule for best objectives of the best PF using SMODE-SF	166
Fig. 5.17. Load bus voltage profiles for the worst VD values using the two algorithms	166
Fig. 6.1. Base configuration of IEEE 33-bus distribution network	169
Fig. 6.2. Base configuration of IEEE 69-bus distribution network	170
Fig. 6.3. Single line diagram of a radial feeder	170
Fig. 6.4. Selected total DG capacity vs real power loss with various optimization methods for case studies of IEEE 33-bus system	177
Fig. 6.5. Bus voltage profiles of IEEE 33-bus system for different case studies	177
Fig. 6.6. Selected total DG capacity vs real power loss with various optimization methods for case studies of IEEE 69-bus system	180
Fig. 6.7. Bus voltage profiles of IEEE 69-bus system for different case studies	180
Fig. 6.8. Convergence of L-SHADE algorithm for Case 5 and Case 15 of RDN loss minimization	181
Fig. 7.1. (a) Linear Wake Model: k -th turbine under the influence of a single m -th turbine (b) i -th turbine partially influenced by the wake of j -th turbine	184
Fig. 7.2. Optimal placement of wind turbines for Case 1	186
Fig. 7.3. Wind probability distribution diagram for Case 3	187
Fig. 7.4. Optimal placement of wind turbines using various algorithms for Case 2	189
Fig. 7.5. Optimal placement of wind turbines using various algorithms for Case 3	190
Fig. 7.6. Convergence of L-SHADE algorithm for Case 3 of windfarm layout optimization	191
Fig. 7.7. Linear approximation of power output curve for Vestas V-80 turbine	193
Fig. 7.8. Wind probability distribution diagram 1 for site 1 – Midland, Texas	194
Fig. 7.9. Wind probability distribution diagram 2 for site 2 – Corpus Christi, Texas	195
Fig. 7.10. Plot of Pareto front for Case 11 (site 1) of windfarm layout optimization problem	200
Fig. 7.11. Plot of Pareto front for Case 12 (site 2) of windfarm layout optimization problem	200

Fig. 7.12. Variation of output power and efficiency with no. of turbines (Case 11, site 1).....	201
Fig. 7.13. Variation of output power and efficiency with no. of turbines (Case 12, site 2).....	201
Fig. 7.14. Optimal layout with 11 turbines (Case 11, site 1).....	202
Fig. 7.15. Optimal layout with 11 turbines (Case 12, site 2).....	202
Fig. 7.16. Optimal layout with 50 turbines (Case 11, site 1).....	202
Fig. 7.17. Optimal layout with 50 turbines (Case 12, site 2).....	203
Fig. 7.18. Plot of Pareto front for Case 13 (site 1) of windfarm layout optimization problem.....	205
Fig. 7.19. Plot of Pareto front for Case 14 (site 2) of windfarm layout optimization problem.....	205
Fig. 7.20. Variation of output power and efficiency with no. of turbines (Case 13, site 1).....	206
Fig. 7.21. Variation of output power and efficiency with no. of turbines (Case 14, site 2).....	206
Fig. 7.22. Plot of selected hub heights for all optimal solutions (Case 13, site 1).....	207
Fig. 7.23. Plot of selected hub heights for all optimal solutions (Case 14, site 2).....	207
Fig. 7.24. Selected hub heights at some discrete optimal solutions (Case 13, site 1).....	208
Fig. 7.25. Selected hub heights at some discrete optimal solutions (Case 14, site 2).....	208
Fig. 7.26. Optimal layout with 11 turbines (Case 13, site 1).....	209
Fig. 7.27. Optimal layout with 11 turbines (Case 14, site 2).....	209
Fig. 7.28. Optimal layout with 50 turbines (Case 13, site 1).....	210
Fig. 7.29. Optimal layout with 50 turbines (Case 14, site 2).....	211
 Fig. A.1. Stacked column representation of optimal transformer taps for all scenarios in ORPD Case 21 ...	230
Fig. A.2. Stacked column representation of optimal transformer taps for all scenarios in ORPD Case 22 ...	230
Fig. A.3. Stacked column representation of optimum VAR compensator settings for all scenarios in ORPD Case 21	231
Fig. A.4. Stacked column representation of optimum VAR compensator settings for all scenarios in ORPD Case 22	231

List of Tables

Table 2.1. The integration of CH techniques with SHADE algorithm	20
Table 3.1. A summary of IEEE bus test systems	44
Table 3.2. Cost and emission coefficients for generators of IEEE 30-bus system.....	44
Table 3.3. Cost and emission coefficients for generators of IEEE 57-bus system.....	45
Table 3.4. Cost coefficients for generators 1 and 2 of IEEE 30-bus system for multi-fuel sources.....	45
Table 3.5. Input parameters for SHADE-XX (XX: SF/EC/SR) algorithm in OPF study	49
Table 3.6. Summary of case studies for single-objective OPF	50
Table 3.7. Statistical summary of case studies using the 3-CH techniques.....	52
Table 3.8. Wilcoxon signed rank test results	52
Table 3.9. Simulation results for best solutions of cases for IEEE 30-bus system	54
Table 3.10. Comparison of 3-CH techniques with previous studies for cases of IEEE 30-bus system	56
Table 3.11. Simulation results for best solutions of cases for IEEE 57-bus system	60
Table 3.12. Comparison of 3-CH techniques with previous studies for cases of IEEE 57-bus system	62
Table 3.13. A summary of case studies for MOOPF	70
Table 3.14. User-defined inputs for MOEA/D-SF algorithm in MOOPF study	71
Table 3.15. Summary of hypervolume indicator values of MOOPF cases applying MOEA/D-SF.....	72
Table 3.16. A comparative study between MOEA/D with penalty factor and MOEA/D-SF	73
Table 3.17. Simulation results for MOOPF Case 1 and Case 2	75
Table 3.18. Simulation results for MOOPF Case 3 and Case 4	76
Table 3.19. Simulation results for MOOPF Case 5 and Case 6	77
Table 3.20. Comparison of the best compromise solutions for MOOPF Cases 1, 2 and 3	79
Table 3.21. Comparison of the best compromise solutions for MOOPF Cases 4, 5 and 6	81
Table 3.22. Comparison of the best individual objectives for MOOPF Case 1	81
Table 3.23. Comparison of the best individual objectives for MOOPF Case 7	87
Table 3.24. Comparison of the best compromise solutions of MOOPF cases for IEEE 57-bus system	87
Table 3.25. Summary of the adapted IEEE 30-bus system for OPF study with wind and solar power	93
Table 3.26. Cost and emission coefficients for thermal generators of the adapted system	94
Table 3.27. PDF parameters for the sources of wind and PV power plants	101
Table 3.28. Simulation results of optimization cases for the adapted IEEE 30-bus system.....	109
Table 4.1. Backward reduction algorithm.....	123
Table 4.2. Selected scenarios and relevant parameters for the scenarios	125
Table 4.3. Input parameters for SHADE-EC algorithm in ORPD study.....	126
Table 4.4. Generator data for IEEE 30-bus system (base case) in ORPD study	127
Table 4.5. Simulation results for ORPD case studies of IEEE30-bus system.....	128
Table 4.6. Comparison of results of ORPD case studies for IEEE 30-bus system	130
Table 4.7. Generator data for IEEE 57-bus system in ORDP study.....	132

Table 4.8. Simulation results for ORPD case studies of IEEE 57-bus system.....	132
Table 4.9. Comparison of results of ORPD case studies for IEEE 57-bus system	134
Table 4.10. Generator data for the adapted IEEE 30-bus system for ORPD study	134
Table 4.11. Expected power loss and voltage deviation with uncertain demand and renewable power	136
Table 4.12. Control variables under extreme scenarios in ORPD Case 21 and Case 22.....	137
Table 5.1. A summary of the adapted IEEE 30-bus system for MOEED study	142
Table 5.2. Cost and emission coefficients of thermal power generators in MOEED study	144
Table 5.3. PDF parameters for stochastic models of renewable sources	151
Table 5.4. Direct, penalty and reserve cost coefficients for stochastic renewable energies	158
Table 5.5. User-defined input data for MOEA/D-SF and SMODE-SF for MOEED study	158
Table 5.6. Summary of hypervolume (HV) indicator values	159
Table 5.7. Simulation results of the optimization algorithms in MOEED study.....	163
Table 5.8. Settings of variables for the best individual objectives of the best PFs	164
Table 6.1. Summary of case studies for RDN loss minimization	172
Table 6.2. Inputs for L-SHADE algorithm in RDN loss minimization study	173
Table 6.3. Simulation results and comparison of RDN case studies for IEEE 33-bus system.....	176
Table 6.4. Simulation results and comparison of RDN case studies for IEEE 69-bus system.....	179
Table 7.1. Wind turbine data and other relevant parameters.....	187
Table 7.2. Comparison of wind turbine optimal placement study Case 2 and Case 3	189
Table 7.3. Wind turbine (Vestas V-80) and other relevant data.....	197
Table 7.4. Input data for MOEA/D algorithm for windfarm layout optimization.....	198
Table 7.5. Data of selected optimal layouts for Case 11 and Case 12	204
Table 7.6. Data of selected optimal layouts for Case 13 and Case 14	211
Table A.1. Load data for IEEE 30-bus system.....	219
Table A.2. Load data for IEEE 57-bus system.....	219
Table A.3. Branch data for IEEE 30-bus system	220
Table A.4. Branch data for IEEE 57-bus system	221
Table A.5. Simulation results of SHADE-EC for OPF Case 10 (min. cost) of IEEE 118-bus system	223
Table A.6. Simulation results of SHADE-EC for OPF Case 11 (min. loss) of IEEE 118-bus system	224
Table A.7. Simulation results of OPF Case AC1: handling discrete variables	225
Table A.8. IEEE 57-bus system generator emission coefficients for MOOPF study	225
Table A.9. Simulation results for MOOPF Case 7.....	226
Table A.10. Simulation results for MOOPF Case 8.....	227
Table A.11. Simulation results for MOOPF Case 9.....	228
Table A.12. Simulation results for MOOPF Case 10.....	229

Chapter 1

1. Introduction

1.1. Motivation and objective

Computational intelligence (CI) gained immense popularity in diverse fields including traditional engineering fields of mechanical, civil and electrical due to its ability to solve challenging problems. Modern electrical networks are huge and interconnected with several generating units, load points and hundreds of buses. The complexity of the network escalates with the introduction of FACTS (flexible AC transmission system) devices, various types of loads and distributed generators (DGs) in the forms of wind turbines, photovoltaics, fuel cells, etc. Further, due to deregulation of the energy market, power industry is undergoing a paradigm shift compelling engineers to look for powerful tools for optimal planning, operation, performance and control of the electrical networks. CI tools in the forms of optimization algorithms, also termed as evolutionary algorithms (EAs), are very useful and efficient methods for solving real-world power engineering problems which are non-convex, discontinuous and non-differentiable. The gradient based search process of the classical numerical optimization methods had the inclination towards untimely convergence to a local optimum. To deal with the shortcomings of classical methods, the field of numerical optimization has experienced a spurt in the last few decades with the advent and advancement of several evolutionary algorithms (EAs). The stochastic, population based direct search approach of EAs can effectively explore the search space for the global optimum, thus avoiding any premature convergence in most cases. In recent years, evolutionary algorithms like genetic algorithm (GA), particle swarm optimization (PSO), simulated annealing (SA), glowworm swarm optimization (GSO), moth flame optimization (MFO), differential evolution (DE), etc. have been applied to various power system problems such as optimal power flow (OPF), economic dispatch (ED), economic-environmental dispatch (EED), optimal reactive power dispatch (ORPD), unit commitment (UC), optimal reconfiguration of radial distribution network (RDN), etc. However, new algorithms are often being introduced and existing algorithms are regularly being improved in the field of CI. Therefore, all these classical problems can be revisited to further enhance the performance of the electrical network, as well as ample scope remains for formulation of new problems incorporating modern power electronics-based FACTS devices and intermittent and uncertain renewable sources. Motivated by these, our research is focused on the field of power system optimization using EAs.

The research works presented in this thesis emphasize primarily on performance evaluation of advanced variants of differential evolution algorithm for single-objective optimization and multi-objective evolutionary algorithms (MOEAs) for multi-objective optimization problems in power system. Classical problems such as OPF and ORPD with conventional thermal generators are studied in detail using the advanced adaptive differential evolution algorithm, and the results are analyzed and compared with previous studies available in the literature. Acknowledging the evolution of smart grid, some new formulations and approaches are also proposed for solving OPF, ORPD and EED problems incorporating stochastic renewable sources such as wind, solar and small hydro power. Furthermore, security and operational constraints are very common in electric network. As the search method of evolutionary algorithms (EAs) is unconstrained, an extensively used methodology to deal with the infeasible solutions found during the search process is the static penalty function approach. The process requires an appropriate selection of penalty coefficients decided largely by a tedious trial and error method. Advanced constraint handling techniques of evolutionary algorithms remain largely untested in power system optimization problems. Proper constraint handling techniques like superiority of feasible solutions (SF), epsilon constraint handling (EC), stochastic ranking (SR), self-adaptive penalty (SP), etc. when integrated with variants of DE and MOEA, these methods can improve the results satisfying system constraints appropriately. In summary, plenty of avenues remain to explore in power system optimization and we attempt some of those problems through our research works presented in this thesis.

1.2. Major contributions of the thesis

The major contributions of the thesis can be summarized as below:

- In Chapter 2, we propose integration of constraint handling techniques SF, EC and SR with single-objective optimization algorithm SHADE. Further, the approach to integrate SF with MOEA/D is also suggested for multi-objective constrained optimization problems.
- In Chapter 3 (section 3.1), a comparative assessment of the performance of SHADE-SF, SHADE-EC and SHADE-SR algorithms is carried out on the problem of OPF with several objectives. The results are summarized, statistically analyzed and compared with similar EA-based past studies available in the literature.

- In Chapter 3 (section 3.2), multi-objective OPF solutions are presented with the application of MOEA/D-SF. The possibility of constraint violation is highlighted when MOEA/D is applied in conjunction with static penalty method.
- In Chapter 3 (section 3.3), a new formulation and solution approach to OPF study are proposed incorporating stochastic wind and solar power. The uncertain and intermittent nature of the renewable sources are modeled using suitable probability density functions (PDFs). The study considers penalty cost for underestimation and reserve cost for overestimation of the scheduled power from the uncertain renewable sources. The variation of these costs is assessed with the change in PDF parameters and scheduled power. Carbon tax is also incorporated to account for the emission.
- In Chapter 4, classical ORPD problem with conventional thermal generators is solved using SHADE-EC algorithm and the results are compared with similar past studies. In addition, the chapter proposes a new formulation of ORPD problem considering uncertainties in load demand, wind and solar power. Scenario-based approach is adopted to perform the stochastic ORPD study. Appropriate scenario generation and scenario reduction methods are implemented.
- In Chapter 5, a novel design of EED problem with thermal, wind, solar and small-hydro power is suggested. The cost model considers all uncertainties arising out of the stochastic sources. Prohibited operating zones of thermal units and network security constraints are also considered in the study. The EED problem is solved applying two MOEAs – MOEA/D and SMODE, in conjunction with the SF constraint handling technique.
- In Chapter 6, loss minimization of radial distribution network is performed. Simultaneous network reconfiguration, DG and SC allocation are considered to minimize network real power loss. Though previously some papers presented studies on simultaneous reconfiguration and DG allocation, the results in our research using L-SHADE are found to be the best. Moreover, case studies with added SCs (together with network reconfiguration and DG allocation) are performed in our research work presented in the chapter.
- In Chapter 7, the prowess of L-SHADE algorithm in optimizing a high dimensional problem with only discrete (integer) variables is expressed through the problem on optimal placement of wind turbines in a windfarm. The single-objective case is a comparative study of the current results and the results of past studies available in the literature. A multi-objective approach to windfarm layout optimization is uncommon.

The effective utilization of a multi-objective evolutionary algorithm in optimizing placement of wind turbines in a windfarm is also presented in the chapter.

1.3. Outline of the thesis

The outline of the thesis is aptly summarized with the chart in [Fig. 1.1](#). Chapter 2 includes a thorough literature review on the algorithms applied in the research work and the relevant optimization problems in power system. Chapter 3 describes single-objective and multi-objective formulations and solutions to OPF problem considering conventional generators, followed by OPF study with stochastic renewable sources. Classical ORPD study and an approach to obtain ORPD solutions of a network consisting of thermal generators, a wind generator and a photovoltaic are provided in Chapter 4. The solution approach to a new formulation of multi-objective EED problem incorporating wind, solar and small-hydro power is presented in Chapter 5. The optimization problem on distribution network loss minimization is described in Chapter 6. Chapter 7 contains the problem on optimal siting of wind turbines in a windfarm. Finally, the conclusion and potential future works are discussed in Chapter 8.

Fig. 1.1. Outline of the thesis

Chapter 2

2. Evolutionary algorithms and power system optimization problems

2.1. Evolutionary algorithms (EAs)

The ‘optimization’ is a process of finding the best feasible solution that corresponds to the minimum or maximum value of an objective function. The need for optimization arises from the purpose of designing solutions which are cost-effective, efficient and optimal. The importance of optimization is paramount especially in the fields of scientific research, engineering and finance. For examples, a manufacturer seeks the most efficient production process for a good yield, an investor aims to maximize return at minimum risk, a traffic planner wants to minimize congestion by finding best possible ways of diverting traffic. In reality, optimization is an intrinsic part of human life and activity. The optimization process may involve a single objective or multiple objectives. In a single-objective optimization, the task of optimization is to find the optimal solution that can minimize (or maximize) one objective function for a system or a process. In a multi-objective optimization where more than one objective is involved, the task of optimization is to find one or more optimal solutions. Evolutionary algorithms (EAs) have been very popular in last few decades for solving optimization problems almost in all fields of engineering, science and finance. These population-based metaheuristics are in general inspired by the biological evolution processes of reproduction, mutation, crossover and selection. Although several algorithms have been applied in power engineering and related fields in the last couple of decades, we focus on differential evolution (DE) algorithm and its advanced variants in this thesis. First section of this chapter describes the algorithms SHADE and L-SHADE for single-objective optimization problems. Subsequently, MOEA/D and SMODE algorithms for multi-objective optimization are discussed. Constraint handling techniques SF, EC and SR cover the third section. Proposed integration of the CH techniques with single and multi-objective EAs concludes the algorithmic section. The literature review on various power system optimization problems is included in section 2.2.

2.1.1 Evolutionary algorithms (EAs) for single-objective optimization

During the last decade, differential evolution (DE) [1] evolved as an efficient and powerful population-based stochastic search technique for solving optimization problems over

continuous search space [2]. Classical DE requires 3-control parameters to be defined by the user: scale factor (F), crossover rate (CR) and population size (Np). The performance of DE is found to be highly dependent on the settings of these control parameters and the chosen mutation/crossover strategies [3]. Therefore, instead of fixed control parameters, online adaptation of these parameters has been tried in many research works. In SHADE [4], the control parameters F and CR are adapted during evolution based on success history of these parameters in previous generations. L-SHADE [5] algorithm incorporates the linear population size reduction technique into SHADE. The population size is linearly reduced in successive generations. More details on recent advancement in DE can be referred in [6]. A brief description of SHADE and L-SHADE algorithms is presented herein. The source codes of both the algorithms can be found in <https://ryojitnabe.github.io/publication>.

2.1.1.1 SHADE algorithm

a) Initialization

The process of DE starts with an initial population (Np vectors each of d dimensions) of randomly generated candidate solutions within the search space specified by lower and upper bounds. In the population, j -th component of the i -th decision vector is initialized as:

$$x_{i,j}^{(1)} = x_{min,j} + rand_{i,j}[0,1] \cdot (x_{max,j} - x_{min,j}) \quad (2.1)$$

where $rand_{i,j}[0,1]$ is a random number between 0 and 1 and superscript ‘1’ signifies initialization. If ‘ Np ’ is the population size and ‘ d ’ is the dimension of decision vector, $i = 1, 2, \dots, Np$ and $j = 1, 2, \dots, d$.

b) Mutation (perturbation)

After initialization, mutation (perturbation) operation of DE creates a mutant/donor vector $v_i^{(g)}$ corresponding to each population member or target vector $x_i^{(g)}$ in the current g -th generation. Classical DE mostly uses DE/rand/1 mutation strategy. SHADE algorithm employs the mutation strategy ‘current-to-pbest/1’ which is expressed as:

$$v_i^{(g)} = x_i^{(g)} + F_i^{(g)} \cdot (x_{pbest}^{(g)} - x_i^{(g)}) + F_i^{(g)} \cdot (x_{R_1^i}^{(g)} - x_{R_2^i}^{(g)}) \quad (2.2)$$

The indices R_1^i & R_2^i are mutually exclusive integers randomly selected from the population range $[1, Np]$; $x_{pbest}^{(g)}$ is chosen from the top $Np \times p$ ($p \in [0,1]$, and the product is rounded up to the nearest integer value) individuals of current generation. The scaling factor $F_i^{(g)}$ corresponds to the i -th individual at g -th generation. The factor is a positive control

parameter for scaling the difference of two vectors. If an element $v_{i,j}^{(g)}$ of the mutant vector goes outside the boundary specified by $[x_{min,j}, x_{max,j}]$, it is corrected as:

$$v_{i,j}^{(g)} = \begin{cases} (x_{min,j} + x_{i,j}^{(g)})/2 & \text{if } v_{i,j}^{(g)} < x_{min,j} \\ (x_{max,j} + x_{i,j}^{(g)})/2 & \text{if } v_{i,j}^{(g)} > x_{max,j} \end{cases} \quad (2.3)$$

c) *Crossover*

In crossover operation, donor vector $v_i^{(g)}$ combines its elements with those of the target vector $x_i^{(g)}$ to form the trial/offspring vector $u_i^{(g)} = (u_{i,1}^{(g)}, u_{i,2}^{(g)}, \dots, u_{i,d}^{(g)})$. Binomial crossover is commonly adopted to operate on each element. The binomial crossover with crossover rate $CR_i^{(g)}$ is expressed as:

$$u_{i,j}^{(g)} = \begin{cases} v_{i,j}^{(g)} & \text{if } j = j_{rand} \text{ or } rand_{i,j}[0,1] \leq CR_i^{(g)}, \\ x_{i,j}^{(g)} & \text{otherwise} \end{cases} \quad (2.4)$$

where j_{rand} is any randomly chosen natural number in $\{1, 2, \dots, d\}$, d being the dimension of the problem.

d) *Parameter adaptation*

At a given generation g , each individual generates a new trial vector with its associated parameters $F_i^{(g)}$ and $CR_i^{(g)}$ which are adapted using –

$$F_i^{(g)} = randc(\mu F_r^{(g)}, 0.1) \quad (2.5)$$

$$CR_i^{(g)} = randn(\mu CR_r^{(g)}, 0.1) \quad (2.6)$$

where $randc(\mu F_r^{(g)}, 0.1)$ is the value sampled from Cauchy distribution with location parameter $\mu F_r^{(g)}$ and scale parameter 0.1; $randn(\mu CR_r^{(g)}, 0.1)$ generates a value following the Normal distribution with mean $\mu CR_r^{(g)}$ and variance 0.1. $\mu F_{r_i}^{(g)}$ is randomly chosen from a set of successful scale factors from the previous generations stored in a memory M of size H ; $\mu CR_{r_i}^{(g)}$ is the one of the means of successful crossover rates from previous generations stored in the memory M [5]. During initialization, all μF and μCR are set to 0.5 (i.e. $\mu F_r^{(1)} = \mu CR_r^{(1)} = 0.5$). At the end of every generation, the memory is updated at certain positions

defined by indices k . At these indices, μF and μCR are modified using weighted Lehmer mean [4]-[5].

e) Selection

The selection operator performs fitness checks to determine whether the target (parent) or the trial (offspring) vector survives to the next generation ($g + 1$). The operation can be mathematically represented as:

$$x_i^{(g+1)} = \begin{cases} u_i^{(g)} & \text{if } f(u_i^{(g)}) \leq f(x_i^{(g)}) \\ x_i^{(g)} & \text{otherwise} \end{cases} \quad (2.7)$$

where $f(\dots)$ is the objective function to be minimized.

2.1.1.2 L-SHADE algorithm

The success of SHADE is attributed to the online adaptation technique of scaling factor F and crossover rate CR . L-SHADE arguably improves the performance of SHADE by introducing dynamic reduction of population size Np following a linear function. At the end of generation g , the population size for the next generation ($g + 1$) is calculated by –

$$Np(g + 1) = \text{round} \left[\left(\frac{Np_{min} - Np_{ini}}{maxeval} \right) \cdot nfeval + Np_{ini} \right] \quad (2.8)$$

Np_{min} is set to 4 because of the mutation strategy adopted in L-SHADE requires minimum 4 individuals. $nfeval$ is the current number of fitness (function) evaluations and ‘ $maxeval$ ’ is the maximum number of fitness (function) evaluations. If $Np(g + 1) < Np(g)$, the $[Np(g) - Np(g + 1)]$ worst ranked individuals are deleted from the population [5].

2.1.2 Multi-objective evolutionary algorithms (MOEAs)

As mentioned before, the task of optimization in a multi-objective optimization problem is to find one or more optimal solutions. The objectives in multi-objective optimization are often conflicting which means one objective cannot be bettered without worsening one or more other objectives. In such a scenario, the extreme solution i.e. the best solution for one of the forming objectives, necessitates compromise on another objective(s). Thus, choice of a solution based solely on one objective is prohibitive. Let us consider the example of buying a flight ticket where the price of ticket and travel time are the decision-making criteria. The points A, B, C, D, E and F in Fig. 2.1 represent various options for flying between two cities - Singapore and New York. We assume that the difference in travel time is due to the waiting time for connecting flight at transit. ‘Option A’ is the most expensive with ticket price of

\$4000, but with least travel time of 16 hours. The cheapest ticket is of \$2000 with travel time of 32 hours if one takes flying ‘option E’. Here the decision-making process of flight booking is not a single objective of either price or travel time. The traveler has few options to choose from with some trade-off between travel time and price. If one selects ‘option B’ instead of ‘option A’, he will be saving on his ticket price by spending more time in transit. Again, if the traveler selects ‘option D’ instead of ‘option E’, he has to shell out more money for buying the ticket, but he can save few hours. So, if we move along options (points) A, B, C, D and E, we cannot better one objective without worsening the other. However, the situation is not the same for ‘option F’. As a flyer, if one chooses ‘option F’, he is definitely losing. He can go for ‘option B’ at the same price with lesser travel time, or he can opt for ‘option D’ of same travel duration at a lesser price. Therefore, ‘option F’ can be improved on both the objectives. The points A, B, C, D and E are called Pareto optimal points, named after the famous Italian economist Vilfredo Pareto. Pareto solutions are also termed as non-dominated solutions where betterment of one objective leads to deterioration of at least one other objective. On contrary, the solution F is a dominated solution.

Fig. 2.1. Illustration of decision-making process in buying a flight ticket

The example of flight options is for a two-objective optimization. In multi-objective optimization, there can be more than two objectives. Mathematically, a multi-objective problem is represented as:

$$\text{Minimize: } F(x) = [f_1(x), f_2(x), \dots, f_M(x)] \quad (2.9)$$

$$\text{subject to: } x \in \Omega$$

where Ω is the decision vector (variable) space, M is the number of objectives.

2.1.2.1 Decomposition based multi-objective evolutionary algorithm (MOEA/D)

Zhang and Li [7] proposed the decomposition based multi-objective evolutionary algorithm (MOEA/D) in 2007. The algorithm applies an aggregation approach after decomposing the multi-objective optimization problem (MOP) into several scalar optimization subproblems. The objective of each subproblem is the weighted sum of constituting objectives of the MOP. For an MOP defined in Eq. (2.9), if Np is the selected population size, there will be Np vectors $x^1, x^2, \dots, x^{Np}$ for the optimization problem, each with d -dimension where d is the number of decision variables. The Pareto optimality is conspicuously described for a two-objective problem with the example of buying a flight ticket. The general definition of Pareto optimality of an M -objective problem is as follows:

a) Pareto optimality

Suppose R^M is the objective space for M -objectives. For $x \in \Omega$, $F(x) \in R^M$, Ω being the decision vector (variable) space. We consider two M -objective vectors, $u', v' \in R^M$. u' is said to dominate v' if and only if $u'_i \leq v'_i$ for every $i \in \{1, 2, \dots, M\}$ and $u'_j < v'_j$ for at least one index $j \in \{1, 2, \dots, M\}$. A point $x^* \in \Omega$ is a Pareto optimal if there is no point $x \in \Omega$ such that $F(x)$ dominates $F(x^*)$ [8]. $F(x^*)$ is termed as the Pareto optimal (objective) vector. In other words, any improvement in a Pareto optimal point in one objective must lead to deterioration of at least one other objective. The set of all Pareto optimal points is called the Pareto set (PS) and the set of all Pareto optimal objective vectors is the Pareto front (PF) [8]. The aim of the multi-objective optimization is to find a set of Pareto optimal solutions (points) that result in Pareto front (PF) in the objective space.

b) Decomposition approach

Decomposition process in MOEA/D begins with the initialization of Np uniformly spread weight vectors, where Np is also the population size. The neighborhood of each weight vector is defined by calculating Euclidean distance between each pair of weight vectors. Np solutions are also initialized, and the MOP is decomposed into Np scalar optimization subproblems. Now, each subproblem is associated with a weight vector and a solution. Two subproblems are neighbors if their weight vectors are neighbors. Fig. 2.2 shows the distribution of Np weight vectors $\lambda^1, \lambda^2, \dots, \lambda^{Np}$ for a bi-objective optimization problem. In Fig. 2.3, the two components $(\lambda_1^m, \lambda_2^m)$ of weight vector λ^m are diagrammatically presented. The objective function of m -th subproblem for the two-objective optimization problem is:

$$g^{te}(x|\lambda^m, z^*) = \max \left\{ \lambda_1^m |f_1(x) - z_1^*|, \lambda_2^m |f_2(x) - z_2^*| \right\} \quad (2.10)$$

where $z^* = (z_1^*, z_2^*)^T$ is the minimum objective value vector that is treated as reference point and the elements of this vector are calculated as $z_1^* = \min\{f_1(x)|x \in \Omega\}$ and $z_2^* = \min\{f_2(x)|x \in \Omega\}$.

Fig. 2.2. Weight vectors for a bi-objective optimization problem

Fig. 2.3. Graphical illustration for a subproblem of a bi-objective function in MOEA/D

The general representation of the objective function of m -th subproblem of an M -objective optimization problem is:

$$g^{te}(x|\lambda^m, z^*) = \max_{1 \leq i \leq M} \{ \lambda_i^m |f_i(x) - z_i^*| \} \quad (2.11)$$

where $z^* = (z_1^*, z_2^*, \dots, z_M^*)^T$ is the minimum objective value vector, treated as the reference point. z^* is all likely to be unknown beforehand and the algorithm uses the lowest values of $f_i(x)$ found so far during the search process to substitute z_i^* . Mathematically, $z_i^* = \min\{f_i(x) | x \in \Omega\}$, where $i = 1, 2, \dots, M$. MOEA/D simultaneously minimizes objective functions of all N subproblems in a single run. The optimization process of a subproblem utilizes the information mainly from the neighboring subproblems. All subproblems are treated equally and given same computational effort in MOEA/D. However, in the variant MOEA/D-DRA (MOEA/D with dynamic resource allocation), varying computational efforts are given on different subproblems based on calculated utilities of the subproblems [8]. In rest of the thesis, though MOEA/D-DRA is not explicitly stated, utilities of subproblems are calculated during the optimization process to effect DRA methodology in MOEA/D and in principle, MOEA/D-DRA algorithm is applied for the power system optimization problems.

In MOEA/D, disparate objectives are required to be normalized, else solutions are all likely to evolve towards the objective(s) with higher magnitude(s). The purpose of normalization is to bring all objective values within 0 to 1 range. The objective function for m -th subproblem in Eq. (2.11) is to be modified as [7]:

$$g^{te}(x | \lambda^m, z^*) = \max_{1 \leq i \leq M} \left\{ \lambda_i^m \left| \frac{f_i(x) - z_i^*}{z_i^{nad} - z_i^*} \right| \right\} \quad (2.12)$$

where z_i^{nad} is the nadir point in the objective space i.e. $z_i^{nad} = \max\{f_i(x) | x \in PS\}$; vector $z^{nad} = (z_1^{nad}, z_2^{nad}, \dots, z_M^{nad})^T$. z^{nad} is evaluated by the algorithm during the search process using all maximum values of $f_i(x)$.

During the search process, MOEA/D with Tchebycheff approach [8]-[9] maintains:

- A population of Np vectors $x^1, x^2, \dots, x^{Np}$.
- Function values of $FV^1, FV^2, \dots, FV^{Np}$ where, $FV^m = \{f_1(x^m), f_2(x^m), \dots, f_M(x^m)\}$ for $m = 1, 2, \dots, Np$ i.e. FV^m is the F -value of x^m .
- $z^* = (z_1^*, z_2^*, \dots, z_M^*)^T$, where z_i^* is the minimum value found till now evaluating $f_i(x)$ for $i = 1, 2, \dots, M$.
- $z^{nad} = (z_1^{nad}, z_2^{nad}, \dots, z_M^{nad})^T$, where z_i^{nad} is the maximum value found thus far evaluating $f_i(x)$ for $i = 1, 2, \dots, M$.
- Utility values of the subproblems, π^m for $m = 1, 2, \dots, Np$.
- Current generation number ' g '.

c) Steps in MOEA/D algorithm

Input: (i) MOP (ii) Number of subproblems, Np (iii) A uniform spread of Np weight vectors, $\lambda^1, \lambda^2, \dots, \lambda^{Np}$ (iv) T : the number of the weight vectors in the neighborhood of each weight vector (v) a termination criterion, *maxeval*.

Output: $\{x^1, x^2, \dots, x^{Np}\}$ and $\{f_1(x^m), f_2(x^m), \dots, f_M(x^m)\}$ for $m = 1, 2, \dots, Np$.

Step 1 - Initialization: Initialize decision vectors with randomly generated solutions in the search space. Initialize Np uniformly spread weight vectors, z^* and z^{nad} . Compute Euclidean distance between each pair of weight vectors to define T -neighbors of each weight vector. Set generation counter, $g = 1$ and utility function value $\pi^m = 1$ for all subproblems.

Step 2 – Selection of subproblems and update of solutions: Each subproblem is associated with a weight vector and a solution. The neighborhood is always defined by the positions of the weight vectors. The N_S neighborhood of a weight vector is the set of N_S closest weight vectors to it and if two weight vectors are neighbors, the respective subproblems are also neighbors. In each generation, subproblems are selected based on their utility values using 10-tournament selection method [8]. Usually, 20% of the total number of subproblems are identified in the process (in each generation). The current solutions corresponding to the selected indices of subproblems are picked up in the current generation for further operation. For each selected solution x^m , MOEA/D does the following [10]:

- i. Set the mating and update range P to be the T -neighborhood of x^m with a large probability δ_p , and the whole population otherwise.
- ii. Randomly select three current solutions from P .
- iii. Generate a new solution y^m by performing mutation and crossover on the selected solutions with pre-defined mutation factor F and crossover rate CR . Repair y^m if it goes outside the range. Compute objective $F(y^m)$.
- iv. If y^m yields better fitness value than current FV of related subproblem, replace a small number (n_r) of solutions in P by y^m .

No solution will be replaced in (iv) above if y^m produces inferior fitness value than what any solution in P does for its subproblem. When such a case happens, the update is deemed to be a failure, else, it is successful.

Step 3 – Stop if the termination criterion i.e. *maxeval* (maximum number of function evaluations) is reached.

Step 4 – $g = g + 1$. At every 50-th generation (i.e. when g is a multiple of 50), the utility function is updated. Go to **Step 2**.

To update the utility in **Step 4** above, compute Λ^m which is the relative decrease of m -th subproblem in last 50 generations. It is defined as [8]:

$$\Lambda^m = \frac{\text{old function value} - \text{new function value}}{\text{old function value}} \quad (2.13)$$

After every 50-generations, utility of m -th subproblem is updated as:

$$\pi^m = \begin{cases} 1 & \text{if } \Lambda^m > 0.001 \\ \left(0.95 + 0.05 \frac{\Lambda^m}{0.001}\right) \pi^m & \text{otherwise} \end{cases} \quad (2.14)$$

2.1.2.2 Summation based multi-objective differential evolution (SMODE)

In summation based multi-objective differential evolution (SMODE) [11]-[12], summation of normalized objective values is used to rank the solutions. The normalization operation given in Eq. (2.15) brings all objective values within the range [0,1]:

$$f_i''(x^m) = \frac{f_i(x^m) - f_{i,min}}{f_{i,max} - f_{i,min}} \quad (2.15)$$

where $f_i''(x^m)$ is the normalized value of solution x^m for i -th objective, $f_{i,min}$ and $f_{i,max}$ are the minimum and maximum values of the i -th objective function.

The normalized values of all objective functions for a solution are summed up, say $F''(x^m) = \sum_{i=1}^M f_i''(x^m)$ where M is the number of objective functions. For Np solutions in the problem, F'' is calculated i.e. $F''(x^m)$ for $m \in \{1, 2, \dots, Np\}$. The solutions are sorted based on the resultant F'' values. The solution that produces a smaller summation of normalized objective values is considered superior to the solution that yields a larger summated value. To illustrate, p -th solution in the population is better than q -th solution if $F''(x^p) < F''(x^q)$. Diversified selection is implemented in SMODE after sorting of solutions. During the evolution process, the diversity in SMODE is ensured by maintaining two sets of populations, a preferential set and a backup set. As the name suggests, members of the preferential set get priority to evolve. If there are insufficient number (less than the population size) of individuals in the preferential set, members from the backup set are selected. When number of individuals in the preferential set is larger than the population size, the required number of individuals are randomly selected to become parents for the

next generation [11]. As a first step in SMODE, the objective space is divided equally into 100 bins. In [11], 80% of the bins are scanned and for each scanned bin, the solution with the lowest sum of normalized objective values is selected to enter the preferential set. The solutions that are not selected enter the backup set. Fig. 2.4 shows 10-individuals (point 1 to 10 in solid circles) in the current population for a two-objective optimization problem. If we select 80% area for scanning, bin no. 1 to 8 for both the objectives will be scanned. Empty bins are not considered for scanning. Solution 1 (point 1) yields lowest sum of objective values in bin 2. So, point 1 is included in the preferential set. Points 4, 3, 5 and 8 are selected into preferential set for bins 3, 4, 5 and 7, respectively. Based on objective 2, points 1, 4, 3, 5, 8, 2 and 9 enter the preferential set. So, finally the members in preferential set are points 1, 2, 3, 4, 5, 8 and 9. Points 6, 7 and 10 (marked in green solid circles) are put into the back-up set. Any point in the yellow shaded area is not included in the preferential set as the selected value of scan percentage is 80. The percentage of bins to be scanned in each generation is user-defined in [11]. While solving multi-objective economic-environmental power dispatch (MOEED) problem, Ref. [98] introduces the concept of stopping point and the scanning process continues until the stopping point is included in the scan. This method does not require input for scan percentage of the gridded area.

Fig. 2.4. SMODE – selection of points in preferential and backup sets

2.1.3 Constraint handling (CH) techniques

As evolutionary algorithms (EAs) are stochastic in nature, infeasible solutions should not be straightaway discarded. A proper constraint handling method when used in conjunction with a compatible evolutionary algorithm, it can drive the search process towards global feasible optima by making use of the information present in the infeasible solutions. Among many constraint handling methods, the most commonly employed method is static penalty where a penalty is added to the fitness of an infeasible solution for violating the constraints. Despite of its simplicity and ease of implementation, the performance of static penalty method heavily depends on the penalty factor which needs to be fine-tuned by trial and error. To avoid the need of fine-tuning of penalty factor, few constraint handling methods that can be employed with EAs are summarized below.

A constrained optimization problem, where d parameters are to be optimized, is usually written in the following form [13]:

$$\begin{aligned} &\text{Minimize: } f(x), x = (x_1, x_2, \dots, x_d) \text{ and } x \in \Omega \\ &\text{subject to: } \begin{cases} h_i(x) \leq 0, & i = 1, \dots, p \\ z_j(x) = 0, & j = p + 1, \dots, N_c \end{cases} \end{aligned} \quad (2.16)$$

where Ω is the entire search space, p is the number of inequality constraints and $(N_c - p)$ is the number of equality constraints. $f(x)$ is the objective function, $h(x)$ is the set of inequality constraints, $z(x)$ is the set of equality constraints. The equality constraints are transformed into inequality constraints and thus total constraint after normalization (subscript 'nor' denotes normalization) of all constraints is represented as:

$$H_i(x) = \begin{cases} \max[h_{i,nor}(x), 0], & i = 1, \dots, p \\ \max[|z_{i,nor}(x)| - \delta_{tol}, 0], & i = p + 1, \dots, N_c \end{cases} \quad (2.17)$$

where δ_{tol} is a tolerance parameter for the equality constraints. The fitness function $f(x)$ is to be minimized so that the optimal solution obtained in the process satisfies the inequality constraint $H_i(x)$. The overall constraint violation for an infeasible solution is the weighted mean of all constraints and it is defined as:

$$vio(x) = \frac{\sum_{i=1}^{N_c} w_i(H_i(x))}{\sum_{i=1}^{N_c} w_i} \quad (2.18)$$

where $w_i (= 1/H_{i,max})$ is a weight parameter, $H_{i,max}$ is the maximum value for violation of constraint $H_i(x)$. In the algorithm, w_i is set as $1/H_{i,max}$, which varies during the evolution to balance the contribution of each constraint in the problem regardless of the different

numerical ranges of all constraints. A brief overview of the three constraint handling techniques used in various constrained power system problems is presented herein.

2.1.3.1 Superiority of feasible solutions (SF)

In SF [14], the comparison is done between a pair of solutions. Solution x_i is considered superior to solution x_j when:

- x_i is feasible but x_j is infeasible.
- Both x_i and x_j are feasible, but x_i yields a smaller objective value (in a minimization problem) than what x_j does.
- Both x_i and x_j are infeasible, but x_i results in a smaller overall constraint violation i.e. $vio(x_i) < vio(x_j)$ as per Eq. (2.18).

Therefore, feasible individuals are always considered better than the infeasible individuals in this technique. Two feasible solutions are compared based on their objective function values only while two infeasible solutions are compared based on their overall constraint violations only. Comparison of infeasible solutions based on the overall constraint violation aims to push the infeasible solutions towards feasible region. Comparison of two feasible solutions on the objective value facilitates to improve the overall quality of the solution.

2.1.3.2 Epsilon (ε) constraint (EC) handling technique

In ε -constraint (EC) handling method [15], the relaxation of overall constraint violation is controlled by the ε -parameter. EC is more effective when the optimization problem contains active constraints. The search process to find feasible solutions can be efficiently handled by controlling the ε -parameter [15]. The ε -parameter is updated till the generation counter (g) reaches a certain defined control generation G_c . When the counter g exceeds G_c , ε -level is set to zero to obtain solutions with no constraint violation. The ε -parameter is updated according to the following equations.

$$\varepsilon(1) = vio(x_\theta) \quad (2.19)$$

$$\varepsilon(g) = \begin{cases} \varepsilon(1) * \left(1 - \frac{g}{G_c}\right)^{cp}, & 0 < g < G_c \\ 0, & g \geq G_c \end{cases} \quad (2.20)$$

where x_θ is the top θ -th individual and $\theta = 0.05 * \text{population size } (Np)$, g is the generation counter. G_c is the number of generations up to which the ε -parameter is controlled and later it is set to zero. The recommended parameter ranges are [15]: $cp \in [2, 10]$ and $G_c \in [0.1 * \text{maxgen}, 0.8 * \text{maxgen}]$, where maxgen is the maximum number of generations. In

EC, selection of an individual is done by comparing the solution with another solution following the same set of rules as in SF. The only difference is that in EC, a solution is regarded as feasible if its overall constraint violation is lower than $\varepsilon(g)$ (instead of zero violation). During initial phase, $\varepsilon(g)$ assumes a small value and later the value is set to zero.

2.1.3.3 Stochastic ranking (SR) method for constraint handling

In evolutionary constrained optimization, it is sometimes necessary to maintain a balance between objective minimization (assuming minimization problem) and overall constraint satisfaction for convergence to a global feasible optimal solution. In [16], a stochastic way, referred to as stochastic ranking (SR), is proposed to achieve the balance between objective optimization and overall constraint violation. SR method employs a probability factor (p_f) to determine whether the objective function value or the overall constraint violation is to be used to rank a solution. The process can be summarized as:

```

If (no constraint violation or  $rand < p_f$ )
    Rank based on the objective values only
Else
    Rank based on the constraint violations only
End
  
```

Therefore, in SR, the comparison between two individuals is based either on their objective values or on their overall constraint violations, as determined randomly. This facilitates the survival of the infeasible solutions with superior objective values during the evolution process so that the search might proceed to a feasible region that contains global feasible optima. SR constraint handling method demonstrates arguably superior performance on constrained optimization problems with disconnected feasible regions. Further, it has been established that the performance of SR improves if the probability factor (p_f) is linearly reduced from 0.475 to 0.025 over all generations instead of a constant value [16]. If $p_{f,1} = 0.475$ for the first generation ($g = 1$) and $p_{f,maxgen} = 0.025$ is for the last generation ($g = maxgen$), the probability for any other generation ($g > 1$) is calculated as:

$$p_{f,g} = p_{f,g-1} - (p_{f,1} - p_{f,maxgen}) / (maxgen - 1) \quad (2.21)$$

2.1.4 Integration of CH techniques with evolutionary algorithms (EAs)

This section describes the integration of single-objective optimization algorithm SHADE individually with each of the constraint handling techniques. Later, the integration technique of SF separately with multi-objective optimization algorithms MOEA/D and SMODE is presented. It is worthwhile to mention that for single-objective constrained optimization, L-SHADE algorithm is not integrated with CH techniques because the algorithm reduces population size in each generation. Reduction of population size in each generation lowers the probability of finding the feasible region and the algorithm may fail to find feasible solutions, or it may arrive at sub-optimal solutions. Hence, SHADE is used as the basic search algorithm when constraint handling using a CH method is necessary.

2.1.4.1 Integration of CH techniques with SHADE algorithm

The selection process of SHADE (and DE) is unconstrained. When SHADE algorithm is integrated with a CH technique, the selection of individuals for the next generation follows the rules of the constraint handling technique. The description of the combined SHADE-XX (XX: SF/EC/SR) algorithm is presented in Table 2.1 and in Fig. 2.5 with a flowchart. While the table describes the process in detail, the flowchart gives an overview of the steps involved. It may be noted that STEP 3 (selection step) of the algorithm loop in Table 2.1 is different for different CH methods (in addition to CH method specific parameters).

Table 2.1. The integration of CH techniques with SHADE algorithm

SHADE-XX (XX: SF/EC/SR)	
INPUT	<ul style="list-style-type: none"> • Dimension of the problem, d. • Population size, Np. • Stopping criteria, maximum number of function evaluations, $maxeval$. • Maximum and minimum values of d-decision variables, in vector forms x_{max} and x_{min}. Where, $x_{max} = [x_{max,1}, \dots, x_{max,d}]$ and $x_{min} = [x_{min,1}, \dots, x_{min,d}]$.
INITIALIZATION	<ul style="list-style-type: none"> • Set generation counter, $g = 1$ and function evaluation counter $nfeval = 0$. • Set SHADE parameters: Memory (M) size $H = 5$, initialize $\mu F = 0.5$ and $\mu CR = 0.5$. • POP: Create population of Np individuals uniformly distributed within range $[x_{min}, x_{max}]$. • Set initial parameters for the CH method. E.g. set $\varepsilon(1)$ [Eq. (2.19)] for EC, and $p_{f,1} = 0.475$, $p_{f,maxgen} = 0.025$ for SR. No specific parameter for SF method.
EVALUATION	<ul style="list-style-type: none"> • Evaluate objective function, constraint function and constraint violation [Eqs. (2.16) - (2.18)] for each individual $x_i \forall i \in \{1, \dots, Np\}$ of POP. • Increase function evaluation counter $nfeval$ by Np.

SHADE-XX (XX: SF/EC/SR)

ALGORITHM LOOP:

- STEP 1
- Update the parameters for the CH method, i.e. ε -parameter for EC and p_f for SR.
 - Perform mutation and crossover for each individual of POP.
 - Generate mutant vector $v_i^{(g)}$ using Eq. (2.2). Repair if necessary using Eq. (2.3).
 - Generate trial vector element $u_{i,j}^{(g)}$ performing crossover according to Eq. (2.4).
 - Formulate trial vector $u_i^{(g)}$ with all elements, this is OFS vector x'_i .
- STEP 2
- Compute objective function, constraint function and constraint violation [Eqs. (2.16) - (2.18)] for each individual $x'_i \forall i \in \{1, \dots, Np\}$ of OFS.
 - Increase function evaluation counter $nfeval$ by Np .
- STEP 3
- In selection, an OFS member becomes the POP member for next generation if the OFS member is better than the corresponding POP member according to rules of the CH method.
- SHADE-SF: An OFS is considered better if it yields lesser constraint violation or zero constraint violation alongwith smaller fitness value (minimization problem) than what the respective old POP member does.
- SHADE-EC: An OFS is considered better if it yields lesser constraint violation than the respective old POP member. An OFS is also treated as better if it produces zero or less than calculated epsilon (ε) constraint violation (calculated by Eq. (2.20)) in a generation alongwith smaller fitness value (minimization problem) than what the respective old POP member does.
- SHADE-SR: An OFS is considered better if it produces zero constraint violation in a generation alongwith smaller fitness value (minimization problem) than what the old POP member does. An OFS member with smaller fitness value but higher constraint violation may also be selected for the next generation if the randomly generated number ($rand$) is less than the SR probability factor p_f in current generation. When $rand > p_f$, the OFS member with lesser constraint violation replaces the POP member.
- In all other cases, OFS is worse. In such cases, old POP member is retained.
 - If OFS is better, memories of μF and μCR are updated as per parameter adaptation technique described in section 2.1.1.1 (d).
- STEP 4
- Is stopping criterion i.e. $nfeval > maxeval$ reached?
 - If yes, STOP.
 - If not, increase generation counter by 1, i.e. $g = g + 1$. Go to algorithm loop STEP 1.

Fig. 2.5. Flowchart for implementation of SHADE-XX (XX: SF/EC/SR)

2.1.4.2 Integration of CH technique SF with MOEA/D

As mentioned in section 2.1.2.1 (b), MOEA/D with Tchebycheff approach [8]-[9] maintains the following during search process:

- A population of Np vectors $x^1, x^2, \dots, x^{Np}$
- Function values of $FV^1, FV^2, \dots, FV^{Np}$ where, $FV^m = \{f_1(x^m), f_2(x^m), \dots, f_M(x^m)\}$ for $m = 1, 2, \dots, Np$ i.e. FV^m is the F -value of x^m .
- $z^* = (z_1^*, z_2^*, \dots, z_M^*)^T$, where z_i^* is the minimum value found till now evaluating $f_i(x)$ for $i = 1, 2, \dots, M$.
- $z^{nad} = (z_1^{nad}, z_2^{nad}, \dots, z_M^{nad})^T$, where z_i^{nad} is the maximum value found thus far evaluating $f_i(x)$ for $i = 1, 2, \dots, M$.

- Utility values of the subproblems, π^m for $m = 1, 2, \dots, Np$.
- Current generation number ' g '.

MOEA/D when integrated with constraint handling technique SF, in addition to above, the algorithm shall maintain:

- A population of Np vectors containing the calculated constraint violation corresponding to each of $x^1, x^2, \dots, x^{Np}$. If N_C is the total number of constraints in the optimization problem, each constraint violation vector is formulated as $CV^m = (CV_1^m, CV_2^m, \dots, CV_{N_C}^m)$ for $m = 1, 2, \dots, Np$. The elements of the vector CV^m are same as H_i for $i = 1, 2, \dots, N_C$ in Eq. (2.17).
- A population of Np vectors containing the maximum calculated constraint violation for each constraint found thus far corresponding to each index $m = 1, 2, \dots, Np$. Mathematically, this can be expressed as, $CV_{max}^m = (CV_{1,max}^m, CV_{2,max}^m, \dots, CV_{N_C,max}^m)$. The elements of the vector CV_{max}^m are same as $H_{i,max}$ (where $i = 1, 2, \dots, N_C$) used to calculate w_i in Eq. (2.18).
- Np values of total constraint violation, calculated with above data using Eq. (2.18), corresponding to each vector $x^1, x^2, \dots, x^{Np}$. We get, $vio(x^m)$ for $m = 1, 2, \dots, Np$ and construct constraint violation vector $ER = [vio(x^1), vio(x^2), \dots, vio(x^{Np})]^T$.
- Vectors z^* and z^{nad} are replaced and updated during the search process based on the solutions obtained. Between feasible and infeasible solutions, objective values of the feasible solution get preference to be suitably selected as z^* or z^{nad} . In a generation, a lower objective value can replace the respective element of z^* only if the constraint violation of the corresponding solution is less than or equal to the earlier solution. The same principle applies for update of z^{nad} . A higher objective value of a better solution in terms of a lesser or equal constraint violation can replace the corresponding element of z^{nad} .

The steps in MOEA/D-SF algorithm can be summarized as below:

Input: (i) MOP (ii) Number of subproblems, Np (iii) A uniform spread of Np weight vectors, $\lambda^1, \lambda^2, \dots, \lambda^N$ (iv) T : the number of the weight vectors in the neighborhood of each weight vector (v) a termination criterion, $maxeval$.

Output: $\{x^1, x^2, \dots, x^{Np}\}$ and $\{f_1(x^m), f_2(x^m), \dots, f_M(x^m), vio(x^m)\}$ for $m = 1, 2, \dots, Np$.

Step 1 - Initialization: Initialize decision vectors with randomly generated solutions in the search space. Calculate total constraint violation $vio(x^m)$ for each initialized decision vector and set all such values as initial violation values. Initialize Np uniformly spread weight vectors, z^* and z^{nad} . If no solution is feasible in initial population, both z^* and z^{nad} are initialized based on objective values of the initialized member that results in least constraint violation. Compute Euclidean distance between each pair of weight vectors to define T -neighbors of each weight vector. Set generation counter, $g = 1$ and utility function value $\pi^m = 1$ for all subproblems.

Step 2 – Selection of subproblems and update of solutions: Each subproblem is associated with a weight vector and a solution. The neighborhood is always defined by the positions of the weight vectors. The N_S neighborhood of a weight vector is the set of N_S closest weight vectors (by Euclidean distance) to it and if two weight vectors are neighbors, the respective subproblems are also neighbors. In each generation, subproblems are selected based on their utility values using 10-tournament selection method [8]. Usually, 20% of the total number of subproblems are identified in the process (in each generation). The current solutions corresponding to the selected indices of subproblems are picked up in the current generation for further operation. For each selected solution x^m , MOEA/D does the following [10]:

- i. Set the mating and update range P to be the T -neighborhood of x^m with a large probability δ_p , and the whole population otherwise.
- ii. Randomly select three current solutions from P .
- iii. Generate a new solution y^m by performing mutation and crossover on the selected solutions with pre-defined mutation factor F and crossover rate CR . Repair y^m if it goes outside the range. Compute objective $F(y^m)$ and total constraint violation $vio(y^m)$.
- iv. If y^m yields lesser constraint violation or zero constraint violation together with better fitness value than current FV of related subproblem, replace a small number (n_r) of solutions in P by y^m .

No solution will be replaced in (iv) above if y^m produces larger constraint violation than what x^m does or zero constraint violation with inferior fitness value to what any solution in P does for its subproblem. When such a case happens, the update is deemed to be a failure, else, it is successful.

Step 3 – Stop if the termination criterion i.e. *maxeval* (maximum number of function evaluations) is reached.

Step 4 – $g = g + 1$. If g is a multiplication of 50, update utilities of all subproblems. Go to **Step 2**.

Flowchart in Fig. 2.6 gives an overview of the steps involved in algorithm MOEA/D-SF.

Fig. 2.6. Flowchart for implementation of algorithm MOEA/D-SF

2.1.4.3 Integration of CH technique SF with SMODE

The integration approach of SF constraint handling technique with SMODE was proposed in [98] for the constrained multi-objective economic-environmental power dispatch (MOEED) problem. In the reference paper, constraint values were all summed up. However, we treat the constraints separately and normalize them before calculating total constraint violation using Eq. (2.18). The constraints are required to be normalized to avoid bias towards any of them [14]. The steps in SMODE-SF algorithm can be summarized as:

Step 1 - Initialization:

- Initialize population of Np individuals with uniform random distribution.
- Evaluate objective function values for each initialized individual.
- Calculate total constraint violation using Eq. (2.18) for each member of initial population after normalization of the constraints.
- Set generation counter, $g = 1$. Define the termination criterion i.e. maximum no. of generations, $maxgen$.

Step 2 - Reproduction:

- Perform DE operations (on top Np individuals) i.e. mutation and crossover with predefined scale factor (F) and crossover rate (CR) to generate Np new offsprings. DE/rand/1 mutation strategy and binomial crossover are adopted [11].
- Repair the offsprings if necessary.
- Evaluate objective functions of the newly generated offsprings.
- Calculate total constraint violation using Eq. (2.18) for each offspring.
- Combine original population members with the offsprings, i.e. total $2Np$ individuals.

Step 3 - Search of feasible solutions:

- Sort the combined population in ascending order based on the values of total constraint violation.
- Identify feasible solutions i.e. solutions with zero constraint violation.
- If number of feasible solutions is less than the population size (Np), **Go to Step 5**.
- If minimum Np feasible individuals are present in the combined population, **Go to Step 4**.

Step 4 - Normalization and selection:

- Compute normalized objective value for each objective and each solution using [Eq. \(2.15\)](#).
- Obtain summation (F'') of the normalized objective values for all solutions (Refer to section 2.1.2.2)
- Find Euclidean distances of all summated normalized objective values from the origin. The solution that produces total normalized objective value closest to the origin is set as the stopping point.
- Divide the objective space equally into 100 bins. Scan these bins until stopping point is included in the scanning process. In each scanned bin, the solution with the lowest sum of normalized objective values is chosen to enter the preferential set.
- Unselected solutions and solutions dominated by stopping point are included in the backup set.

Step 5 - Termination:

- Increase generation counter by 1 i.e. $g = g + 1$.
- If stopping criteria $maxgen$ is reached, Stop. Else **Go to Step 2**.

Flowchart for implementation of the algorithm SMODE-SF is provided in [Fig. 2.7](#).

Fig. 2.7. Flowchart for implementation of algorithm SMODE-SF

2.2. Power system optimization problems

This research work is titled as “Evolutionary algorithms for solving power system optimization problems”. Over the last few decades, researchers have attempted many power system optimization problems of different nature and complexity using metaheuristic optimization techniques. This section presents a survey on selected power system optimization problems available in the literature and attempted in our research work.

2.2.1 Optimal power flow (OPF)

Since its inception more than half a century ago, the optimal power flow (OPF) remains a widely cultivated topic among power system research communities across the globe due to the intriguing multi-faceted challenges it poses. The OPF is formulated as a single or a multi-objective problem of minimizing fuel cost, emission, transmission loss, voltage deviation, etc. with constraints on generator capability, line capacity, bus voltage and power flow balance. OPF program determines optimal settings of control variables, following which operation of the electric network becomes economical and efficient. Major control variables refer to the generated real power and generator bus voltages of the network. The latter controls the reactive power flow which is further compensated by adding capacitor banks of appropriate ratings to the network feeding usually the inductive loads. Voltage vectors of load buses and complex power flows in the lines determined during the process of optimization represent the optimal operating state that would result in single or multiple objectives of the network being largely fulfilled. In summary, OPF involves intricate calculations with multiple variables and finding optimal solutions while satisfying all constraints simultaneously is the most difficult part one encounters.

Earlier, classical numerical methods were popularly used to solve the OPF problem. The main disadvantage of a classical numerical optimization method is that it often converges to local optima due to the gradient based search method it employs. Handling inequality constraints becomes difficult with gradient-based and newton methods. OPF relationships are simplified to ensure convexity while implementing non-linear programming (NLP) and quadratic programming (QP) as these methods rely on convexity to obtain the optimal solution. Linear programming (LP) is meant to handle linear functions for input-output relationship. Interior point (IP) method is computationally fast and efficient, however, improper step size may lead to an infeasible solution for the sub-linear problem in the original non-linear domain. Moreover, IP method suffers from bad initial, optimality and termination criteria. A detailed review of these methods can be found in [17]-[18]. To overcome the above-

mentioned drawbacks of classical optimization methods, several population-based evolutionary algorithms (EAs) have been introduced in the field of numerical optimization in last few decades. The stochastic search method of EAs can efficiently explore the search space in quest of global optima. Some of the earliest works that applied stochastic population-based methods to OPF were genetic algorithm [19], evolutionary programming [20], etc. In recent years, numerous EAs have been applied to the OPF problem. A few standard objectives of OPF were optimized in [21] for IEEE bus systems using differential search algorithm (DSA), an effective algorithm for real-valued numerical optimization problems. Daryani *et. al.* [22] proposed improvement on standard group search optimization (GSO) algorithm with adaptation to develop adaptive group search optimization (AGSO) to perform study on OPF. Chaib *et. al.* [23] applied backtracking search optimization algorithm (BSA) to perform OPF calculation with multi-fuel options and valve-point effect in thermal generators. Improved colliding bodies optimization (ICBO) algorithm [24] increased the number of colliding bodies in each iteration to enhance performance of the algorithm when applied to the problem of OPF. Ref. [25] proposed and applied moth swarm algorithm (MSA) on numerous objectives of OPF for various bus systems to exhibit fast execution time and quick convergence of the algorithm. Chaos theory was incorporated in artificial bee colony to form chaotic artificial bee colony (CABC) in [26] and security constrained OPF was solved. To enhance exploration capability and population diversity of biogeography-based optimization algorithm (BBO), adaptive real coded BBO (ARCBBO) was suggested in [27] and applied to OPF problem. Dynamic adjustment of control parameters in adaptive partitioning flower pollination algorithm (APFPA) [28] showed higher convergence speed and better accuracy than FPA for OPF solutions. In fuzzy harmony search algorithm (FHSA) [29], effect of fuzzy based automatic adjustment of pitch adjustment rate and bandwidth of harmony search algorithm was studied in applying to the problem of OPF. In solving OPF, Levy mutation strategy for teaching-learning based optimization (LTLBO) [30] introduced a Levy mutation operator to enhance exploration at early search stages. Krill herd algorithm (KHA) [31] and its variant stud krill herd algorithm (SKH) [32]-[33] have also been popular in finding OPF solutions. Grenade explosion method (GEM) [34] and glowworm swarm optimization (GSO) [35] have also shown promising results for OPF as reported in respective papers. Modified imperialist competitive algorithm (MICA) and teaching learning algorithm (TLA) were hybridized (MICA-TLA) in [36] to improve local search and convergence of original ICA algorithm in finding OPF solutions. As evident from the OPF literature review, either basic or the improved version of an algorithm was tried.

OPF problem is solved for many different objectives which are often contradicting. So, multi-objective formulations and solutions of OPF are also available in the literature. A common approach to deal with multiple objectives in OPF is the weighted sum in which a predetermined weight factor is assigned to each objective. The weight factor is decided after a few trials with a judgement on desired outcome of certain objectives. While the references listed above for OPF dealt mostly with single-objective cases, weighted sum approach was presented using differential search algorithm (DSA) [21], backtracking search optimization algorithm (BSA) [23], improved colliding bodies optimization (ICBO) [24], moth swarm algorithm (MSA) [25] and adaptive partitioning flower pollination algorithm (APFPA) [28]. However, weighted sum method leads to only one Pareto solution with a set of weight factors in a complete run of the algorithm. For obvious reasons, a set of solutions with multi-objective algorithms is preferred to a single solution with weighted sum approach. A limited number of publications reported multi-objective approach to the problem of OPF. Moreover, the performance of a proper constraint handling technique of evolutionary algorithms (EAs) has not been tested in MOOPF problem. MOEA/D was adopted to solve MOOPF with 2 and 3-objectives in [37] where constraints were dealt with static penalty function approach. MOOPF witnessed implementation of multi-objective particle swarm optimization (MOPSO) in [37] and non-dominated sorting genetic algorithm-II (NSGA-II) in [37]-[38]. An enhanced self-adaptive differential evolution with mixed crossover (ESDE-MC) strategy was proposed in [39] to perform MOOPF on IEEE 30-bus and IEEE 57-bus systems for mostly 2-objective cases together with a couple of 4-objective cases. Niknam *et. al.* [40] proposed a mutation operator to come up with modified shuffle frog leap algorithm (MSFLA) and solve a 2-objective case (cost and emission) on IEEE 30-bus system. Ref. [41] studied the 2-objective (cost and emission) optimization case for the two standard bus systems using modified teaching-learning based optimization algorithm (MTLBO). The study cases of ref. [41] were reperformed in [42] using modified Gaussian bare-bones imperialist competitive algorithm (MGBICA) and in [43] using improved strength *Pareto* evolutionary algorithm (ISPEA). Non-dominated sorting multi-objective opposition-based gravitation search algorithm (NSMOOGSA) [44] was applied to several 2-objective cases of IEEE 30-bus system. Multi-objective differential evolution (MDE) based solution methodology was investigated in [45] on several 2-objective, a few 3 and 4-objective cases of OPF for IEEE 57-bus system. In studying MOOPF problem, imperialist competitive algorithm was modified to propose combined modified imperialist competitive algorithm (CMICA) [46], multi-objective modified imperialist competitive algorithm (MOMICA)

[47] and multi-objective imperialist competitive algorithm (MOICA) [48]. Bio-inspired modified multi-objective flower pollination algorithm (B-MMOFPA) [49] exhibited competitive performance on several 2 and 3-objective cases of OPF. In summary, the reference papers performed the optimization task applying different algorithms with two or more objectives on single or multiple test systems.

While abovementioned references dealt with only thermal generators, a system consisting of thermal and wind power generators has been studied in pursuit of minimum generation cost in the literature. *Gbest* guided artificial bee colony (GABC) was applied in [50] to improve OPF results that had been recorded in earlier publications with similar experimental set up. Panda *et. al.* [51] proposed modified bacteria foraging algorithm (MBFA) and introduced doubly fed induction generator (DFIG) model in OPF framework to define limits on reactive power generation capability. Static synchronous compensator (STATCOM), an additional reactive power supporting device, was incorporated in [52] for study of a system with wind and thermal power generators and the OPF problem was solved using ant colony optimization (ACO) and MBFA. Shi *et. al.* [53] proposed a paradigm for modeling the cost of wind-generated electricity. The problem on scheduling of generators for economic dispatch is more commonplace for system with thermal power and wind generators. In an OPF dispatching program, ref. [54] presented a stochastic model of wind generation. In attempting the same problem, Mishra *et. al.* [55] included DFIG model of wind turbine. Zhou *et. al.* [56] proposed dynamic economic dispatch (DED) model with penetration of large scale wind power considering risk reserve constraints. Ref. [57] incorporated emission, valve-point loading effect of generators in DED problem. OPF management for an isolated hybrid system with photovoltaic (PV), diesel generator and battery was presented in [58]. Pumped hydro storage was introduced in [59] as an alternate form of storage for a similar standalone hybrid system consisting of a PV, a wind turbine and a diesel generator. Integration of wind and solar power into the grid has been studied in a few publications. However, these papers focused primarily on real-time scheduling of generators for economical operation considering various pricing strategies between the utility operator and the independent system operator (ISO). Economic dispatch being main objective, ref. [60] considered minute-to-minute variation of renewable energy sources. Hybrid system in [61] included diesel generator with optimization platform being basic MATLAB functions. In economic dispatch (ED) problem, system constraints especially limitations on network parameters may have often been ignored; however, complying with network constraints is a must in OPF. Ref. [62] mentioned of system constraints, but details on satisfying those

constraints had not explicitly been addressed. Furthermore, voltage profile throughout the network, emission aspects are generally not addressed in ED problem, but in OPF problem. In summary, optimal power flow study in a network consisting of thermal, wind power generators and photovoltaic (PV) needs further attention.

2.2.2 Optimal reactive power dispatch

Optimal reactive power dispatch (ORPD) is a sub-problem of optimal power flow (OPF). Control and management of reactive power are necessary in the system so that voltages at all system buses remain within acceptable limits and network real power loss is minimum. Reactive power flow cannot be avoided in the system as most system loads are inductive and components such as transformers and transmission lines consume reactive power. Therefore, in a network, the reactive power generation should be sufficient to supply the VAR (volt-ampere reactive) consumers but should not be high enough to cause excessive heat losses and unwanted voltage drops. In ORPD, minimization of system real power loss is set as an objective with the basic concept that reactive power flow incurs real (active) power loss. In a typical network, generator bus voltages, settings of passive devices such as transformers and shunt VAR compensators are adjusted to achieve the desired objective. During optimization, constraints on load bus voltages, generator reactive power capabilities, line capacities and power balance must be satisfied. Cumulative voltage deviation of load buses in the network is also set as an objective in ORPD problem. This objective ensures that voltages at consumer terminals are closed to the desired level (usually 1 p.u.) with control of reactive power flow. However, this objective does not ensure lowest real power loss of the system. Nevertheless, the objectives are framed based on the importance exercised on certain aspects of the network.

Numerous articles studied the ORPD problem for systems consisting of conventional thermal units. In earlier days, classical mathematical methods such as quadratic programming [63] and interior-point methods [64] were extensively used. With the advancement of computational intelligence, abundant evolutionary algorithms are being tried and tested on non-linear, non-convex power system optimization problems including ORPD. Basic form of differential evolution (DE) was applied to optimize ORPD objectives in [65]. Quasi-oppositional based learning for population initialization was incorporated in differential evolution to form quasi-oppositional differential evolution (QODE) in [66] to propose solutions for ORPD on standard bus systems with conventional generators. In quasi-oppositional teaching-learning based optimization algorithm (QOTLBO) [67], the same

philosophy of quasi-oppositional learning was infused in teaching-learning based optimization algorithm. A newly surfaced nature-inspired optimization method called moth-flame optimization (MFO) was applied in [68] to minimize single-objective functions of ORPD. In attempting the same problem, Rajan *et. al.* [69] tried to establish efficacy and robustness of exchange market algorithm (EMA) due to presence of both exploration and exploitation at two phases, viz. balanced market and oscillation market, of the algorithm. The variants of gravitational search algorithms such as improved gravitational search algorithm (IGSA) [70], opposition-based gravitational search algorithm (OGSA) [71], etc. also have been popularly used for ORPD problem. In finding solutions for ORPD, hybridized algorithms like hybrid particle swarm optimization and imperial competitive algorithms (PSO-ICA) [72], hybrid Nelder–Mead simplex based firefly algorithm (HFA) [73], hybrid modified imperialist competitive algorithm and invasive weed optimization (MICA-IWO) [74], etc. performed better in combined manner than when applied individually with their respective constituting algorithms. Fuzzy adaptive heterogeneous comprehensive learning particle swarm optimization (FAHCLPSO) [75] algorithm and Gaussian bare-bones water cycle algorithm (NGBWCA) [76] showed competitive results for solutions of ORPD. In summary, either basic or the improved version of an algorithm was tried in the literature for real-parameter optimization problem of ORPD. Multi-objective formulation and solutions of ORPD are found in [77] using multi-objective grey wolf optimizer (MGWO), in [78] using multi-objective particle swarm optimization.

ORPD incorporating uncertain load and wind power was studied in some publications. Probabilistic multi-objective optimal power flow considering correlation in wind speed and the load was presented in [79]. Load uncertainty was modeled with two-point estimate method (TPEM) [80] in multi-objective ORPD problem. An enhanced firefly algorithm was proposed in [81] for multi-objective optimal active/reactive power dispatch with load and wind power generation uncertainties. Scenario-based approach for uncertainty modeling of load and wind power generation was proposed in [82]-[84]. Stochastic multi-objective ORPD (SMO-ORPD) integrating wind power generation uncertainties was studied in [82] with objectives of minimizing real power loss and voltage stability. Ref. [83] considered two objectives of minimizing real power loss and O&M (operation and maintenance) cost of windfarm for ORPD problem. Real power loss, voltage deviation and voltage stability index were considered as the objectives of optimization for ORPD problem in [84]. However, no literature has performed ORPD study with uncertain load demand, wind and solar power.

The formulation and solutions of ORPD problem considering uncertainties in demand and renewable power sources are presented in Chapter 4.

2.2.3 Economic-environmental dispatch

Economic-environmental dispatch (EED), also termed as economic-emission dispatch, has two aspects of consideration. Economic dispatch (ED) deals with economic consideration of generation units in a power system. Optimization on this front aims to minimize generation or fuel cost by optimal scheduling of generators to mitigate certain load demand in a specified interval. Emission objective performs similar task of scheduling generation units with the target of minimizing volume of greenhouse gases that emanate from conventional thermal power generators. Classical single-objective ED problem considers only economic aspect of power dispatch. However, due to environmental regulation and carbon tax imposition in many countries, more importance is exercised on controlling emission. Thus, formulation of optimization problem with both the objectives of cost and emission becomes necessary so that a compromised solution can be obtained. Irrespective of the number of objectives for power dispatch problem, all constraints pertaining to generator capacity, network operation and security are to be satisfied.

In recent times, several articles studied single-objective ED problem applying evolutionary algorithms. Adarsh *et al.* [85] implemented chaotic bat algorithm (CBA) to perform the optimization. A new hybrid grey wolf optimizer (HWGO) with addition of mutation and crossover operators into grey wolf optimizer was proposed in [86] to solve the same single-objective ED problem. Multi-fuel option and valve-point loading effect of steam turbine generators were introduced in [87] in solving ED problem. Delshad *et al.* [88] performed the study using backtracking search algorithm (BSA) with added complexity of generator prohibited operating zone (POZ) to ref. [87]. To include emission as an objective, formulation of multi-objective EED (MOEED) was necessary. In an effort to solve MOEED problem, weighted sum approach was adopted in [89] in applying modified artificial bee colony (MABC). Similar weighted sum approach was taken in [90] using classical genetic algorithm. The parameter free bare-bones multi-objective particle swarm optimization (BB-MOPSO), proposed in [91], showed improved results on MOEED. BB-MOPSO was found superior to MOPSO. Rao *et al.* [92] introduced adaptive clonal selection algorithm for the multi-objective optimization. The MOEED problem in these references dealt with thermal generators only. EED problem with thermal and wind energy sources has also been studied in recent years. Mondal *et al.* [93] added penalty cost for underestimation and reserve cost

for overestimation of stochastic wind power in solving MOEED problem using gravitational search algorithm (GSA). Quantum inspired particle swarm optimization (QPSO) was used in [94] for stochastic EED with uncertain wind power and carbon tax. Total operation cost of thermal and wind generators was demonstrated with single-objective model using Gbest guided artificial bee colony (GABC) in [95]. Refs. [93]-[95] transformed the multi-objective EED problem into a single-objective problem, thereby, whole set of non-dominated solutions in the multi-objective problem could not be utilized for dispatch decision making. Multi-objective evolutionary algorithms have been applied to EED problem with wind generators in few publications. In employing non-dominated sorting genetic algorithm-II (NSGA-II) for MOEED problem, ref. [96] included valve-point effect in addition to penalty and reserve costs for stochastic wind power. A practical 2m-point model was used for wind power uncertainty in [97] when applying online meta-heuristic for the MOEED problem. Qu *et al.* [98] adopted summation based multi-objective differential evolution (SMODE) to solve the problem where stochastic wind power was treated as a constraint. Similar approach was taken in [99] when applying multi-objective evolutionary algorithm based on decomposition (MOEA/D) coupled with penalty function method for handling system constraints. Modified teaching learning algorithm (MTLA) was applied in [100] to obtain the set of Pareto optimal solutions while adopting same model for wind energy as in [97]. EED with thermal-solar power was studied in [101] where in implementing particle swarm optimization (PSO) the multi-objective problem was converted into a single-objective one.

The problem formulation and solution with thermal, wind and solar power units all together in a power system need more research as only a few publications could be traced regarding the same. Single-objective dynamic ED solutions with all these three types of sources were proposed in [60]. Reddy [62] performed optimal scheduling with thermal-wind-solar power alongwith battery storage. These studies were all for single-objective optimization cases. The present research (in Chapter 5) addresses multi-objective economic-environmental (MOEED) power dispatch with thermal, wind, solar and small-hydro power generators. No literature performed even single-objective ED with all these renewable sources together. The detailed approach and study results are presented in Chapter 5.

2.2.4 Distribution network loss minimization

Distribution network acts as the interface between transmission network and consumer load points. The configuration of the distribution network is usually closed-loop, though the operation is radial. The distribution network contains both sectionalizing and tie switches.

Although fundamentally both switches are same, tie switches in the network are the switches that remain open to maintain radial nature of the network. Any sectionalizing switch (normally closed) of base configuration of the network can be opened during reconfiguration so that it becomes a tie switch. The optimal reconfiguration decides the appropriate switches, opening of which effect the minimum power loss. The process must ensure that no consumer is isolated and radiality of the network is retained. Distributed generators (DGs) such as diesel generators, photovoltaic (PV) systems, small wind turbines, etc. are also added to the radial distribution network (RDN) to boost capacity, reduce losses and improve voltage profile of the network. Though DG offers several benefits, it poses certain challenges when integrated in the distribution network. DG introduces bidirectional power flow in the distribution network which may possibly be designed for unidirectional power flow. This requires review and probable revamp of system protection relay co-ordination [102]. If DGs are not properly sized and located, they may lead to overvoltage and excessive loss [103].

Again, system loads specifically induction motors, transformers, transmission lines and cables are inductive in nature. These loads consume VAR and introduces lagging power factor in the system resulting in losses and poor performance of the system. Some of the DG technologies such as PV and fuel cell deliver active power only, while others can supply both active and reactive power e.g. synchronous generators driven by kinetic energy originated from various sources. Shunt capacitors (SCs) are passive devices that can deliver reactive power to compensate for the lagging VAR of the network. While DGs are more effective in reducing real power loss of the system, shunt capacitors complement the performance of DG when used in combination. Researchers have demonstrated the usefulness of shunt capacitors in reducing energy loss, enhancing feeder loading capacity and improving supply reliability [104]-[105] of the network.

Several research works performed loss minimization with only reconfiguration of the network. Some metaheuristics recently applied to the problem include runner root algorithm (RRA) [106], cuckoo search algorithm (CSA) [107], modified bacterial foraging optimization algorithm (MBFOA) [108] and modified particle swarm optimization (MPSO) [109]. Many works focused on optimal sizing and placement of DGs only in pursuit of minimum power loss. Analytical method [110] and evolutionary algorithms like generic algorithm (GA) [111], particle swarm optimization (PSO) [112], hybrid ant colony optimization (ACO) and artificial bee colony (ABC) [113] have all been tried for single or

multiple types of DGs. While impact of size and location of either DG or shunt capacitor has extensively been studied, a network comprising both of these items requires further attention. Naik *et al.* [114] took analytical approach to optimally size and locate both capacitor and DG. Aman *et al.* [115] adopted PSO with much improved results. In most recent papers, heuristic methods such as hybrid harmony search algorithm (HSA) and particle artificial bee colony (PABC) [116], intersect mutation differential evolution (IMDE) [117] and back-tracking search algorithm (BSA) [118] have all been applied for optimal capacity and placement of both DG and shunt capacitor (SC). To reduce search space of the algorithm and hence the computational burden, Naik *et al.* [114] and Muthukumar *et al.* [116] approached location optimization based on real power loss sensitivity factors of buses. In a radial network, this factor is the ratio of change in real power loss in the line connecting the bus to change in active or reactive power at the same bus. The bus with highest real power loss sensitivity factor with respect to injection of real power into that bus and the bus with highest real power loss sensitivity factor with respect to injection of reactive power into that bus are selected as the candidate buses for accommodating the DG and the SC, respectively.

A limited number of studies have been executed for simultaneous system reconfiguration and allocation of DGs. Ref. [119] employed fireworks algorithm (FWA) to perform the optimization task. Adaptive cuckoo search algorithm (ACSA) [120] improved the results obtained by FWA. A heuristic method named uniform voltage distribution based constructive reconfiguration algorithm (UVDA) [121] reported some of the best results on the problem of network reconfiguration accompanied by DG allocation. However, no literature performed optimal network reconfiguration together with optimal sizing and placement of DGs and SCs. In Chapter 6, our research on RDN loss minimization presents several case studies on network reconfiguration, allocations of DGs and SCs – individually and collectively.

2.2.5 Optimal siting of wind turbines in a windfarm

Enormous growth in the sector of renewable energy is anticipated for a sustainable future and for the stricter norms that are being imposed on carbon emission. A popular, fast growing form of naturally replenishable energy is the wind energy where the power in the wind is extracted by the turbine through rotation of its blades. Wind turbines, in general, are installed in a cluster at a potentially windy site. However, careful study and judgement are pre-

requisites to place the wind turbines in a windfarm as wake effect induced by upstream turbines affects the output of downstream turbines, thereby reducing total power output from the windfarm. Mosetti *et al.* [122] proposed binary coded genetic algorithm (GA) to optimize windfarm layout with objective of minimizing cost per unit power output (e.g. cost per kW) from the windfarm. Grady *et al.* [123] improved the results employing same method but with higher number of generations. Mittal [124] in his research showed fine grid spacing in windfarm could further increase the power output. Emami *et al.* [125] took weighted sum approach of the objective function consisting of both cost and power. Marmidis *et al.* [126] adopted Monte Carlo simulation method to optimize the objective of cost per unit power output for the simplest wind condition. Binary particle swarm optimization with time varying acceleration coefficient (BPSO-TVAC) in [127] showed competitive results on windfarm layout optimization with objective of cost per kW. Ant colony optimization (ACO) algorithm, a co-operative agent approach was proposed in [128]. Greedy algorithm with consideration of levelized cost of energy (LCOE) was studied in [129]. Ref. [130] optimized locations of wind turbines in a windfarm using same greedy algorithm for multiple hub heights of the wind turbines. Global windfarm cost model incorporating initial investment and yearly income on net generated energy was established in [131]. Analytical modeling of windfarm with multi-level extended pattern search was presented in [132]. All these articles considered optimization of a single objective of either maximizing power output or minimizing cost per kW. Furthermore, refs. [122]-[128] adopted simplified cost model proposed in [122] where cost was a function of only number of turbines in the windfarm.

Multi-objective genetic algorithm (MOGA) based optimization of windfarm was proposed by Chen *et al.* [133]. However, the authors in [133] focused only on a specific value of installed capacity. In other words, mainly one Pareto solution was utilized in the optimization process. The validity and usefulness of complete Pareto front (i.e. all non-dominated solutions in the multi-objective optimization) were not discussed. Ref. [134] adopted multi-objective random search algorithm with optimization objectives being number of turbines and cable length. The Pareto front in [134] was found to be quite narrow and irregular with all solutions being not feasible as mentioned in the paper. Our research, included in Chapter 7, presents a comparative study on single-objective optimization cases of windfarm layout. The second part in Chapter 7 covers a multi-objective approach and related case studies with real wind turbine and wind data for optimal siting of wind turbines in a windfarm.

Chapter 3

3. Optimal power flow study

3.1. Single-objective optimal power flow study

Optimal power flow (OPF) is a highly non-linear complex optimization problem where the steady state parameters of an electrical network need to be determined for its economical and efficient operation. The complexity of the problem escalates with ubiquitous presence of constraints in the problem. Solving OPF remains a popular but challenging task among power system researchers. In last couple of decades, numerous evolutionary algorithms (EAs) have been applied to find optimal solutions with different objectives of OPF. However, the search method adopted by EAs is unconstrained. Static penalty function method has been extensively used to discard infeasible solutions found during the search process. In this approach, penalty coefficients are selected by trial and error method. Small penalty coefficient over-explores the infeasible region, thus delaying the process of finding feasible solutions, and may prematurely converge to an infeasible solution. On the other hand, large penalty coefficient may not explore the infeasible region properly, thereby resulting in untimely convergence [13]. In this section of the chapter, superiority of feasible solutions (SF), ϵ -constraint (EC) and stochastic ranking (SR) methods of constraint handling are applied to OPF problem with success history based adaptive differential evolution (SHADE) being the basic search algorithm. The performance of these CH techniques is assessed, results are statistically compared and analyzed in detail. It is worthwhile to note that OPF problem has both equality and inequality constraints. Equality constraints are the power balance equations where both active and reactive power generated in the network must be equal to the sum of respective demands and losses in the network. Convergence of power flow to a solution ensures that the power balance equations are automatically satisfied. Inequality constraints on slack generator power, reactive power output of the generators, bus voltage limits and line capacities need special attention. A CH method works on its own way in handling inequality constraints. The methods are all successfully implemented to the OPF problem on standard IEEE 30, IEEE 57 and IEEE 118-bus test systems. Generation cost, emission, real power loss and voltage stability of the network are all individually (as single-objective) optimized. Case studies with multi-fuel options for the generators and valve-point loading effect are also considered. Although the study cases mostly consider all continuous variables, handling of discrete variables is also discussed and results of a case study with discrete variables are appended to the result section. Simulation results are compared and

critically investigated against constraint violation with most recent studies on optimal power flow (OPF) found in the literature.

The organization of rest of the part of this section is done in following way. Sub-section 3.1.1 includes a review of mathematical model including applicable constraints pertaining to power flow in the network. In sub-section 3.1.2, calculations for various objectives of OPF are provided with useful numerical values. Sub-section 3.1.3 discusses the simulation results and comparison followed by concluding remarks in sub-section 3.1.4.

3.1.1 Mathematical formulation of optimal power flow

The OPF is a non-linear, non-convex optimization problem and it minimizes certain objectives in the power system subject to many equality and inequality constraints. Mathematically, OPF is represented as:

$$\begin{aligned} &\text{Minimize: } f(x, u) \\ &\text{subject to: } \begin{cases} h(x, u) \leq 0 \\ z(x, u) = 0 \end{cases} \end{aligned} \quad (3.1)$$

where x is the vector of control or independent variables, u is the vector of state or dependent variables. $f(x, u)$: the objective function of OPF, $h(x, u)$: the set of inequality constraints, $z(x, u)$: the set of equality constraints.

a) Control (independent) variables

The set of variables that can control the power flow in the network is represented in vector form as:

$$x = [P_{G2} \dots P_{GNG}, V_{G1} \dots V_{GNG}, T_1 \dots T_{NT}, Q_{C1} \dots Q_{CNC}] \quad (3.2)$$

where P_{Gi} is the i -th bus generator active power (except swing generator). Selection of bus 1 as swing bus is representative only and swing bus can be any one of the generator buses. V_{Gi} is the voltage magnitude at i -th PV bus (generator bus), T_j is the j -th branch transformer tap, Q_{Ck} is the shunt compensation at k -th bus. NG , NC and NT are the number of generators, shunt VAR compensators and transformers, respectively. A control variable can assume any value within its range. In reality, transformer taps are not continuous. However, the tap settings expressed here are in p.u. and absolute value of voltage is not accounted for. Hence for study purpose and to compare with past reported results, all control variables including tap settings are considered continuous for most of the study cases. Discrete steps for transformers and shunt capacitors are accounted for in one specific case study.

b) State (dependent) variables

The state of power system is defined by the state variables which can be expressed in vector u as:

$$u = [P_{G1}, V_{L1} \dots V_{LNL}, Q_{G1} \dots Q_{GNG}, S_{l1} \dots S_{lnl}] \quad (3.3)$$

where P_{G1} is the generator active power at slack (or swing) bus, Q_{Gi} is the reactive power of generator connected to bus i , V_{Lp} is the bus voltage of p -th load bus (PQ bus) and line loading of q -th line is given by S_{lq} . NL is the number of load buses and nl is the number of transmission lines.

c) Constraints

As mentioned before, OPF problem has both equality and inequality constraints which are to be satisfied. The constraints are segregated and provided herein.

i. Equality constraints

In OPF, power balance equations are the equality constraints and those are represented as:

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{NB} V_j [G_{ij} \cos(\delta_{ij}) + B_{ij} \sin(\delta_{ij})] = 0 \quad \forall i \in NB \quad (3.4)$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} V_j [G_{ij} \sin(\delta_{ij}) - B_{ij} \cos(\delta_{ij})] = 0 \quad \forall i \in NB \quad (3.5)$$

where $\delta_{ij} = \delta_i - \delta_j$, is the difference in voltage angles of bus i and bus j , NB is the number of buses, P_D and Q_D are active and reactive load demands, respectively. G_{ij} is the transfer conductance and B_{ij} is the susceptance between buses i and j , respectively. In this study, the equality constraints are satisfied by Newton-Raphson method of power flow with the aid of MATPOWER [135] software.

ii. Inequality constraints

The inequality constraints in OPF reflect the operating limits of the equipment present in the power system and also the limits imposed on lines and load buses to guarantee system security.

- Generator constraints: $V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{max} \quad \forall i \in NG \quad (3.6)$

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max} \quad \forall i \in NG \quad (3.7)$$

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max} \quad \forall i \in NG \quad (3.8)$$

- Transformer constraints: $T_j^{min} \leq T_j \leq T_j^{max} \quad \forall j \in NT \quad (3.9)$

- Shunt compensator constraints: $Q_{Ck}^{min} \leq Q_{Ck} \leq Q_{Ck}^{max} \forall k \in NC$ (3.10)

- Security constraints: $V_{Lp}^{min} \leq V_{Lp} \leq V_{Lp}^{max} \forall p \in NL$ (3.11)

$$S_{lq} \leq S_{lq}^{max} \forall q \in nl$$
 (3.12)

Among the inequality constraints, the control variables are self-limiting. The optimization algorithm selects a feasible value for each such variable within the defined range. Effective techniques for handling of inequality constraints pertaining to state or dependent variables are the applied methods of SF, EC and SR.

3.1.2 Objective functions of OPF

To assess the performance of various constraint handling (CH) techniques, several case studies have been performed for standard IEEE 30, 57 and 118-bus test systems. Table 3.1 includes a summary of major components (viz. generators, transformers, shunt compensators etc.) installed in the test systems and other relevant parameters. In 30-bus and 57-bus systems, bus 1 is the swing bus or slack bus, often termed as $V\delta$ bus. Bus 69 is the swing bus in 118-bus system. In power flow study, the role of swing bus is to balance active and reactive power in the system satisfying power balance Eq. (3.4) and Eq. (3.5). For convenience, voltage magnitude (V) of swing bus is considered as 1 p.u. while the voltage angle (δ) as 0 degree. All other bus voltages and their angles are expressed w.r.t the swing bus, the values of which are obtained as the output of load flow study. Calculations for OPF objectives are described subsequently.

a) Minimization of fuel cost

This is the most basic objective function of OPF studied almost in all papers. The association between fuel cost (\$/h) (or generation cost) and generated power (MW) is approximated by the quadratic relationship. The objective function of cost to be minimized is described as:

$$f(x, u) = \text{Cost}, C_0 = \sum_{i=1}^{NG} a_i + b_i P_{Gi} + c_i P_{Gi}^2 \quad (3.13)$$

where a_i, b_i, c_i are the cost coefficients of the i -th generator producing output power P_{Gi} . Cost and emission coefficients for the generators of IEEE 30-bus system are listed in Table 3.2. These coefficients for the generators of IEEE 57-bus system are provided in Table 3.3. Cost coefficients for generators of IEEE 118-bus system are all derived from ref. [135].

Table 3.1. A summary of IEEE bus test systems

Items	IEEE 30-bus system [136]		IEEE 57-bus system		IEEE 118-bus system	
	Quantity	Details	Quantity	Details	Quantity	Details
Buses	30	Table A.1 (Appendix)	57	Table A.2 [135] (Appendix)	118	[135]
Branches	41	Table A.3 (Appendix)	80	Table A.4 [135] (Appendix)	186	[135]
Generators	6	Buses: 1 (swing) , 2, 5, 8, 11 and 13	7	Buses: 1 (swing) , 2, 3, 6, 8, 9 and 12	54	Buses: 1, 4, 6, 8, 10, 12, 15, 18, 19, 24, 25, 26, 27, 31, 32, 34, 36, 40, 42, 46, 49, 54, 55, 56, 59, 61, 62, 65, 66, 69 (swing) , 70, 72, 73, 74, 76, 77, 80, 85, 87, 89, 90, 91, 92, 99, 100, 103, 104, 105, 107, 110, 111, 112, 113 and 116
Shunt VAR compensation	9	Buses: 10, 12, 15, 17, 20, 21, 23, 24 and 29	3	Buses: 18, 25 and 53	14	Buses: 5, 34, 37, 44, 45, 46, 48, 74, 79, 82, 83, 105, 107 and 110
Transformer with tap changer	4	Branches: 11, 12, 15 and 36	17	Branches: 19, 20, 31, 35, 36, 37, 41, 46, 54, 58, 59, 65, 66, 71, 73, 76 and 80	9	Branches: 8, 32, 36, 51, 93, 95, 102, 107 and 127
Control variables	24	-	33	-	130	-
Connected load	-	283.4 MW, 126.2 MVar	-	1250.8 MW, 336.4 MVar	-	4242 MW, 1439 MVar
Allowable range for load bus voltage	24	[0.95 – 1.05] p.u.	50	[0.94 – 1.06] p.u.	64	[0.94 – 1.06] p.u.

Table 3.2. Cost and emission coefficients for generators of IEEE 30-bus system

Sl. no.	Generator	Bus	a (\$/h)	b (\$/MWh)	c (\$/MW ² h)	d (\$/h)	e (rad/MW)	φ	ψ	ω	τ	ζ
1	$G1$	1	0	2	0.00375	18	0.037	4.091	-5.554	6.490	0.0002	2.857
2	$G2$	2	0	1.75	0.01750	16	0.038	2.543	-6.047	5.638	0.0005	3.333
3	$G5$	5	0	1	0.06250	14	0.040	4.258	-5.094	4.586	0.000001	8
4	$G8$	8	0	3.25	0.00834	12	0.045	5.326	-3.550	3.380	0.002	2
5	$G11$	11	0	3	0.02500	13	0.042	4.258	-5.094	4.586	0.000001	8
6	$G13$	13	0	3	0.02500	13.5	0.041	6.131	-5.555	5.151	0.00001	6.667

Table 3.3. Cost and emission coefficients for generators of IEEE 57-bus system

Sl. no.	Generator	Bus	a (\$/h)	b (\$/MWh)	c (\$/MW ² h)	φ	ψ	ω	τ	ζ
1	$G1$	1	0	20	0.0775795	4.091	-5.554	6.49	0.0002	0.286
2	$G2$	2	0	40	0.01	2.543	-6.047	5.638	0.0005	0.333
3	$G3$	3	0	20	0.25	6.131	-5.555	5.151	0.00001	0.667
4	$G6$	6	0	40	0.01	3.491	-5.754	6.39	0.0003	0.266
5	$G8$	8	0	20	0.0222222	4.258	-5.094	4.586	0.000001	0.8
6	$G9$	9	0	40	0.01	2.754	-5.847	5.238	0.0004	0.288
7	$G12$	12	0	20	0.0322581	5.326	-3.555	3.38	0.002	0.2

Table 3.4. Cost coefficients for generators 1 and 2 of IEEE 30-bus system for multi-fuel sources

Generator	Bus	a (\$/h)	b (\$/MWh)	c (\$/MW ² h)	P_{Gi1}^{min}	P_{Gi1}^{max}	a (\$/h)	b (\$/MWh)	c (\$/MW ² h)	P_{Gi2}^{min}	P_{Gi2}^{max}
$G1$	1	55	0.7	0.005	50	140	82.5	1.05	0.0075	140	200
$G2$	2	40	0.3	0.01	20	55	80	0.6	0.02	55	80

b) Minimization of cost considering multiple fuels

Thermal generating plants have multi-fuel sources such as coal, natural gas and oil for different power output ranges of a unit. In such cases, the fuel cost function or curve is divided into piecewise quadratic cost functions (shown in Fig. 3.1) depending on the number and nature of fuels used.

The cost considering multi-fuel options for i -th generator is mathematically expressed as:

$$f_i(x, u) = a_{ik} + b_{ik}P_{Gi} + c_{ik}P_{Gi}^2 \text{ for fuel}_k \quad (3.14)$$

within power output range $P_{Gi_k}^{min} \leq P_{Gi} \leq P_{Gi_k}^{max}$; k being the fuel option. The objective function reflecting the total cost is given by:

$$f(x, u) = \text{Cost}, C_{om} = \left(\sum_{i=1}^{NG} f_i(x, u) \right) \quad (3.15)$$

For IEEE 30-bus system under study, first two generating units are considered to have multi-fuel options. The corresponding coefficients and power output ranges (MW) are given in Table 3.4. Costs for the remaining 4-units are same as in Table 3.2.

Fig. 3.1. Cost curves of a generator with single fuel and multi-fuel options

c) Enhancement of voltage stability in the network

Voltage stability problems are receiving growing attention in power systems as network collapses have been experienced in past due to voltage instability. The stability of a power system is characterized by its ability to maintain all bus voltages within acceptable limits

under normal condition and after being subjected to a disturbance. A system enters into the state of voltage instability when a disturbance, increase in load demand or change in system condition causes a progressive and uncontrollable decrease in voltage [137]. Systems with long transmission lines and heavy loading are more prone to voltage instability problem. In power system, improving voltage stability of a system is an important aspect. L -index of each bus serves as a good indicator of power system stability [138]. The value of the index varies from 0 to 1, with 0 being the no load case while 1 signifies voltage collapse.

If a power system has NL number of load (PQ) buses and NG number of generator (PV) buses, the value of L -index L_j of bus j is defined as:

$$L_j = \left| 1 - \sum_{i=1}^{NG} F_{ji} \frac{V_i}{V_j} \right|, \text{ where } j = 1, 2, \dots, NL \quad (3.16)$$

$$\text{and } F_{ji} = -[Y_{LL}]^{-1}[Y_{LG}]$$

where sub-matrices Y_{LL} and Y_{LG} are obtained from system YBUS matrix after separating load (PQ) buses and generator (PV) buses as represented in Eq. (3.17).

$$\begin{bmatrix} I_L \\ I_G \end{bmatrix} = \begin{bmatrix} Y_{LL} & Y_{LG} \\ Y_{GL} & Y_{GG} \end{bmatrix} \begin{bmatrix} V_L \\ V_G \end{bmatrix} \quad (3.17)$$

The L -index is calculated for all load buses and the maximum of all those values acts as the global indicator for system stability. Therefore, the objective function of system stability is given by:

$$f(x, u) = L_{max} = \max(L_j), \text{ where } j = 1, 2, \dots, NL \quad (3.18)$$

d) Minimization of emission

Generation of electrical power from conventional sources of energy emits harmful gases into the environment. The amount of SO_x , NO_x emission in tonnes per hour (t/h) increases with increase in generated power (in p.u. MW) following the relationship given in Eq. (3.19). Minimization of emission is set as the objective of OPF.

$$f(x, u) = \text{Emission}, E = \sum_{i=1}^{NG} [(\varphi_i + \psi_i P_{Gi} + \omega_i P_{Gi}^2) \times 0.01 + \tau_i \exp(\zeta_i P_{Gi})] \quad (3.19)$$

where, $\varphi_i, \psi_i, \omega_i, \tau_i$ and ζ_i are all emission coefficients associated with the i -th thermal generator. These coefficients are provided in Table 3.2 for generators of IEEE 30-bus system, and in Table 3.3 for generators of IEEE 57-bus system.

e) *Minimization of real power loss*

The power loss in transmission system is unavoidable as the lines have inherent resistance.

The real power loss (in MW) to be minimized is expressed as:

$$f(x, u) = \text{Loss} = \sum_{q=1}^{nl} G_{q(ij)} [V_i^2 + V_j^2 - 2V_i V_j \cos(\delta_{ij})] \quad (3.20)$$

where $\delta_{ij} = \delta_i - \delta_j$, is the difference in voltage angles between bus i and bus j and $G_{q(ij)}$ is the transfer conductance of branch q connecting buses i and j .

f) *Minimization of fuel cost considering valve-point loading effect*

The generator cost function is not smooth because of valve-point loading effect. The flow of steam to the turbine blades is controlled through different nozzle groups. Due to wire drawing effect, opening of valves suddenly increases the fuel cost. Therefore, the cost curve becomes non-smooth with many ripples [87] as shown in Fig. 3.2. The additional cost due to valve-point effect is accounted for in modulus of a sinusoidal function.

Fig. 3.2. Cost curves of a generator with and without valve-point loading effect

The objective of minimization of generating fuel cost with valve-point effect is given by:

$$f(x, u) = \text{Cost}, C = \sum_{i=1}^{NG} a_i + b_i P_{Gi} + c_i P_{Gi}^2 + \left| d_i \times \sin \left(e_i \times (P_{Gi}^{min} - P_{Gi}) \right) \right| \quad (3.21)$$

where d_i and e_i are the coefficients that represent the valve-point loading effect. The factors used for calculations are provided in Table 3.2 for generators of IEEE 30-bus system.

g) *Minimization of voltage deviation*

Voltage deviation is a measure of voltage quality in the network. The index of deviation is also important from security aspect. The indicator is formulated as the cumulative sum of deviations of voltages at all load buses in the network from nominal value of unity. Mathematically it is expressed as:

$$f(x, u) = VD = \left(\sum_{p=1}^{NL} |V_{Lp} - 1| \right) \quad (3.22)$$

3.1.3 Case studies, results and comparisons of single-objective OPF cases

Case studies, simulation results of application of SHADE-SF, SHADE-EC and SHADE-SR algorithms are tabulated, and also detailed system by system explanation and comparative analyses are provided in this section. The algorithms are described in Chapter 2, section 2.1.1.1 and section 2.1.4.1, and step-by-step approach for solving a constrained optimization problem is provided in Table 2.1. The proposed algorithms are developed using MATLAB software and simulations are carried out on a computer with Intel Core i5 CPU @2.7GHz and 4GB RAM. User-defined input parameters for the algorithms are presented in Table 3.5. Table 3.6 summarizes the objectives of various case studies performed for the test systems with all the 3 algorithms. The parameters, which are to be optimized for a specific case, are ticked in corresponding cells of the table. The population sizes (in Table 3.5) are selected after several trial runs. Increasing number of individuals in the population adversely affects the algorithm in finding feasible solutions. Again, for a case study of IEEE 30-bus system, 30,000 function evaluations are performed in a single complete run of the algorithm. A total of 36,000 function evaluations of objective functions are carried out for IEEE 57-bus system in one run. Due to large number of control variables in 118-bus system, 200,000 function evaluations are set as the stopping criteria in a case study. Each case is run 30 times independently to perform statistical analysis and evaluate the performance of the 3-constraint handling techniques.

Table 3.5. Input parameters for SHADE-XX (XX: SF/EC/SR) algorithm in OPF study

Parameter	IEEE 30-bus	IEEE 57-bus	IEEE 118-bus
Dimension of optimization problem, d	24	33	130
Population size, Np	50	60	100
Constant, cp (for EC method only)	5	5	5
Maximum no. of function evaluations, $maxeval$	30,000	36,000	200,000
Decision variable range $[x_{min}, x_{max}]$	Refer to tabulated results		

Table 3.6. Summary of case studies for single-objective OPF

Case no.	Test system	Basic fuel cost	Multi-fuel cost	Voltage stability	Emission	Power loss	Voltage deviation	Valve-point effect
Case 1	IEEE 30-bus system	✓						
Case 2			✓					
Case 3				✓				
Case 4					✓			
Case 5						✓		
Case 6		✓						✓
Case 7	IEEE 57-bus system	✓						
Case 8							✓	
Case 9						✓		
Case 10	IEEE 118-bus system	✓						
Case 11						✓		

a) *Statistical comparison among SHADE-SF, SHADE-EC and SHADE-SR algorithms*

The statistical summary of 30 runs for each study case performed (i.e. Case 1 to Case 11) using different constraint handling techniques with SHADE as the basic search algorithm is presented in Table 3.7. The columns indicate the best, worst, mean and standard deviation values for the objective function in each case. It is evident that no single method is able to provide best fitness or best mean values in all the cases. Further, we carry out Wilcoxon signed rank test to compare the performance between any two algorithms. The procedure applied for a comparative performance analysis between algorithm ‘A’ and algorithm ‘B’ on a specific case study using signed rank test [139] is described below.

- Gather all fitness values over 30 runs of the objective in a case study for both the algorithms
- Compute R^+ , the sum of ranks for runs in which algorithm ‘A’ outperforms algorithm ‘B’
- Compute R^- , the sum of ranks for runs in which algorithm ‘B’ outperforms algorithm ‘A’
- Calculate p -value which determines the significance of results in a statistical hypothesis test. The smaller the p -value, the stronger the proof against null hypothesis H_0 .

The results obtained using Wilcoxon signed rank test are presented in [Table 3.8](#). The column H_0 defines whether the null hypothesis is valid. If null hypothesis is valid (i.e. $H_0 = \text{'Yes'}$ with a significance level, $\alpha = 0.05$), the performance of two methods is statistically same in the case study. SHADE-SF and SHADE-EC perform equally in all cases except in Case 1, Case 8 and Case 10. SHADE-EC is found superior in these 3 cases. SHADE-SR is outperformed by both SHADE-SF and SHADE-EC in all cases except in Case 4 where all algorithms perform equally well. An interesting point to note is in the performance comparison between SHADE-SF and SHADE-EC. Though their performance is statistically same across most of the cases, no single algorithm could attain minimum best and minimum mean values in all the cases. However, in general, EC proves to be a better performer than SF for larger systems with more decision variables. The factors influencing the performance of a CH technique are the nature of the objective function and the constraints, the extents of feasible and infeasible regions in the solution space, and the way the CH technique works. Basic SF technique sometimes may not be able to maintain population diversity and can stagnate especially when the ratio between feasible region and search space is small and initial population has a few feasible solutions [\[140\]](#). The limited number of feasible solutions during the initial phase of search process can deter SF from attaining optimum values in the trial runs. Though EC and SF methods follow the same set of selection rules, the former selects infeasible solutions with a certain degree of violation during initial phase based on the epsilon (ϵ) value. This facilitates a more effective exploration of the search space near the boundary of feasible and infeasible regions. SR method is claimed to be more effective for problems having disconnected feasible regions as the method works on a probabilistic operator that can select an infeasible solution with higher constraint violation but better fitness value during evolution at any stage [\[13\]](#). However, the SR method is found to be less suitable than the other two methods on OPF problem, particularly for the large electrical network. It can be inferred from the statistical analysis that selecting the most appropriate CH method for a real-world problem evaluated under different scenarios is a difficult task. Gauging the extent of non-linearity in objective function or assessing the nature of constraints or delimiting the feasible region is not straightforward. It is advisable to assess the performance of a few CH techniques to find the best performing method on a particular problem.

Table 3.7. Statistical summary of case studies using the 3-CH techniques

Case no.	SHADE-SF				SHADE-EC				SHADE-SR			
	Best	Worst	Mean	Std. dev	Best	Worst	Mean	Std. dev	Best	Worst	Mean	Std. dev
Case 1	800.5104	800.5121	800.5110	0.00045	800.5103	800.5112	800.5106	0.00024	800.5179	800.5446	800.5245	0.00554
Case 2	646.4798	646.5123	646.4868	0.00841	646.4796	646.546	646.4874	0.01164	646.5464	646.7456	646.628	0.04969
Case 3	0.13637	0.13678	0.13647	0.00008	0.13641	0.1366	0.13648	0.00005	0.13751	0.139	0.13821	0.00036
Case 4	0.20482	0.20482	0.20482	0	0.20482	0.20482	0.20482	0	0.20482	0.20482	0.20482	0
Case 5	3.1004	3.1012	3.1006	0.00017	3.1004	3.1012	3.1006	0.00014	3.1017	3.105	3.1029	0.00074
Case 6	834.4260	834.4398	834.4288	0.0025	834.4267	834.4343	834.4294	0.00209	834.8014	836.5437	835.4056	0.44022
Case 7	41666.15	41667.23	41666.49	0.24803	41666.18	41667.53	41666.56	0.30702	41670.35	41680.34	41673.3	2.23652
Case 8	0.58508	0.59457	0.58937	0.00298	0.58403	0.59400	0.58810	0.00207	0.60005	0.63797	0.61910	0.00828
Case 9	9.8753	10.0136	9.8901	0.0292	9.8717	9.9095	9.8813	0.00843	9.9727	10.2527	10.0810	0.0641
Case 10	134939.9	135057.4	134970.3	29.2665	134930.8	134964.7	134939.1	8.3209	135188.1	135503	135343.8	77.4512
Case 11	16.2661	17.1183	16.6842	0.22385	16.1763	17.0757	16.6046	0.21499	17.7872	19.3847	18.3611	0.42213

Table 3.8. Wilcoxon signed rank test results

Case no.	SHADE-SF vs SHADE-EC				SHADE-SF vs SHADE-SR				SHADE-EC vs SHADE-SR			
	R+	R-	p-value	H ₀	R+	R-	p-value	H ₀	R+	R-	p-value	H ₀
Case 1	57.5	377.5	5.40×10^{-4}	No	465	0	1.73×10^{-6}	No	465	0	1.73×10^{-6}	No
Case 2	224	241	0.86121	Yes	465	0	1.73×10^{-6}	No	465	0	1.73×10^{-6}	No
Case 3	266.5	198.5	0.48397	Yes	465	0	1.73×10^{-6}	No	465	0	1.73×10^{-6}	No
Case 4	0	0	1	Yes	0	0	1	Yes	0	0	1	Yes
Case 5	233.5	231.5	0.98358	Yes	465	0	1.73×10^{-6}	No	465	0	1.73×10^{-6}	No
Case 6	308	157	0.12043	Yes	465	0	1.73×10^{-6}	No	465	0	1.73×10^{-6}	No
Case 7	284	181	0.28948	Yes	465	0	1.73×10^{-6}	No	465	0	1.73×10^{-6}	No
Case 8	130	335	0.035	No	465	0	1.73×10^{-6}	No	465	0	1.73×10^{-6}	No
Case 9	151	314	0.09368	Yes	465	0	1.73×10^{-6}	No	465	0	1.73×10^{-6}	No
Case 10	23	442	1.64×10^{-5}	No	465	0	1.73×10^{-6}	No	465	0	1.73×10^{-6}	No
Case 11	184	281	0.31849	Yes	465	0	1.73×10^{-6}	No	465	0	1.73×10^{-6}	No

b) System 1: IEEE 30-bus test system

In [Table 3.9](#), we list down settings of all control and state (dependent) variables along with their allowable ranges for the best fitness value obtained for the objective function in a case study pertaining to IEEE 30-bus test system using one of the 3-CH techniques (SF, EC and SR). Active power of swing generator and reactive power of all generators are state or dependent variables, treated as constraints in the optimization. Values of these variables are listed here to show that the CH techniques duly comply with the limits of these constraining variables. Limits of allowable reactive power for generators are derived from ref. [\[135\]](#). Last row of the table indicates the approximate time needed by the processor (CPU) for one run of a case study. It is worthwhile to note that different runs of stochastic population-based optimization algorithm produce slightly different optimum objective values. However, decision variables are found to be in similar ranges and convergence characteristics are of similar nature. [Table 3.10](#) presents comparison of results obtained using the 3-CH techniques in present study with past studies for all cases.

In **Case 1** of optimizing basic fuel cost, SHADE-SF and SHADE-EC algorithms lead to fuel costs of **800.5104 \$/h** and **800.5103 \$/h**, respectively satisfying all system constraints, more precisely conforming to the limits of important inequality constraints on generator reactive power, line capacity and load bus voltage. Among all inequality constraints, constraint on load bus voltage is critical as the operating voltages of load buses are often found to be near the limits. Some of the recent articles recorded better results than what have been achieved by the 3-methods in present study. A careful observation of those results reveals violation of voltage limits [0.95 p.u.-1.05 p.u.], thus rendering the solutions infeasible. cursory glance at voltage profiles of load buses in [Fig. 3.3](#) leads to the presumption that the violation has all likely occurred exceeding the upper limit. This situation of overvoltage is undesirable as it may stress the system and often lead to failure of the connected equipment. For the 30-bus system, a total of 24 load buses (PQ bus) are present. Theoretically, if all these buses operate at the limits, the maximum possible cumulative sum of absolute values of voltage deviations (VD in [Eq. \(3.22\)](#)) would be 1.2 p.u. (i.e. 24×0.05 p.u.). The reported VD values in some publications are higher than 1.2 p.u. in many cases. As it turns out, the contentious results are output of static penalty method which is sensitive to selection of penalty coefficient. In comparison [Table 3.10](#), such cases are highlighted with footnotes.

In this specific problem of OPF, limits on all state or dependent variables are duly satisfied in our study. In static penalty function approach, the constraints on these variables are violated in many cases, possibly without cognizance of the programmer. Moreover, the superiority of a proper CH technique lies in its ability to find the best result by allowing operation near to the limits without violating those. Fig. 3.3 indicates the voltage profiles of load buses for the case studies performed for IEEE 30-bus system. The voltage profile for a case study corresponds to the control variables obtained using the best performing method in that case as listed in Table 3.9. Clearly, all the best solutions comply with the voltage limits.

Table 3.9. Simulation results for best solutions of cases for IEEE 30-bus system

Parameters	Min	Max	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
Algorithm			SHADE- EC	SHADE- EC	SHADE- SF	SHADE- SF	SHADE- SF	SHADE- SF
P _{G2} (MW)	20	80	48.7205	55	79.9358	67.5729	80	48.6033
P _{G5} (MW)	15	50	21.3789	24.1485	49.9279	50	50	18.9668
P _{G8} (MW)	10	35	21.2453	35	34.9949	35	35	10
P _{G11} (MW)	10	30	11.9455	18.4973	29.982	30	30	10
P _{G13} (MW)	12	40	12	17.4911	12.0049	40	40	12
V ₁ (p.u.)	0.95	1.10	1.0849	1.0769	1.0505	1.0633	1.0621	1.0837
V ₂ (p.u.)	0.95	1.10	1.0654	1.0617	1.048	1.0572	1.0579	1.0619
V ₅ (p.u.)	0.95	1.10	1.0338	1.033	1.07	1.0377	1.0383	1.0291
V ₈ (p.u.)	0.95	1.10	1.0384	1.0417	1.0556	1.0442	1.0446	1.0361
V ₁₁ (p.u.)	0.95	1.10	1.0965	1.0803	1.0994	1.072	1.0862	1.0963
V ₁₃ (p.u.)	0.95	1.10	1.041	1.0474	1.0925	1.0523	1.0519	1.0594
Q _{C10} (MVar)	0.0	5.0	1.5679	4.7349	4.9984	4.5995	0.0019	4.9991
Q _{C12} (MVar)	0.0	5.0	4.9293	3.1425	0.0047	4.5153	4.8797	0.6113
Q _{C15} (MVar)	0.0	5.0	4.0291	4.5294	0.0218	4.1318	4.2512	3.9302
Q _{C17} (MVar)	0.0	5.0	5	4.9978	0.7415	5	5	5
Q _{C20} (MVar)	0.0	5.0	3.9476	3.8701	0.1468	3.8928	3.9925	4.0438
Q _{C21} (MVar)	0.0	5.0	5	5	0	5	5	5
Q _{C23} (MVar)	0.0	5.0	2.8719	2.5915	0.1001	3.0714	2.9967	3.1763
Q _{C24} (MVar)	0.0	5.0	5	5	0.0047	5	5	5
Q _{C29} (MVar)	0.0	5.0	2.4675	2.3085	0.0002	2.3532	2.3653	2.4896
T ₁₁ (p.u.)	0.90	1.10	1.0544	1.085	1.0452	1.0888	1.0817	1.02
T ₁₂ (p.u.)	0.90	1.10	0.9331	0.9025	0.9	0.9	0.9	1.0004
T ₁₅ (p.u.)	0.90	1.10	0.9687	0.9785	1.0335	0.995	0.996	0.9869
T ₃₆ (p.u.)	0.90	1.10	0.9741	0.9737	0.9632	0.9768	0.9771	0.9771
Fuel cost (\$/h)			800.5103	646.4796	920.5253	944.3884	967.6634	834.4260
Emission (t/h)			0.36626	0.28352	0.22541	0.20482	0.20727	0.42184
Loss (MW)			9.0301	6.7370	4.6382	3.2344	3.1004	10.4764
VD (p.u.)			0.90872	0.91327	0.91163	0.88327	0.89347	0.86971
L-index (max)			0.13817	0.13800	0.13637	0.13870	0.13854	0.13906
P _{G1} (MW)	50	200	177.1398	139.999	81.1928	64.0615	51.5004	194.3062
Q _{G1} (MVar)	-20	150	6.5403	2.7752	-19.968	-1.8701	-2.3808	6.3944
Q _{G2} (MVar)	-20	60	25.644	20.1403	-19.9797	12.433	12.3268	20.3957
Q _{G5} (MVar)	-15	62.5	27.6196	26.8991	60.5040	23.7337	23.7778	26.1143
Q _{G8} (MVar)	-15	48.7	29.2390	29.594	48.6971	29.3037	29.4711	29.5624
Q _{G11} (MVar)	-10	40	28.1825	25.0611	26.9362	23.1223	27.9534	24.4803
Q _{G13} (MVar)	-15	44.7	-6.6169	-1.7205	33.2606	2.7097	2.4505	7.1732
CPU Time (sec.)			164.8	161.7	165.6	164.5	160.7	159.9

Fig. 3.3. IEEE 30-bus system – load bus voltage profiles for the best solutions in all cases

In **Case 2** of minimizing cost for multiple fuels, the present study with SHADE-EC finds a cost of **646.4796 \$/h** which turns out to be the best value when compared with the valid results achieved by other algorithms. In **Case 3** of voltage stability indicator, i.e. minimization of maximum ‘L-index (max)’ or L_{max} of the system load buses, SHADE-SF gives best output of **0.13637**, marginally better than the other equivalent algorithms. Objective of emission in tonnes per hour (t/h) and other useful calculated parameters obtained by SHADE-SF, SHADE-EC and SHADE-SR in **Case 4** are almost same with those reported by algorithms MSA [25] and ARCBBO [27]. Studies of **Case 5** by SHADE-SF and SHADE-EC result in real power loss of **3.1004 MW**, comparable with the results summarized in the table. Valve-point loading effect is considered in **Case 6** to arrive at a higher cost than in **Case 1** with final value of cost being **834.4260 \$/h**, obtained by SHADE-SF algorithm. In summary, although variation in performance is observed among 3-CH techniques, results of one or more methods employed in our study are among the best reported results on the problem of OPF. Moreover, the objective of this study is not to prove superiority on mere numerical values, but to demonstrate strict compliance with the system constraints by the CH techniques.

Table 3.10. Comparison of 3-CH techniques with previous studies for cases of IEEE 30-bus system

Case no.	Algorithm	Fuel cost (\$/h)	Emission (t/h)	Loss (MW)	VD (p.u.)	L-index (max)
Case 1	SHADE-SF	800.5104	0.36625	9.0297	0.91297	0.13815
	SHADE-EC	800.5103	0.36626	9.0301	0.90872	0.13817
	SHADE-SR	800.5179	0.36625	9.0274	0.89491	0.13814
	AGSO [22]	801.75	0.3703	-	-	-
	ARCBBO [27]	800.5159	0.3663	9.0255	0.8867	0.1385
	SKH [33]	800.5141	0.3662	9.0282	-	0.1382
	Mod PSO [25]	800.5164	0.36624	9.0354	0.90488	0.13825
	BSA [23]	799.0760 ^a	0.3671	8.6543	1.9129 ^a	0.1273
	ICBO [24]	799.0353 ^a	-	8.6132	1.9652 ^a	0.1261
	APFPA [28]	798.9144 ^a	-	8.5800	1.9451 ^a	-
	FHSA [29]	799.914 ^a	-	-	1.5265 ^a	-
	GEM [34]	799.0463 ^a	0.3665	8.6257	1.9312 ^a	0.1264
	GA [40]	803.2332	0.3829	-	-	-
	DE [141]	799.0827 ^a	-	8.63	1.8505 ^a	0.1277
Case 2	SHADE-SF	646.4798	0.28352	6.7390	0.92132	0.13793
	SHADE-EC	646.4796	0.28352	6.7370	0.91327	0.13800
	SHADE-SR	646.5464	0.28348	6.7539	0.91607	0.13814
	MSA [25]	646.8364	0.28352	6.8001	0.84479	0.13867
	LTLBO [30]	647.4315	0.2835	6.9347	0.8896	-
	GABC [50]	647.03	-	6.8160	0.8010	-
	BSA [23]	646.1504 ^a	0.2833	6.6233	1.0273 ^a	0.1378
	ICBO [24]	645.1668 ^a	-	6.3828	1.8232 ^a	0.1282
Case 3	SHADE-SF	920.5253	0.22541	4.6382	0.91163	0.13637
	SHADE-EC	880.1431	0.27305	5.9204	0.87921	0.13641
	SHADE-SR	819.1216	0.27316	6.6860	0.82295	0.13751
	SKH [33]	814.0100	0.3740	9.9056	-	0.1366
	GEM [34]	816.9095 ^a	0.2802	6.2313	1.8320 ^a	0.1257
	DE [141]	915.2172 ^a	-	3.626	2.1064 ^a	0.1243
Case 4	SHADE-SF	944.3884	0.20482	3.2344	0.88327	0.13870
	SHADE-EC	944.3888	0.20482	3.2343	0.88704	0.13867
	SHADE-SR	944.3853	0.20482	3.2358	0.88383	0.13879
	MSA [25]	944.5003	0.20482	3.2358	0.87393	0.13888
	DSA [21]	944.4086	0.20583	3.2437	-	0.12734
	AGSO [22]	953.629	0.2059	-	-	-
	ARCBBO [27]	945.1597	0.2048	3.2624	0.8647	0.1387
	GEM [34]	943.6358 ^a	0.2048 ^a	3.0160	1.9504 ^a	0.1269
Case 5	SHADE-SF	967.6634	0.20727	3.1004	0.89347	0.13854
	SHADE-EC	967.6635	0.20727	3.1004	0.89254	0.13855
	SHADE-SR	967.6169	0.20726	3.1017	0.88941	0.13868
	MSA [25]	967.6636	0.20727	3.1005	0.88868	0.13858
	Mod PSO [25]	967.6523	0.20727	3.1031	0.90632	0.13816
	ARCBBO [27]	967.6605	0.2073	3.1009	0.8913	0.1386
	APFPA [28]	965.6590 ^a	-	2.8463 ^a	2.0720 ^a	-
	GEM [34]	966.7473 ^a	0.2072	2.8863 ^a	1.9755 ^a	0.1265
Case 6	SHADE-SF	834.4260	0.42184	10.4764	0.86971	0.13906
	SHADE-EC	834.4267	0.42190	10.4800	0.84425	0.13926
	SHADE-SR	834.8014	0.42124	10.5284	0.55816	0.14239
	BSA [23]	830.7779 ^a	0.4377	10.2908	1.2050 ^a	0.1363
	ICBO [24]	830.4531 ^a	-	10.2370	1.7450 ^a	0.1289
	APFPA [28]	830.4065 ^a	-	10.2178	1.8909 ^a	-

^aInfeasible solution, constraint on load bus voltage is violated

Fig. 3.4. Comparative convergence among 3-CH techniques for Case 1 of IEEE 30-bus system

Fig. 3.5. Comparative convergence among 3-CH techniques for Case 2 of IEEE 30-bus system

Graphical comparisons of convergence of 3-CH techniques for Case 1, Case 2 and Case 6 of cost-related objective functions are illustrated in Fig. 3.4, Fig. 3.5 and Fig. 3.9 respectively. The convergence speed is not remarkably different between SHADE-SF and SHADE-EC. Rapid and sudden convergence is observed for both the methods during initial phase of the search process. SHADE-SR converges to the optimal solution slowly with stagnation at some intermediate points. For Cases 3, 4 and 5, the convergence characteristics are indicated in Fig. 3.6, Fig. 3.7 and Fig. 3.8, respectively. The convergence of SHADE-SR is a bit irregular and abrupt in Case 3. The objective function of L -index is highly dependent on the

most critical constraint on load bus voltage. The SR technique is unable to find feasible solutions easily at later stages of the search process, thus delaying the process of convergence. In general, SF and EC techniques converge to optimal solutions in about 15000 function evaluations.

Fig. 3.6. Comparative convergence among 3-CH techniques for Case 3 of IEEE 30-bus system

Fig. 3.7. Comparative convergence among 3-CH techniques for Case 4 of IEEE 30-bus system

Fig. 3.8. Comparative convergence among 3-CH techniques for Case 5 of IEEE 30-bus system

Fig. 3.9. Comparative convergence among 3-CH techniques for Case 6 of IEEE 30-bus system

c) System 2: IEEE 57-bus test system

Settings of control and state variables alongwith their ranges for the best fitness values of study cases for 57-bus test system are listed in [Table 3.11](#). In [Table 3.12](#), the results of all 3-CH techniques (SF, EC and SR) are compared with most recent studies available in the literature. As it turns out, SHADE-EC leads to best fitness values in all the cases except Case 7. Similar to system 1 of 30-buses, constraints are all diligently satisfied by the constraint handling methods. Ranges for generator reactive power are derived from ref. [\[135\]](#) and

found to be quite narrow for some generators. The CH techniques duly satisfy the limits as the listed values of generator reactive power suggest. Further, the permissible range of load bus voltage for 57-bus system is between [0.94 p.u.-1.06 p.u.]. Theoretically, if all 50-load buses of the system operate at the limits, the maximum possible value of aggregate voltage deviation (VD in Eq. (3.22)) would be 3 p.u. (i.e. 50×0.06 p.u.). Reported VD value in one case is found to be higher than 3 p.u. and the same is marked with a footnote in comparison Table 3.12. The reference paper pertaining to the case study adopted the common static penalty function approach for constraint handling.

Table 3.11. Simulation results for best solutions of cases for IEEE 57-bus system

Parameters	Min	Max	Case 7	Case 8	Case 9
Algorithm			SHADE-SF	SHADE-EC	SHADE-EC
P_{G2} (MW)	30	100	90.1933	36.0640	30.0005
P_{G3} (MW)	40	140	45.0113	126.8327	134.4989
P_{G6} (MW)	30	100	70.5598	31.9526	99.9908
P_{G8} (MW)	100	550	460.4698	286.0578	306.3598
P_{G9} (MW)	30	100	96.4382	99.9952	99.9995
P_{G12} (MW)	100	410	360.1313	379.2715	409.9965
V_1 (p.u.)	0.95	1.10	1.0667	1.0018	1.0720
V_2 (p.u.)	0.95	1.10	1.0644	1.0012	1.0673
V_3 (p.u.)	0.95	1.10	1.0564	1.0136	1.0667
V_6 (p.u.)	0.95	1.10	1.0599	1.003	1.0623
V_8 (p.u.)	0.95	1.10	1.0762	1.0238	1.0703
V_9 (p.u.)	0.95	1.10	1.0508	1.0126	1.0512
V_{12} (p.u.)	0.95	1.10	1.0518	1.0414	1.0574
Q_{C18} (MVar)	0	20	6.4838	0.0181	0.5089
Q_{C25} (MVar)	0	20	12.079	19.9938	14.5328
Q_{C53} (MVar)	0	20	11.6409	20	13.1704
T_{19} (p.u.)	0.90	1.10	0.9598	1.0994	1.0504
T_{20} (p.u.)	0.90	1.10	1.0018	0.9081	0.9238
T_{31} (p.u.)	0.90	1.10	1.0077	0.9697	1.0092
T_{35} (p.u.)	0.90	1.10	0.9979	1.0491	1.0888
T_{36} (p.u.)	0.90	1.10	1.0100	1.0919	0.9472
T_{37} (p.u.)	0.90	1.10	1.0343	1.0052	1.0120
T_{41} (p.u.)	0.90	1.10	0.9946	0.9967	0.9964
T_{46} (p.u.)	0.90	1.10	0.9619	0.9187	0.9545
T_{54} (p.u.)	0.90	1.10	0.9132	0.9000	0.9156
T_{58} (p.u.)	0.90	1.10	0.9812	0.9286	0.9885
T_{59} (p.u.)	0.90	1.10	0.9660	0.9889	0.9723
T_{65} (p.u.)	0.90	1.10	0.9760	1.0118	0.9788
T_{66} (p.u.)	0.90	1.10	0.9386	0.9000	0.9438
T_{71} (p.u.)	0.90	1.10	0.9742	0.9682	0.9773
T_{73} (p.u.)	0.90	1.10	0.9936	1.0025	0.9917
T_{76} (p.u.)	0.90	1.10	0.9648	0.9001	0.9612
T_{80} (p.u.)	0.90	1.10	1.0036	0.9939	0.9922
Fuel cost (\$/h)			41666.15	46712.91	44561.62
Emission (t/hr)			1.3535	1.2990	1.1048
Loss (MW)			14.8532	17.7602	9.8717
VD (p.u.)			1.6969	0.5840	1.8007

Parameters	Min	Max	Case 7	Case 8	Case 9
L -index (max)			0.27840	0.30137	0.27824
P_{G1} (MW)	0	576	142.8496	308.3865	179.8255
Q_{G1} (MVar)	-140	200	45.9805	-49.5419	42.2949
Q_{G2} (MVar)	-17	50	49.9968	49.984	49.9956
Q_{G3} (MVar)	-10	60	34.6583	59.9953	34.0146
Q_{G6} (MVar)	-8	25	-7.9439	-7.514	-7.3523
Q_{G8} (MVar)	-140	200	53.5066	44.3925	48.1243
Q_{G9} (MVar)	-3	9	8.997	8.9983	8.9962
Q_{G12} (MVar)	-150	155	57.0863	154.6501	48.7102
CPU Time (s)			231.6	224.4	221.7

Case 7 of minimizing basic objective of fuel cost leads to a value of **41666.15 \$/h** using SHADE-SF, the lowest when compared with other valid results of recent studies as depicted in [Table 3.12](#). Further, network loss is also among the best (14.8532 MW) with the recommended settings of control variables by SHADE-SF algorithm. **Case 8** is for the single-objective optimization of minimizing voltage deviation. The value reported by any of the three techniques is much better than the comparable study by APFPA [28], though with the sacrifice of fuel cost. The cost increases from previous studies following the recommended settings of control variables. Refs. [31] and [45] considered higher limits for shunt VAR compensators (upto 30 MVar); hence straight comparison with present study is not valid. Study in **Case 9** of minimizing real power loss leads to the lowest value of **9.8717 MW**, attained by SHADE-EC algorithm. In general, fitness values achieved by the 3-methods in all cases are better than most other reported values in the literature.

Curves in [Fig. 3.10](#) describe the voltage profiles of load buses for the best solutions of case studies performed for IEEE 57-bus system. Clearly all voltages are within allowable limits. It may be noted that many bus voltages are found to be very close to the upper limit in a couple of case studies. This very fact reiterates the need of extra caution in satisfying voltage constraint so that no system bus experiences overvoltage.

Fig. 3.10. IEEE 57-bus system – load bus voltage profiles for the best solutions of Cases 7, 8 & 9

Table 3.12. Comparison of 3-CH techniques with previous studies for cases of IEEE 57-bus system

Case no.	Algorithm	Fuel cost (\$/h)	Emission (t/h)	Loss (MW)	VD (p.u.)	L-index (max)
Case 7	SHADE-SF	41666.15	1.3535	14.8532	1.6969	0.27840
	SHADE-EC	41666.18	1.3550	14.8551	1.6948	0.27890
	SHADE-SR	41670.35	1.3513	14.9901	1.5292	0.28226
	MSA [25]	41673.72	1.9526	15.0526	1.5508	0.28392
	DSA [21]	41686.82	-	-	1.0833	0.24353
	ICBO [24]	41697.33	-	15.5470	1.3173	0.27760
	ARCBBO [27]	41686	-	15.3769	-	-
	APFPA [28]	41628.75 ^a	-	14.0470	3.5571 ^a	-
	LTLBO [30]	41679.55	-	15.1589	-	-
	PSO [30]	41699.52	-	-	-	-
	MICA-TLA [36]	41675.05	-	15.0149	1.6161	-
	DE [45]	41682	-	-	-	-
Case 8	SHADE-SF	46224.48	1.2678	15.5524	0.5851	0.30149
	SHADE-EC	46712.91	1.2990	17.7602	0.5840	0.30137
	SHADE-SR	44437.78	1.2030	14.711	0.6001	0.30013
	APFPA [28]	43485.93	-	12.1513	0.8909	-
	KHA [31]	42006.44	-	-	0.5810 ^b	0.2985
	DE [45]	-	-	-	0.5839 ^b	-
Case 9	SHADE-SF	44504.52	1.1063	9.8753	1.7780	0.27854
	SHADE-EC	44561.62	1.1048	9.8717	1.8007	0.27824
	SHADE-SR	44567.62	1.1053	9.9727	1.5937	0.28454

^aInfeasible solution, constraint on load bus voltage is violated

^bHigher limits for the shunt compensators have been considered

Convergence curves applying 3-CH techniques are superimposed for Case 7 in Fig. 3.11 which shows reasonably fast convergence to the fitness value for SHADE-SF and SHADE-EC. SHADE-EC appears to have converged faster than the other methods. All the curves are

shown starting after a certain number of function evaluations. It is worthwhile to mention that the algorithm (CH technique) looks for feasible solutions during initial phase of the search process. The actual convergence to optimal solution starts when the search process enters the feasible region. For 30-bus system, the CH techniques easily find the feasible region. But possibly due to narrow limits of generator reactive power in 57-bus system, the algorithm takes few hundreds (or sometimes few thousands) of evaluations to find the feasible zone. The convergence curves do not indicate the initial phase of search process when the fitness progression is erratic. Convergence curves of Case 8 are drawn in Fig. 3.12. Very slow convergence is observed for SHADE-SR algorithm and it requires much higher number of function evaluations to arrive at an optimal solution. The comparative study on convergence for Case 9 of minimizing real power loss is presented in Fig. 3.13. In general, SHADE-SR needs more function evaluations than the others to find feasible solutions and subsequently to converge to optimal solutions.

Fig. 3.11. Comparative convergence among 3-CH techniques for Case 7 of IEEE 57-bus system

Fig. 3.12. Comparative convergence among 3-CH techniques for Case 8 of IEEE 57-bus system

Fig. 3.13. Comparative convergence among 3-CH techniques for Case 9 of IEEE 57-bus system

d) System 3: IEEE 118-bus test system

To verify effectiveness of the proposed method, the large-scale IEEE 118-bus system is considered for study purpose. As observed in [Table 3.7](#), performance of SHADE-EC is the best for IEEE 118-bus system with a large number of decision variables. A total of 200,000 function evaluations (with execution time of about 35 minutes) are performed for a study case. The control variables and calculated parameters pertaining to the best fitness values obtained in the two cases (Case 10 and Case 11) are provided in [Table A.5](#) and [Table A.6](#)

in the Appendix. Allowable ranges of generator real power [135] are explicitly mentioned in the table. Shunt compensator ratings are selectable within 0 to 25 MVar. Permissible ranges of generator bus voltage and transformer tap setting are within [0.95-1.10] and [0.90-1.10], respectively. The optimal value of fuel cost in **Case 10** is **134930.8 \$/h**, and that of real power loss in **Case 11** is **16.1763 MW**, both are achieved by SHADE-EC algorithm. The system has a large number of control variables and constraints, and the number of critical constraints on generator reactive power and load bus is 118. All the constraints are duly satisfied by the algorithm. Load bus voltage profiles for both the study cases are exhibited in Fig. 3.14. Convergence characteristics for the cases are shown in Fig. 3.15. Due to presence of huge number of constraints, the algorithm takes about 30000 function evaluations to find the first set of feasible solutions. The convergence to optimal solutions is observed in about 150,000 function evaluations.

Fig. 3.14. IEEE 118-bus system – load bus voltage profiles for the best solutions of Cases 10 & 11

Fig. 3.15. Convergence curves of Case 10 and Case 11 (SHADE-EC) for IEEE 118-bus system

e) Additional case study, Case AC1 – handling discrete variables

This section of the study considers cost minimization of IEEE 30-bus system considering discrete variables in the optimization process. In DE and SHADE, discrete variables can be easily handled by ‘rounding off’ operation. Here, settings of shunt compensators (capacitors) and taps of transformers are considered as discrete variables. The capacitor can be switched in at discrete steps of 200 kVAr (i.e. 0.2 MVar). Transformer tap is considered within the range from 0.90 p.u. to 1.10 p.u. The possible transformer taps considered in this case study are [0.90-0.92-0.94-...-1.08-1.10] p.u. During search process, the control variables on shunt capacitor ratings and transformer taps are simply rounded off (upto required decimal points) to the nearest multiples of 0.2 (MVar) and 0.02 (p.u.), respectively. The rounding off operation is performed after crossover operation in each generation of the algorithm. The optimization case on generation cost is run with all the three algorithms i.e. SHADE-SF, SHADE-EC and SHADE-SR. SHADE-EC algorithm achieves the minimum cost value of **800.5192 \$/h**, which is slightly higher than the best value obtained in Case 1 of same objective with all continuous variables. The complete results of all algorithms with control variables and other calculated parameters are provided in [Table A.7](#) in the Appendix.

3.1.4 Conclusion: single-objective OPF study

This section of the chapter on OPF discusses in detail the application and usefulness of three constraint handling techniques - SF, EC and SR with SHADE being the basic search

algorithm for optimal power flow (OPF) problem which consists of non-linear objectives and non-linear constraints. A list of conclusions of this section of the chapter is as follows:

- A comparative study among the 3-constraint handling (CH) techniques points out the difficulty in guaranteeing superiority of a CH technique over others under various scenarios of a real-world problem.
- The performance characteristics of SF and EC methods are very much comparable.
- Stochastic ranking (SR) technique lags behind the others in minimizing OPF objectives.
- Reduction in hourly operation cost has been established almost in all the cases studied under the scope of this work.

Furthermore, the importance of an efficient constraint handling technique is paramount. As substantiated in our study, without proper constraint handling method and especially with static penalty function approach, limits on network parameters may often be unknowingly violated. Violating physical or security constraints of network components may compromise system safety, lead to excessive losses, malfunction and often failure of the components. So, operating the network within defined limits is the pre-requisite for secure and proper operation. Recommended settings by the CH techniques successfully lead to the desired condition of the network. Furthermore, the proposed algorithms in this study perform noticeably better than many other equivalent optimization methods in finding solutions for OPF objectives.

3.2. Multi-objective optimal power flow study

In section 3.1 of this chapter, many single-objective cases of OPF are solved. In present socio-economic scenario, consideration of more than one objective in OPF formulation and solution becomes necessary. During earlier days, usual formulation of OPF involved a single objective, predominantly minimization of fuel (generation) cost. Statutory regulation and imposition of carbon tax in many countries have increased importance on reduction of greenhouse gas emission. Maintaining high level of power quality requires minimal voltage deviation from the rated value and reduction of transmission loss to any extent signifies commercial benefit to the utilities. Therefore, it is essential to consider emission, voltage deviation and power loss alongwith fuel cost in OPF objective formulation. Solution of multi-objective OPF (MOOPF) necessitates effective technique as the problem is highly non-linear and objectives are often conflicting. A suitable multi-objective evolutionary algorithm can generate Pareto front (PF) that contains several non-dominated optimal solutions with a trade-off among different objectives.

In this study of MOOPF, MOEA/D algorithm is applied on several 2, 3 and 4-objective cases of standard IEEE 30-bus and IEEE 57-bus test systems. The algorithm is discussed in detail in Chapter 2, section 2.1.2.1. The computational complexity of MOEA/D is less than multi-objective genetic local search (MOGLS) [142] and nondominated sorting genetic algorithm-II (NSGA-II) [143] as presented in [7]. Disparate objectives can easily be accounted for in MOEA/D by simple normalization of the objectives. The algorithm has been successfully applied to power engineering problems such as integrated power distribution and vehicle charging systems [144], economic emission dispatch (EED) [145], unit commitment [146] MOOPF [37], etc. As EED problem is also closely linked to power flow in the network (together with MOOPF), the effectiveness of the algorithm to solve OPF problem has already been established by the results reported in these papers. However, the algorithm was originally developed for unconstrained multi-objective problems. Constraints in MOOPF have been handled by penalty function approach till now. This approach is sensitive to selection of penalty coefficient. Inappropriate selection of penalty coefficient may lead to violation of system constraints as analyses of case studies in section 3.1 show. Therefore, caution must be exercised in selecting only feasible solutions when penalty function method is used. A proper constraint handling (CH) technique relieves the burden of user choosing a penalty coefficient. The CH technique when employed with a compatible evolutionary

algorithm (EA) guides the search process towards feasible region and helps to demarcate boundary between infeasible and feasible regions. In this chapter, we explore the performance of a well-established CH technique, superiority of feasible solutions (SF) [14], in the problem of MOOPF. The integration approach of SF with MOEA/D is discussed in Chapter 2, section 2.1.4.2. As mentioned earlier, OPF problem has both equality and inequality constraints. Power balance equations constitute the equality constraints in which both active and reactive power generated in the network must be equal to the sum of respective demands and losses in the network. Power balance equations are inevitably satisfied when power flow converges to a solution. Inequality constraints on slack generator power, reactive power output of the generators, load bus voltage limits and line capacities need effective handling technique. While static penalty approach can perform the task to an extent, we investigate the results and compliance to system constraints for the whole Pareto front (PF) when each objective is added with a penalty term. Thereafter, results of study cases and conformance to the limits of system constraints with MOEA/D-SF are discussed, analyzed and compared with MOEA/D with static penalty method. The comparison is further extended to cases where different algorithms are applied to MOOPF study in the literature.

In organizing rest of this section of the chapter, sub-section 3.2.1 includes a summary of the MOOPF objectives, case studies and user-defined inputs for the algorithm MOEA/D-SF. The simulation results and comparisons are provided in detail in sub-section 3.2.2. The conclusion on MOOPF is drawn in sub-section 3.2.3.

3.2.1 Objectives, case studies for MOOPF and input for MOEA/D-SF

In order to assess the performance of MOEA/D-SF, standard IEEE 30 and IEEE 57-bus test systems are selected and several case studies with 2, 3 and 4-objectives have been performed. The summary of components like generators, transformers, shunt compensators etc. installed in the two systems and other relevant useful parameters have already been provided in Table 3.1. Generator cost coefficients used in MOOPF study are listed in Table 3.2 and Table 3.3. For IEEE 30-bus system, the study utilizes generator emission coefficients as in Table 3.2. However, emission coefficients for the generators in IEEE 57-bus system are altered (from single-objective cases) to compare the results with past studies. The data on emission coefficients of generators in IEEE 57-bus system are provided in Table A.8 in the Appendix. Calculations of various objective functions such as fuel cost, emission, voltage deviation and power loss are described in detail in section 3.1 of this chapter. It may also be noted that the fuel cost used for MOOPF study is the basic fuel cost without valve-point loading effect.

The multi-objective cases are formulated with 2 or more of the objectives. The case studies are summarized in Table 3.13. In a specific case study, the constituting objectives are ticked in corresponding boxes.

Table 3.13. A summary of case studies for MOOPF

IEEE 30-bus test system					IEEE 57-bus test system				
Case no.	Fuel cost	Emission	Voltage deviation	Power loss	Case no.	Fuel cost	Emission	Voltage deviation	Power loss
Case 1	✓	✓			Case 7	✓	✓		
Case 2	✓		✓		Case 8	✓		✓	
Case 3	✓	✓		✓	Case 9	✓		✓	✓
Case 4	✓	✓	✓		Case 10	✓	✓	✓	✓
Case 5	✓		✓	✓					
Case 6	✓	✓	✓	✓					

The selected parameters of MOEA/D-SF for the MOOPF study are presented in Table 3.14. A weight vector of an M -objective optimization problem can be defined as $\lambda^m = (\lambda_1^m, \lambda_2^m, \dots, \lambda_M^m)^T$ for $m = 1, 2, \dots, Np$. Each element in a weight vector can take a value from $\{0, 1/H, 2/H, \dots, H/H\}$ i.e. $\lambda_i^m \in \{0, \frac{1}{H}, \frac{2}{H}, \dots, \frac{H}{H}\}$ for $i = 1, 2, \dots, M$ [7]. H is called the resolution of weight vectors. The number of weight vectors (i.e. also population size Np) is decided by H and M (no. of objectives) as $Np = C_{M-1}^{H+M-1}$. In this specific problem of OPF, $H = 199, 23$ and 12 are considered for 2, 3 and 4-objective cases, respectively. The corresponding numbers of weight vectors and population sizes are $Np = 200, 300$ and 455 . Further in Table 3.14, population size (Np), maximum number of function evaluations and crossover rate (CR) are slightly altered from what have been proposed in [8]. A larger population size means additional computational burden. As MOEA/D with a reasonable population size can generate evenly distributed Pareto front [7], we have reduced the population size. F and CR values are chosen after few trials. The probability to update only the neighbors (δ_p) is maintained high and the selected neighborhood size (T) is same as recommended in [8]. As an obvious fact, neighborhood size (T) and number of neighboring solutions to update (n_r) are integers. Any fraction is rounded down to the nearest integer value. The proposed algorithm is developed using MATLAB software and simulations are carried out on a computer with Intel Core i5 CPU @2.7GHz and 4GB RAM.

Table 3.14. User-defined inputs for MOEA/D-SF algorithm in MOOPF study

Parameter	Value
Population size, Np	200 (for 2 objectives) 300 (for 3 objectives) 455 (for 4 objectives)
Number of weight vectors (equals Np)	200 / 300 / 455
Neighborhood size, T	$0.1 * Np$
Probability to update the neighbor (or the whole population otherwise), δ_p	0.9
Max number of positions replaced by better new solution in each subproblem at every generation, n_r	$0.01 * Np$
Maximum number of function evaluation, $maxeval$	100000
Crossover rate, CR	0.7
Mutation factor, F	0.5

3.2.2 Results and comparisons of MOOPF case studies

a) The best Pareto front (PF) and the best compromise solution

Each case study is run 10 times independently. So, out of 10 Pareto fronts (PFs), we select the best Pareto front (PF) by evaluating the quality of PFs employing well-known hypervolume (HV) [147]-[148] performance indicator. Hypervolume (HV) indicator can evaluate both convergence and diversity of the solutions in the PFs generated by multi-objective evolutionary algorithms (MOEAs). The calculation of HV indicator requires a reference point. In the current problem of OPF, different objectives have different numerical ranges. Therefore, the objectives are normalized to have a uniform range $[0, 1]$ and $(1, 1 \dots 1)^M$ is considered as the reference point with M being the number of objectives in multi-objective optimization. In addition, HV is approximated through Monte Carlo method by using one million sampling points. On a given problem, when comparing different PFs, the PF with the largest HV is considered the best. Table 3.15 presents a summary of HV indicator values (maximum, minimum, mean and standard deviation) over 10 runs of the case studies performed using MOEA/D-SF.

The best compromise solution is extracted from the set of non-dominated solutions of best Pareto front using fuzzy decision-making technique [39]. The membership function value of each objective function is calculated as:

$$\mu_m^k = \begin{cases} 1 & \text{for } f_m^k \leq f_m^{\min} \\ \frac{f_m^{\max} - f_m^k}{f_m^{\max} - f_m^{\min}} & \text{for } f_m^{\min} < f_m^k < f_m^{\max} \\ 0 & \text{for } f_m^k \geq f_m^{\max} \end{cases} \quad (3.23)$$

where μ_m^k is the membership function value of m -th objective for k -th non-dominated solution; $f_m^{\min}, f_m^{\max}$ represent the minimum and maximum fitness values for the m -th

objective function among all non-dominated solutions; f_m^k is the fitness value of m -th objective for k -th non-dominated solution. For each non-dominated solution, the normalized membership function is formulated as:

$$\mu^k = \frac{\sum_{m=1}^M \mu_m^k}{\sum_{k=1}^{N_d} \sum_{m=1}^M \mu_m^k} \quad (3.24)$$

where N_d is the total number of non-dominated solutions and M is the number of objectives. The solution with highest μ^k value is the best compromise solution.

Table 3.15. Summary of hypervolume indicator values of MOOPF cases applying MOEA/D-SF

Case no.	Max	Min	Mean	Std dev
Case 1	0.8291	0.8243	0.8272	0.0016
Case 2	0.8952	0.6169	0.7843	0.1056
Case 3	0.7062	0.7015	0.7031	0.0013
Case 4	0.8227	0.8163	0.8195	0.0027
Case 5	0.7793	0.7730	0.7766	0.0024
Case 6	0.6858	0.6745	0.6789	0.0038
Case 7	0.8499	0.8211	0.8389	0.0088
Case 8	0.9409	0.7791	0.8959	0.0519
Case 9	0.8492	0.8018	0.8298	0.0145
Case 10	0.7529	0.7197	0.7380	0.0126

b) Comparison between MOEA/D with penalty factor and MOEA/D-SF

In this subsection the performance, especially conformance to the limits of system constraints using MOEA/D with static penalty and MOEA/D-SF is investigated. To apply penalty factor, the constraint violations are converted to weighted values. As an example, the calculation of violation in slack generator rating is:

$$P_{vio,G1} = \begin{cases} \frac{P_{G1} - P_{G1,max}}{P_{G1,max} - P_{G1,min}} & \text{if } P_{G1} > P_{G1,max} \\ \frac{P_{G1,min} - P_{G1}}{P_{G1,max} - P_{G1,min}} & \text{if } P_{G1} < P_{G1,min} \end{cases} \quad (3.25)$$

Similar approach is taken in calculating the violation of other constraints viz. load bus voltage, generator reactive power and transmission line capacity. The calculated values are summed, and the summated value is added to each objective after multiplying with a suitable penalty factor. In static penalty approach, penalty factor (or penalty coefficient) shall be carefully selected such that the magnitude of penalty becomes almost of the same order as the objective function [149]. Therefore, for IEEE 30-bus system, the penalty factor selected is 100 for cost (in \$/h) objective. For objectives of loss (in MW), emission (in tonnes/hour)

and voltage deviation (VD in p.u.), the selected penalty factors are 10, 1 and 1, respectively. In case studies of IEEE 57-bus system, penalty factors of 1000, 10, 1 and 1 are selected for cost, loss, emission and VD objectives, respectively. Selected 2-objective, 3-objective and 4-objective cases are performed using MOEA/D with penalty factor. A total of 10 trial runs for each case are carried out (with MOEA/D-penalty) and results are compared with the output of equal number of trial runs using MOEA/D-SF. The summary of comparison of best compromise solutions over all trial runs is provided in [Table 3.16](#). Best compromise solution is the compromised solution from best Pareto front having maximum HV value. ‘Number of violations’ is the total instances of constraint violations in Pareto optimal solutions over all 10 runs. The number of recorded violations depends on the chosen penalty factors and objectives involved in the optimization. As observed, the violation is more frequent in larger system with many system components. Best compromise solutions, obtained by the two approaches in a case, cannot dominate each other over all objectives.

Table 3.16. A comparative study between MOEA/D with penalty factor and MOEA/D-SF

Case no.	Objectives	MOEA/D with penalty factor		MOEA/D-SF	
		Best Comp	No. of violations	Best Comp	No. of violations
Case 1 (30-bus)	Cost (\$/h)	822.716	19	829.515	0
	Emission (t/h)	0.25970		0.25011	
Case 3 (30-bus)	Cost (\$/h)	879.098	215	881.012	0
	Emission (t/h)	0.21886		0.21642	
	Loss (MW)	4.1233		4.1441	
Case 6 (30-bus)	Cost (\$/h)	854.846	102	883.322	0
	Emission (t/h)	0.23185		0.21867	
	Loss (MW)	5.1218		4.4527	
	VD (p.u.)	0.1520		0.1322	
Case 7 (57-bus)	Cost (\$/h)	42112.86	137	42160.09	0
	Emission (t/h)	1.3307		1.3183	
Case 9 (57-bus)	Cost (\$/h)	42238.57	202	42059.16	0
	VD (p.u.)	0.6997		0.6729	
	Loss (MW)	11.9526		12.2996	

To gauge the extent of violation with penalty function approach, we further examine the non-dominated solutions where constraint violation has occurred. The violation is because of some load bus voltages exceeding the specified upper limit. Voltage profiles for some of the Pareto optimal solutions in Case 9 (IEEE 57-bus system) are presented in [Fig. 3.16](#). The overvoltage is found to be at load bus (PQ bus) nos. 7, 25, 45, 51, etc. The case of violation

presented here is typical and instances of other violations are also for overvoltage in one or more load buses. The constraint on load bus voltage is the most difficult constraint to satisfy in OPF as the allowable range of voltage is quite narrow. Also, the voltage is sensitive to selected ratings of capacitor banks (shunt compensators), settings of generator terminal (bus) voltages and transformers taps. Therefore, extra caution is necessary in satisfying voltage constraint to avoid the occurrence of overvoltage.

Fig. 3.16. Violation of constraint on load bus voltage for some solutions in MOOPF Case 9 with penalty function approach

One might argue that the extent of overvoltage for the cases portrayed here is not significant. A larger penalty coefficient might do away with the violation. It may be noted that, large penalty coefficients affect the quality of solutions and may result in poor convergence. In these case studies, instances of constraint violation are observed even with a careful selection of penalty coefficients. An inconsiderate selection will lead to a greater violation, sometimes even without cognizance of the programmer. Our claim can further be corroborated with simple observation of parameters in [23], [24] and [37] among which ref. [37] applied MOEA/D with penalty factor for IEEE 30-bus system. As mentioned in section 3.1 of this chapter, under no circumstances VD value (as per Eq. (3.22)) shall exceed 1.2 p.u. The reported VD values in Case 6 and 7 of ref. [37] are higher than 1.2 p.u. (reported VD values are 1.6087 p.u., 1.3732 p.u., 1.8423 p.u., etc.). So, surely bus voltage limits are violated in these cases. Although VD values are not reported in many other cases, we suspect similar violations in some more cases in [37]. This very fact reiterates the need of a proper constraint handling technique to comply with critical constraints in a constrained optimization problem.

Later, we plot the load bus voltage profiles obtained applying MOEA/D-SF for maximum VD values in all cases to demonstrate compliance with the limits of the constraint.

c) IEEE 30-bus system: detailed results and comparison

Settings of all control variables alongwith their allowable ranges for the best solutions of individual objective functions over all trial runs and best compromise solutions are listed in Table 3.17, Table 3.18 and Table 3.19 for the case studies pertaining to IEEE 30-bus system. Best compromise solution is extracted from the best Pareto front with the highest HV value. The control variables and other calculated parameters in the tables are self-explanatory. Tabulated data reveal that MOEA/D can achieve a wide range for the individual objectives. In other words, the Pareto front is adequately diverse. Slack generator active power (P_{G1}) and reactive power of all other generators are state or dependent variables, treated as constraints in the optimization. Values of these variables are listed here to confirm compliance with the limits of these constraining variables. For easy reference, the values of reactive power for generators in all cases are plotted in scatter diagram in Fig. 3.17. It is worthwhile to mention that lower limits of the generator reactive power (Q_{Gi}^{min}) are specifically mentioned in [136], though upper limits (Q_{Gi}^{max}) are not fixed. We follow ref. [135] for selection of Q_{Gi}^{max} . Clearly the algorithm adheres to the reactive power limits in all study cases performed in this literature. The last row shows the value of worst aggregate voltage deviation (VD in Eq. (3.22)) of load buses in a case study over all trial runs. It is presumed that if voltage limits are satisfied for worst (maximum) VD value (and the corresponding solution), the voltages of load buses will be bound within the defined range for all other solutions with smaller VD values. The voltage profiles corresponding to these highest VD values are shown in Fig. 3.18. It is observed from the profiles that the constraint on load bus voltage is duly satisfied by MOEA/D-SF. As it turns out, the collective VD value shall be much lower than 1.2 p.u. in order to restrict individual bus voltages within the limits.

Table 3.17. Simulation results for MOOPF Case 1 and Case 2

Control & state variables	Min	Max	Case 1 – Best solutions			Case 2 – Best solutions		
			Cost	Emission	Comp	Cost	VD	Comp
P_{G2} (MW)	20	80	49.4324	63.0179	58.6477	48.4257	47.1984	48.7542
P_{G5} (MW)	15	50	21.3661	48.9700	26.7416	21.6498	21.9086	21.3753
P_{G8} (MW)	10	35	21.2362	34.9945	34.9865	20.8600	24.3970	21.8895
P_{G11} (MW)	10	30	11.0790	29.9955	25.3571	12.2014	12.4876	11.9817
P_{G13} (MW)	12	40	12.0288	40.0	24.5212	12.2159	12.8541	12.0073
V_1 (p.u.)	0.95	1.10	1.0855	1.0632	1.0723	1.0827	1.0154	1.0606
V_2 (p.u.)	0.95	1.10	1.0643	1.0539	1.0594	1.0626	1.0036	1.0390
V_5 (p.u.)	0.95	1.10	1.0337	1.0365	1.0318	1.0319	1.0160	1.0075

Control & state variables	Min	Max	Case 1 – Best solutions			Case 2 – Best solutions		
			Cost	Emission	Comp	Cost	VD	Comp
V ₈ (p.u.)	0.95	1.10	1.0371	1.0437	1.0403	1.0372	1.0087	1.0074
V ₁₁ (p.u.)	0.95	1.10	1.0963	1.0817	1.0852	1.0659	1.0734	1.0316
V ₁₃ (p.u.)	0.95	1.10	1.0472	1.0562	1.0583	1.0427	1.0119	1.0106
Q _{C10} (MVar)	0	5.0	0.3824	3.0732	0.0108	0.5272	4.9847	4.9511
Q _{C12} (MVar)	0	5.0	2.4688	4.3699	2.6876	4.8548	1.4361	3.6690
Q _{C15} (MVar)	0	5.0	3.4051	2.7653	0.6280	3.8359	4.9835	4.6738
Q _{C17} (MVar)	0	5.0	4.9372	1.7718	4.7893	4.7760	0.0220	0.8798
Q _{C20} (MVar)	0	5.0	3.4530	1.5909	3.9702	4.8082	4.9985	5.0
Q _{C21} (MVar)	0	5.0	4.9761	4.3688	4.9870	2.2106	5.0	4.8907
Q _{C23} (MVar)	0	5.0	3.8714	3.7950	4.9864	4.6778	5.0	4.9755
Q _{C24} (MVar)	0	5.0	3.8306	3.4807	4.9727	4.7774	4.9606	4.9602
Q _{C29} (MVar)	0	5.0	2.7297	3.4897	2.2466	2.0622	2.6080	2.5932
T ₁₁ (p.u.)	0.90	1.10	1.0367	1.0127	1.0320	1.0722	1.0988	1.0559
T ₁₂ (p.u.)	0.90	1.10	0.9547	0.9613	0.9466	0.9176	0.9002	0.9098
T ₁₅ (p.u.)	0.90	1.10	0.9739	0.9959	0.9930	1.0019	0.9816	0.9993
T ₃₆ (p.u.)	0.90	1.10	0.9803	0.9829	0.9738	0.9875	0.9706	0.9745
Fuel cost (\$/h)			800.600	932.966	829.515	800.719	806.247	802.406
Emission (t/h)			0.36718	0.20564	0.25011	0.36596	0.35918	0.3656
Loss (MW)			9.0914	3.3951	5.6788	9.0666	10.3264	9.5408
VD (p.u.)			0.8287	0.8166	0.8851	0.6007	0.0899	0.1362
P _{G1} (MW)	50	200	177.349	69.817	118.825	177.113	174.881	176.933
Q _{G1} (MVar)	-20	150	10.1709	3.1232	1.3387	6.4071	-19.963	10.9091
Q _{G2} (MVar)	-20	60	21.2768	6.1084	18.0275	21.6286	-5.3367	25.4351
Q _{G5} (MVar)	-15	62.5	28.6402	25.8261	26.4698	28.0835	61.2676	30.8488
Q _{G8} (MVar)	-15	48.7	28.4782	34.5178	28.2218	32.1513	48.3834	29.6257
Q _{G11} (MVar)	-10	40	27.0661	18.6029	21.5988	22.2465	38.0335	15.7643
Q _{G13} (MVar)	-15	44.7	-0.6507	6.7972	7.0874	4.0515	2.4546	1.3453
Worst VD (p.u.)			0.9479			0.6007		

Table 3.18. Simulation results for MOOPF Case 3 and Case 4

Control & state variables	Case 3 – Best solutions				Case 4 – Best solutions			
	Cost	Emission	Loss	Comp	Cost	Emission	VD	Comp
P _{G2} (MW)	47.3864	67.7632	79.9922	60.7211	48.8338	68.5536	67.6379	65.0532
P _{G5} (MW)	21.2672	50.0	50.0	38.645	21.4617	50.0	49.9606	27.6573
P _{G8} (MW)	22.1317	35.0	35.0	34.898	21.1688	34.944	34.9847	34.7495
P _{G11} (MW)	12.2571	30.0	30.0	29.9789	11.2257	29.9946	29.9659	26.6536
P _{G13} (MW)	12.0008	40.0	40.0	35.3787	12.0254	40.0	39.6758	25.8342
V ₁ (p.u.)	1.0810	1.0647	1.0623	1.0655	1.0820	1.0362	0.9985	1.0231
V ₂ (p.u.)	1.0578	1.0586	1.0575	1.0565	1.0638	1.0302	0.9971	1.0084
V ₅ (p.u.)	1.0228	1.0398	1.0379	1.0309	1.0300	1.0202	1.0172	1.0109
V ₈ (p.u.)	1.0285	1.0427	1.0447	1.0421	1.0412	1.0210	1.0078	1.0039
V ₁₁ (p.u.)	1.0899	1.0831	1.0889	1.0899	1.0378	1.0338	1.0486	1.0482
V ₁₃ (p.u.)	1.0495	1.0536	1.0573	1.0536	1.0633	1.0253	1.0196	1.0006
Q _{C10} (MVar)	4.7873	3.4127	1.0404	3.4575	4.3599	1.2021	4.9487	2.7179
Q _{C12} (MVar)	4.2070	2.2467	0.0124	4.4682	1.013	1.2667	1.2675	4.9488
Q _{C15} (MVar)	4.0306	4.1441	3.3510	3.3899	3.9885	3.7403	4.9979	4.2037
Q _{C17} (MVar)	4.6459	4.2544	4.7417	3.1023	2.7097	0.1432	0.1515	1.9006

Control & state variables	Case 3 – Best solutions				Case 4 – Best solutions			
	Cost	Emission	Loss	Comp	Cost	Emission	VD	Comp
QC ₂₀ (MVar)	3.9857	4.0973	4.4369	2.9271	0.0002	4.9917	4.9987	4.5142
QC ₂₁ (MVar)	4.9403	4.2605	4.6777	4.8614	4.8959	4.9839	5.0	4.7531
QC ₂₃ (MVar)	1.7757	2.9845	3.7141	2.7488	4.3221	4.9981	4.9813	4.7594
QC ₂₄ (MVar)	4.8260	3.4603	4.9642	4.6846	4.9921	4.9726	4.9812	3.9477
QC ₂₉ (MVar)	1.1658	3.1101	2.7253	3.1583	2.8098	2.61	0.9201	2.4010
T ₁₁ (p.u.)	1.0464	1.0207	1.0912	1.0434	1.0676	1.0195	1.0658	1.0602
T ₁₂ (p.u.)	0.9463	0.9364	0.90	0.9377	0.901	0.9104	0.9021	0.9003
T ₁₅ (p.u.)	0.9859	0.9955	0.9919	0.9947	0.9891	1.0113	1.0022	0.9625
T ₃₆ (p.u.)	0.9783	0.9834	0.9791	0.9815	0.9873	0.9774	0.9509	0.9616
Fuel cost (\$/h)	800.965	944.759	967.654	881.012	800.763	946.56	945.575	842.446
Emission (t/h)	0.3669	0.20483	0.20726	0.21642	0.36838	0.20494	0.20529	0.24062
Loss (MW)	9.1179	3.2606	3.1045	4.1441	9.151	3.4918	4.1078	6.1188
VD (p.u.)	0.7026	0.912	0.8927	0.8652	0.7024	0.2451	0.0898	0.1092
P _{G1} (MW)	177.475	63.9	51.514	87.922	177.836	63.4	65.283	109.571
Q _{G1} (MVar)	13.8123	-0.7813	-0.9511	-1.3498	2.4682	-2.3348	-18.836	4.5886
Q _{G2} (MVar)	19.285	14.8068	10.621	15.6907	27.6417	7.3831	-16.153	-10.262
Q _{G5} (MVar)	24.4524	25.9479	23.4098	22.1252	25.2266	34.3242	56.1556	52.9862
Q _{G8} (MVar)	23.0973	29.0724	28.7306	28.9844	41.4413	41.5696	46.2265	41.1683
Q _{G11} (MVar)	27.0245	18.0722	30.2248	24.9783	9.6766	10.1074	25.372	24.6781
Q _{G13} (MVar)	3.5536	4.0417	6.552	4.1844	11.5059	7.9511	9.0667	-6.7905
Worst VD (p.u.)	0.9621				0.9215			

Table 3.19. Simulation results for MOOPF Case 5 and Case 6

Control & state variables	Case 5 – Best solutions				Case 6 – Best solutions				
	Cost	VD	Loss	Comp	Cost	Emission	VD	Loss	Comp
P _{G2} (MW)	48.2982	78.7347	79.9583	53.7352	49.2377	67.4109	80.0	79.9136	60.2738
P _{G5} (MW)	21.0567	49.9986	50.0	34.77	21.0883	49.9881	49.9987	50.0	42.2638
P _{G8} (MW)	22.4636	33.0475	34.9473	34.1951	24.1642	34.9262	34.8029	34.9636	34.9908
P _{G11} (MW)	11.7922	29.6832	29.9501	25.5401	11.5755	29.9635	30.0	29.9646	27.6255
P _{G13} (MW)	12.1744	39.9809	40.0	21.0239	12.0138	40.0	40.0	40.0	32.3265
V ₁ (p.u.)	1.0863	1.0094	1.0618	1.0385	1.0836	1.0573	1.0025	1.0614	1.0307
V ₂ (p.u.)	1.0660	1.0126	1.0567	1.0232	1.0605	1.0526	1.003	1.0577	1.0199
V ₅ (p.u.)	1.0318	1.0159	1.0376	1.0007	1.0316	1.0334	1.0152	1.0391	0.9995
V ₈ (p.u.)	1.0366	1.0058	1.0445	1.0077	1.0398	1.0414	1.0073	1.0404	1.0052
V ₁₁ (p.u.)	1.0682	1.0282	1.0869	1.0206	1.0923	1.0636	1.0741	1.085	1.0487
V ₁₃ (p.u.)	1.0513	1.0019	1.0535	1.0084	1.0557	1.0651	1.0045	1.0619	1.0225
QC ₁₀ (MVar)	2.4368	4.9813	2.2702	2.8110	2.4598	1.8761	4.978	2.7664	4.3729
QC ₁₂ (MVar)	4.5770	1.4857	0.5469	2.0835	0.3633	1.4546	0.2133	3.1283	1.9288
QC ₁₅ (MVar)	3.8517	4.9985	4.7902	3.9254	4.7753	4.1351	4.964	3.7911	4.8896
QC ₁₇ (MVar)	0.7006	0.1335	4.9607	4.1501	0.0026	4.6466	0.3048	3.7919	4.9724
QC ₂₀ (MVar)	3.8589	4.9919	2.8438	4.8141	1.5165	2.9651	4.9939	2.8409	4.8724
QC ₂₁ (MVar)	4.5481	4.9220	4.5912	4.5756	4.5349	3.7876	4.9957	4.3194	4.3806
QC ₂₃ (MVar)	0.8898	5.0	2.9763	4.4367	3.9999	3.105	4.9985	4.4275	4.5916
QC ₂₄ (MVar)	3.7669	4.991	4.9134	4.3672	0.0288	4.1594	4.9663	4.0564	4.7495
QC ₂₉ (MVar)	4.7603	2.6897	3.4278	0.9076	2.8941	2.4388	2.5906	2.2152	0.4252
T ₁₁ (p.u.)	1.0310	1.0334	1.0764	1.0305	1.028	1.0837	1.0975	1.066	1.0732
T ₁₂ (p.u.)	0.9305	0.9023	0.9188	0.9176	0.9539	0.9172	0.9002	0.9195	0.9071

Control & state variables	Case 5 – Best solutions				Case 6 – Best solutions				
	Cost	VD	Loss	Comp	Cost	Emission	VD	Loss	Comp
T_{15} (p.u.)	0.9740	0.9708	0.9949	0.9804	0.9819	1.0186	0.9751	1.0081	1.0221
T_{36} (p.u.)	1.0009	0.9647	0.9805	0.9528	0.9924	0.9894	0.9644	0.9737	0.9503
Fuel cost (\$/h)	800.810	963.083	967.436	836.711	801.019	944.052	968.971	967.408	883.322
Emission (t/h)	0.36493	0.20747	0.20728	0.25003	0.35866	0.20489	0.2074	0.20726	0.21867
Loss (MW)	9.0596	3.7631	3.1196	5.8223	8.9455	3.2981	3.7706	3.1252	4.4527
VD (p.u.)	0.7194	0.0928	0.8543	0.1258	0.6748	0.6144	0.0915	0.8640	0.1322
P_{G1} (MW)	176.674	55.718	51.664	119.958	174.266	64.409	52.37	51.684	90.372
Q_{G1} (MVar)	9.4167	-19.170	-0.6274	6.7239	13.6698	-6.6183	-16.587	-3.7947	0.3018
Q_{G2} (MVar)	28.7689	14.9206	9.3719	14.6619	12.406	12.2561	-7.2089	13.6985	8.4412
Q_{G5} (MVar)	26.8555	47.1849	23.6564	30.295	28.7412	23.2282	50.0093	25.5262	26.7427
Q_{G8} (MVar)	31.841	43.7133	28.6725	43.1215	36.3582	29.5873	39.2136	22.4013	28.124
Q_{G11} (MVar)	16.1665	13.5674	28.2925	10.0479	25.8495	23.1675	39.0849	26.2506	25.0788
Q_{G13} (MVar)	2.0411	-3.8742	5.7651	-0.43	7.5889	18.0304	-1.2978	10.4088	10.8016
Worst VD (p.u.)	0.9551				0.9451

Fig. 3.17. IEEE 30-bus system – generator reactive power values for the best solutions in MOOPF cases

Fig. 3.18. IEEE 30-bus system – load bus voltage profiles for the worst VD values in MOOPF cases

Table 3.20. Comparison of the best compromise solutions for MOOPF Cases 1, 2 and 3

Optimization method	Case 1		Case 2		Case 3		
	Cost (\$/h)	Emission (t/h)	Cost (\$/h)	VD (p.u.)	Cost (\$/h)	Emission (t/h)	Loss (MW)
MOEA/D-SF	829.515	0.2501	802.406	0.1362	881.012	0.2164	4.1441
MOEA/D [37]	833.72	0.2438	799.99 ^a	0.3540	902.54	0.2107	3.4594
MOPSO [37]	833.86	0.2483	800.03 ^a	0.4422	891.48	0.2144	3.9557
NSGA-II [37]	835.59	0.2449	800.06 ^a	0.4486	903.79	0.2103	3.7917
MOMICA [47]	865.066	0.2221	804.96	0.0952	-	-	-
ESDE [39]	833.474	0.2540	-	-	-	-	-
ESDE-MC [39]	830.718	0.2483	-	-	-	-	-
ISPEA [43]	865.95	0.2234	-	-	-	-	-
SPEA2 [43]	860.983	0.2305	-	-	-	-	-
GBICA [42]	830.852	0.2488	-	-	-	-	-
MGBICA [42]	830.851	0.2484	-	-	-	-	-
MSFLA [40]	823.278	0.29078	-	-	-	-	-

^aInfeasible solution, constraint on load bus voltage is violated

Table 3.20 and Table 3.21 present comparison of best compromise solutions of MOEA/D-SF and other optimization algorithms. In **Case 1** of cost and emission optimization, best compromise values are **829.515 \$/h** and **0.2501 t/h**, achieved by MOEA/D-SF. MSFLA [40] gives the lowest cost value, but with significantly high level of emission. Barring MSFLA [40], the cost figure given by MOEA/D is the lowest among other remaining algorithms. It is worthwhile to note that reference [39] considers load bus voltage limits in the range of [0.90 p.u.-1.10 p.u.], much wider range than the actual range [0.95 p.u.-1.05 p.u.] considered in all other publications including in our study. The selection of best compromise solution

depends on distribution of non-dominated solutions along Pareto front (PF). [Fig. 3.19](#) reveals that PF of MOEA/D-SF has low concentration of solutions near extreme minimum emission (maximum cost). That is why the compromise solution is slightly favorable towards cost objective. Simultaneous optimization of cost and voltage deviation in **Case 2** by MOEA/D-SF leads to the best minimum value for cost objective in best compromise solution (among valid results).

OPF study with more than two objectives is rare in the literature. In 3-objective optimizations of **Case 3** (in [Table 3.20](#)), **Case 4** and **Case 5** (in [Table 3.21](#)), no single solution can dominate others over all objectives as observed from the tabulated results of some tested algorithms. Among best compromise solutions of MOEA/D-SF, cost objective is the lowest in **Case 3** while voltage deviation (VD) is the least in **Case 4** and **Case 5**. In study **Case 6** with 4-objectives, best compromise solution of MOEA/D-SF has 3-objectives dominating the comparable algorithm MOMICA [\[47\]](#). The cost objective is better in MOMICA [\[47\]](#) because of poor diversity of the algorithm. In comparison of cost objective, while MOEA/D-SF attains maximum cost in the range of 968 \$/h, MOMICA [\[47\]](#) achieves only about 873 \$/h. [Table 3.22](#) shows comparison of the best individual objectives for **Case 1**. Most of the reference papers did not report these values, rather reported only best compromise solutions. Therefore, the table includes comparison of the best individual objectives of the algorithms that are available in the literature. The data listed in the table suggest that MOEA/D-SF could achieve the best cost objective while other comparable algorithms reported lower emission values.

Table 3.21. Comparison of the best compromise solutions for MOOPF Cases 4, 5 and 6

Optimization method	Case 4			Case 5			Case 6			
	Cost (\$/h)	Emission (t/h)	VD (p.u.)	Cost (\$/h)	VD (p.u.)	Loss (MW)	Cost (\$/h)	Emission (t/h)	VD (p.u.)	Loss (MW)
MOEA/D-SF	842.446	0.2406	0.1092	836.711	0.1258	5.8223	883.322	0.2187	0.1322	4.4527
MOEA/D [37]	850.28	0.2332	0.1155	831.81	0.1355	5.9926	-	-	-	-
MOPSO [37]	846.93	0.2386	0.2188	827.82	0.1588	6.5929	-	-	-	-
NSGA-II [37]	825.86	0.2648	0.1421	843.14	0.1931	6.4917	-	-	-	-
B-MMOFPA [49]	-	-	-	843.18	0.1745	5.7886	-	-	-	-
MOMICA [47]	-	-	-	-	-	-	830.188	0.2523	0.2978	5.5850

Table 3.22. Comparison of the best individual objectives for MOOPF Case 1

Parameter	MTLBO [41]		MGBICA [42]		MOICA [48]		MOEA/D [37]		MOEA/D-SF	
	Min. Cost	Min. Emission	Min. Cost	Min. Emission	Min. Cost	Min. Emission	Min. Cost	Min. Emission	Min. Cost	Min. Emission
Fuel cost (\$/h)	801.892	945.196	801.140	942.840	801.145	943.745	799.29 ^a	944.30	800.600	932.966
Emission (t/h)	0.3665	0.2049	0.3296	0.2048	0.3296	0.2048	0.3593 (VD = 2.713)	0.2048	0.36718	0.20564

^aInfeasible solution, constraint on load bus voltage is violated

Fig. 3.19. The best Pareto fronts with MOEA/D-SF and MOEA/D-penalty for MOOPF Case 1

Fig. 3.19 indicates Pareto fronts (PFs) for MOEA/D-SF and MOEA/D with penalty factor approach for **Case 1**. All PFs here represent the best PF with maximum HV value among all trial runs in a case study. Comparative PFs are drawn for the cases compared and listed in Table 3.16 (except Case 6 of 4-objectives). The nature and profile of PFs using both the methods are similar, including for the cases where PFs applying MOEA/D with penalty are not included in this section of the chapter. Though it is reminded that constraint violations are reported in MOEA/D with penalty function approach. In addition, Pareto solutions of MOEA/D-SF dominate majority of the non-dominated solutions given by MOEA/D with penalty factor in many cases.

Pareto front (PF) of another 2-objective optimization of **Case 2** is shown in Fig. 3.20. Regular profiles of PFs can be seen in comparative plots of **Case 3** in Fig. 3.21. In general, MOEA/D-SF can attain much diverse and well distributed PFs for all the cases. More complex PFs can be found for 3-objective study cases, **Case 4** and **Case 5**, presented in Fig. 3.22 and Fig. 3.23, respectively. MOEA/D-SF arrives at approximate Pareto solutions for these cases. All the PFs when assessed against the PFs of equivalent study cases in [37], are found to be very much alike. However, superiority of MOEA/D-SF lies in its ability to strictly comply with the limits of system constraints. Fig. 3.24 is for parallel coordinates plot of the Pareto solutions of best PF in **Case 6**. The objective values are required to be normalized to execute the plot. The diagram shows a fairly good distribution of solutions with the 4-objective optimization case study using MOEA/D-SF.

Fig. 3.20. The best Pareto front with MOEA/D-SF for MOOPF Case 2

Fig. 3.21. The best Pareto fronts with MOEA/D-SF and MOEA/D-penalty for MOOPF Case 3

Fig. 3.22. The best Pareto front with MOEA/D-SF for MOOPF Case 4

Fig. 3.23. The best Pareto front with MOEA/D-SF for MOOPF Case 5

Fig. 3.24. Parallel coordinates plot of the best PF solutions with MOEA/D-SF for MOOPF Case 6

d) IEEE 57-bus system: detailed results and comparison

Settings of all control variables alongwith their allowable ranges for the best solutions of individual objective functions over all trial runs and best compromise solutions are listed in [Table A.9](#), [Table A.10](#), [Table A.11](#) and [Table A.12](#) in the Appendix for **Case 7**, **Case 8**, **Case 9** and **Case 10**, respectively pertaining to IEEE 57-bus system. Like earlier cases, best compromise solution is extracted from best Pareto front with highest HV value. The limits imposed on generator reactive power capability are taken from ref. [135]. Reactive power ranges for some of the generators are quite narrow. The recorded data in the tables in Appendix and scatter in [Fig. 3.25](#) clearly demonstrate that the algorithm duly complies with the constraints on generator reactive power in all the cases. The worst aggregate voltage deviation (VD in [Eq. \(3.22\)](#)) of load buses in a case study over all trial runs is shown in last row of the table. For the system, the permissible range of load bus voltage is [0.94 p.u.-1.06 p.u.]. For 50-load buses (PQ buses), theoretically, the maximum possible collective voltage deviation is 3 p.u. (i.e. 50×0.06 p.u.). Voltage profiles for the worst VD values are presented in [Fig. 3.26](#) for all study cases. As it transpires from the diagram, realistically, VD value shall be much lower to comply with specified voltage bounds. Furthermore, the optimal operating voltages of many load buses are found near to the upper limit. This very fact reiterates the need of an effective constraint handling technique for the constrained OPF problem.

Fig. 3.25. IEEE 57-bus system – generator reactive power values for the best solutions in MOOPF cases

Fig. 3.26. IEEE 57-bus system – load bus voltage profiles for the worst VD values in MOOPF cases

Table 3.23. Comparison of the best individual objectives for MOOPF Case 7

Parameter	GBICA [42]		MGBICA [42]		MOEA/D-SF	
	Min. Cost	Min. Emission	Min. Cost	Min. Emission	Min. Cost	Min. Emission
Fuel cost (\$/h)	41740.29	43541.02	41715.71	43641.42	41683.39	45387.44
Emission (t/h)	1.8683	1.1881	1.8445	1.1724	1.8670	1.0814

Table 3.24. Comparison of the best compromise solutions of MOOPF cases for IEEE 57-bus system

Optimization method	Case 7		Case 8		Case 9			Case 10			
	Cost (\$/h)	Emission (t/h)	Cost (\$/h)	VD (p.u.)	Cost (\$/h)	Loss (MW)	VD (p.u.)	Cost (\$/h)	Emission (t/h)	VD (p.u.)	Loss (MW)
MOEA/D-SF	42160.09	1.3183	41822.11	0.6079	42059.16	12.2996	0.6729	42648.69	1.3437	0.6713	11.886
ISPEA [43]	42444.55	1.2904	-	-	-	-	-	-	-	-	-
NSGA-II [43]	43567.77	1.2979	-	-	-	-	-	-	-	-	-
SPEA2 [43]	42320.25	1.4054	-	-	-	-	-	-	-	-	-
ESDE [39]	42863.32	1.2662	-	-	-	-	-	-	-	-	-
ESDE-MC [39]	42857.49	1.2191	-	-	-	-	-	-	-	-	-
GBICA [42]	42138.37	1.3941	-	-	-	-	-	-	-	-	-
MGBICA [42]	42369.07	1.2940	-	-	-	-	-	-	-	-	-
MOMICA [47]	41886.80	1.4784	-	-	-	-	-	41983.06	1.4960	0.7970	13.697
MOICA [47]	41919.71	1.6010	-	-	-	-	-	41998.57	1.7605	0.8748	13.335
MDE [45]	-	-	41843	0.5962	42070	12.4024	0.6933	-	-	-	-
CMICA4 [46]	-	-	-	-	41781.73	13.9936	0.8127	-	-	-	-
NSGA-II [46]	-	-	-	-	41930.94	21.5325	2.6699	-	-	-	-
MOPSO [46]	-	-	-	-	41901.36	16.8022	2.0059	-	-	-	-

A limited number of multi-objective optimization studies have been performed in past for IEEE 57-bus system. Table 3.23 compares the best individual objectives given by MOEA/D-SF with the reported results of GBICA [42] and MGBICA [42] for **Case 7**. Algorithm MOEA/D-SF outperforms these two algorithms on individual best objectives. This proves better diversity of present algorithm. Table 3.24 presents comparison of best compromise solutions of current study with past studies available in the literature. In **Case 7**, MOMICA [47], MOICA [47] and GBICA [42] report better cost values (but with higher emission levels) than what MOEA/D does. Like GBICA [42], MOMICA [47] and MOICA [47] also suffer from low diversity. While MOEA/D-SF can achieve maximum cost of about 45387 \$/h (i.e. minimum emission level of 1.0814 t/h), MOMICA [47] and MOICA [47] can attain only about 43600 \$/h. The best compromise solutions of these algorithms have lower cost values (than MOEA/D-SF) precisely for this reason. ESDE-MC [39] achieves lowest emission level with cost being higher than some other comparable algorithms. In best compromise solutions of **Case 8** and **Case 9**, no algorithm can dominate all others on all objectives. However, MOEA/D-SF achieves better loss and voltage deviation (VD) than what others attain. In 4-objective optimization **Case 10**, MOEA/D can outperform the solutions given by MOMICA [47] and MOICA [47] in 3 objectives. However, the two comparable algorithms yield smaller costs for the reason stated in comparison of **Case 7**.

Fig. 3.27. The best Pareto fronts with MOEA/D-SF and MOEA/D-penalty for MOOPF Case 7

Fig. 3.27 and Fig. 3.29 show comparative studies of best Pareto fronts (PFs) applying MOEA/D-SF and MOEA/D with penalty factor approach for **Case 7** and **Case 9**, respectively. PF solutions in **Case 7** trace almost same trajectory for the two methods, though

the diversity of solutions is slightly better with MOEA/D-SF. Like 30-bus system, one needs to be careful with the Pareto optimal solutions of penalty method as some solutions violate the load bus voltage limits. A more regular distribution of Pareto optimal solutions is observed in **Case 9** of 3-objective optimization with MOEA/D-SF. [Fig. 3.28](#) is for the best PF pertaining to **Case 8**. In this case, PF with reasonably good diversity and distribution is achieved by MOEA/D-SF algorithm. A good distribution of Pareto solutions is also observed in parallel coordinates plot in [Fig. 3.30](#) for the 4-objective optimization **Case 10** using MOEA/D-SF.

Fig. 3.28. The best Pareto front with MOEA/D-SF for MOOPF Case 8

Fig. 3.29. The best Pareto fronts with MOEA/D-SF and MOEA/D-penalty for MOOPF Case 9

Fig. 3.30. Parallel coordinates plot of the best PF solutions with MOEA/D-SF for MOOPF Case 10

3.2.3 Conclusion: multi-objective OPF study

Multi-objective non-linear optimization has been a difficult problem to deal with due to presence of two or more objectives, often conflicting one another. The complexity of the problem escalates in presence of non-linear constraints. This section of the chapter discusses in detail the application and usefulness of a proper constraint handling technique, superiority of feasible solutions (SF), in conjunction with MOEA/D in multi-objective optimal power flow (MOOPF) problem. The results of MOEA/D-SF for MOOPF problem are highly competitive in the context of achieving compromise solutions. Though the compromise solution is not always the best, it is not dominated over all objectives by the solutions of other comparable algorithms. The conclusions of this section of the chapter can be summarized as below:

- SF method can effectively handle constraints in constrained multi-objective optimization problems with MOEA/D being the basic optimization algorithm.
- The MOEA/D-SF can achieve very good diversity and convergence for several OPF objectives satisfying all network constraints.
- Pareto solutions, compromise solutions and extreme values (i.e. minimum individual objectives) of the algorithm MOEA/D-SF are among the best.

Moreover, satisfying system constraints is of paramount importance and an efficient constraint handling technique can play significant roles in that. As substantiated in our study, static penalty function approach often yields control parameter settings following which

network constraints may be violated. Such condition of the electrical network or network component is undesirable. Each Pareto solution given by MOEA/D-SF signifies a set of control parameter settings which, if followed, can successfully lead to an acceptable condition of the network.

3.3. Optimal power flow study with stochastic wind and solar power

Classical optimal power flow with conventional (thermal) generators discussed so far is a non-linear complex problem with non-linear constraints. Incorporating intermittent nature of solar and wind energy escalates the complexity of the problem. This section of the chapter proposes an approach to solve optimal power flow combining stochastic wind and solar power with conventional thermal power in the system. Weibull and lognormal probability density functions (PDFs) are used to forecast the wind and photovoltaic power, respectively. The objective function considers reserve cost for overestimation and penalty cost for underestimation of intermittent renewable sources. Besides, emission factor is also included in the objectives of selected case studies.

The biggest challenge in incorporating wind and solar (Photovoltaic or PV) power in grid integration is their intermittent nature. Normally wind or solar farms are owned by private operators. Grid / independent system operator (ISO) signs an agreement of purchasing certain amount of power (scheduled power) from these private operators. But as generation from these renewable sources is uncertain, sometimes, the power output may be more than the scheduled power leading to underestimation of the available amount. ISO is to bear the penalty cost as surplus power goes wasted if not utilized. On contrary, overestimation is the scenario when the generated power is less than the scheduled power. To mitigate power demand, ISO needs to keep spinning reserve which adds up to the operating cost of the system. The objective function of OPF formulated in this section considers direct, penalty and reserve costs of renewable energy in addition to the generation cost of thermal power units. Wind speed distribution is modeled using Weibull PDF and solar irradiance distribution is with lognormal PDF. IEEE 30-bus system is modified in this study to accommodate wind and solar power generators. Generation cost is optimized and the effect of change in reserve and penalty costs on optimal scheduling is studied. On the aspect of emission - fossil fuel driven thermal generators emit harmful gases into the environment while renewable sources do not. Carbon tax [94] is imposed in some countries in proportion to the volume of emitted greenhouse gases. In selected case studies, carbon tax amount is entwined with the objective function to study the effect on generator scheduling. SHADE-SF algorithm, discussed in Chapter 2 section 2.1.4.1, is employed for the optimization case studies in this work. The selected algorithm is proven to perform very well on the problem of OPF as observed in section 3.1.3.

The organization of rest of this section of the chapter is done in following way. Sub-section 3.3.1 includes a review of mathematical model including applicable constraints pertaining to OPF problem. In sub-section 3.3.2, modeling of uncertainties in wind and solar power is presented. Sub-section 3.3.3 discusses the case studies and simulation results, followed by concluding remarks in sub-section 3.3.4.

3.3.1 Mathematical models of OPF incorporating stochastic wind and solar power

Table 3.25 summarizes basic parameters of the modified IEEE 30-bus network. The adapted network consists of three thermal generators, two wind generators and one PV array. One-line diagram of the modified system is presented in Fig. 3.31. There are 11 control variables for the optimization case study as listed in the table. Transformer tap settings are considered fixed at 1 p.u. Further, as both wind and solar (PV) power outputs are variables, the fluctuation in power output must be balanced by combining outputs from all the generators and the reserve. Thus, total generation cost consists of operation costs of all the generators, penalty and reserve costs which are explained later.

Table 3.25. Summary of the adapted IEEE 30-bus system for OPF study with wind and solar power

Items	Quantity	Details
Buses	30	Table A.1 (Appendix)
Branches	41	Table A.3 (Appendix)
Thermal generators ($TG1, TG2, TG3$)	3	Buses: 1 (swing), 2 and 8
Wind generators ($WG1, WG2$)	2	Buses: 5 and 11
PV unit (PV)	1	Bus: 13
Control variables	11	Scheduled real power for 5 generators: $TG2, TG3, WG1, WG2$ and PV ; bus voltages of all generator buses (6 nos.)
Connected load	-	283.4 MW, 126.2 MVar
Allowable range for load bus voltage	24	[0.95 – 1.05] p.u.

a) Cost model of thermal power generators

The cost calculation for thermal generating units is explained in sub-section 3.1.2 of this chapter. We consider cost with valve-point loading effect as in Eq. (3.21), reproduced here for convenience. Total generation cost (\$/h) of thermal units:

$$C_T(P_{TG}) = \sum_{i=1}^{N_{TG}} a_i + b_i P_{TGi} + c_i P_{TGi}^2 + \left| d_i \times \sin \left(e_i \times (P_{TGi}^{min} - P_{TGi}) \right) \right| \quad (3.26)$$

where a_i, b_i, c_i, d_i and e_i are all cost coefficients of the i -th thermal generator producing power output P_{TGi} . Number of thermal generators is N_{TG} . P_{TGi}^{min} is the minimum power of the

i -th thermal unit. All cost and emission coefficients for the thermal generating units used in the calculations are provided in Table 3.26.

Fig. 3.31. The adapted IEEE 30-bus system for OPF study with stochastic wind and solar power

Table 3.26. Cost and emission coefficients for thermal generators of the adapted system

Gen #	Bus	a (\$/h)	b (\$/MWh)	c (\$/MW ² h)	d (\$/h)	e (rad/ MW)	φ	ψ	ω	τ	ζ
TG1	1	0	2	0.00375	18	0.037	4.091	-5.554	6.49	0.0002	6.667
TG2	2	0	1.75	0.01750	16	0.038	2.543	-6.047	5.638	0.0005	3.333
TG3	8	0	3.25	0.00834	12	0.045	5.326	-3.55	3.38	0.002	2

b) Direct cost of wind and photovoltaic power

Unlike conventional thermal power generators, solar and wind power generators require no fuel. Therefore, in the case where wind/solar power plants are owned by the independent system operator (ISO), the direct cost component may not exist (as no fuel is needed) unless the ISO wants to assign some payback for initial set-up or to assign this as the maintenance

and renewal cost [150]. But when wind or PV power plants are owned by private parties, ISO pays a price proportional to the scheduled power contractually agreed.

Direct cost involved with wind power from j -th plant is modeled as a function of scheduled power:

$$C_{w,j}(P_{ws,j}) = g_j P_{ws,j} \quad (3.27)$$

where g_j is the direct cost coefficient associated with j -th wind power plant, $P_{ws,j}$ is the scheduled power from the same plant.

Similar to wind power plant, direct cost pertaining to k -th PV power plant is:

$$C_{s,k}(P_{ss,k}) = h_k P_{ss,k} \quad (3.28)$$

where h_k is the direct cost coefficient associated with k -th PV power plant, $P_{ss,k}$ is the scheduled power from the same plant.

c) Cost evaluation of uncertainties in wind power

A situation may arise when actual power delivered by the wind farm is less than the estimated value. This is termed as overestimation of power from the uncertain source. The system operator needs to have spinning reserve for such scenarios to provide uninterrupted supply to the consumers. The cost of committing the reserve to meet over-estimated power is termed as reserve cost [52].

Reserve cost for the j -th wind power plant is defined as:

$$\begin{aligned} C_{Rw,j}(P_{ws,j} - P_{wav,j}) &= K_{Rw,j}(P_{ws,j} - P_{wav,j}) \\ &= K_{Rw,j} \int_0^{P_{ws,j}} (P_{ws,j} - p_{w,j}) f_w(p_{w,j}) dp_{w,j} \end{aligned} \quad (3.29)$$

where $K_{Rw,j}$ is the reserve cost coefficient pertaining to j -th wind power plant, $P_{wav,j}$ is the actual available power from the same plant. $f_w(p_{w,j})$ is the wind power probability density function for j -th wind power plant. Calculation of probabilities of output power at various wind speeds are discussed later in sub-section 3.3.2.

On contrary to the overestimation case, there may be a condition in the network when actual power delivered by the wind farm is higher than the estimated value. The renewable source output is underestimated in such a case. The surplus power is wasted if it is not possible to utilize by reducing power output from conventional generators. ISO needs to pay a penalty cost for the surplus amount.

Penalty cost for the j -th wind power plant is defined as:

$$\begin{aligned} C_{PW,j}(P_{wav,j} - P_{ws,j}) &= K_{PW,j}(P_{wav,j} - P_{ws,j}) \\ &= K_{PW,j} \int_{P_{ws,j}}^{P_{wr,j}} (p_{w,j} - P_{ws,j}) f_w(p_{w,j}) dp_{w,j} \end{aligned} \quad (3.30)$$

where $K_{PW,j}$ is the penalty cost coefficient for the j -th wind power plant, $P_{wr,j}$ is rated output from the same windfarm.

d) Cost evaluation of uncertainties in photovoltaic power

Like wind power plants, PV power plants also have intermittent and uncertain output. In principle, approach to over and under estimation of solar power shall be same as the wind power. However, solar radiation follows lognormal PDF [151], different from wind speed distribution which is well known to trail Weibull PDF. For convenience in calculation, the reserve and penalty cost models for PV power are developed based on the concept presented in [53].

Reserve cost for the k -th solar power plant is:

$$\begin{aligned} C_{RS,k}(P_{ss,k} - P_{sav,k}) &= K_{RS,k}(P_{ss,k} - P_{sav,k}) \\ &= K_{RS,k} * f_s(P_{sav,k} < P_{ss,k}) * [P_{ss,k} - E(P_{sav,k} < P_{ss,k})] \end{aligned} \quad (3.31)$$

where $K_{RS,k}$ is the reserve cost coefficient pertaining to k -th solar power plant, $P_{sav,k}$ is the actual available power from the same plant. $f_s(P_{sav,k} < P_{ss,k})$ is the probability of solar power shortage i.e. actual power below the scheduled power ($P_{ss,k}$), $E(P_{sav,k} < P_{ss,k})$ is the expectation of PV power below $P_{ss,k}$.

Penalty cost for the underestimation of k -th solar power plant is:

$$\begin{aligned} C_{PS,k}(P_{sav,k} - P_{ss,k}) &= K_{PS,k}(P_{sav,k} - P_{ss,k}) \\ &= K_{PS,k} * f_s(P_{sav,k} > P_{ss,k}) * [E(P_{sav,k} > P_{ss,k}) - P_{ss,k}] \end{aligned} \quad (3.32)$$

where $K_{PS,k}$ is the penalty cost coefficient pertaining to k -th solar power plant, $f_s(P_{sav,k} > P_{ss,k})$ is the probability of solar power surplus i.e. actual power above the scheduled power ($P_{ss,k}$), $E(P_{sav,k} > P_{ss,k})$ is the expectation of solar power above $P_{ss,k}$.

e) Emission and carbon tax

The calculation of emission from thermal generators is presented in sub-section 3.1.2 of this chapter. The equation to be used is same as Eq. (3.19) and re-written here for easy reference.

Emission in tonnes/hour -

$$\text{Emission, } E = \sum_{i=1}^{N_{TG}} [(\varphi_i + \psi_i P_{TGi} + \omega_i P_{TGi}^2) \times 0.01 + \tau_i \exp(\zeta_i P_{TGi})] \quad (3.33)$$

where $\varphi_i, \psi_i, \omega_i, \tau_i$ and ζ_i are all emission coefficients associated with the i -th thermal generator. Emission coefficients for the thermal generating units are provided in [Table 3.26](#).

In recent years, due to global warming, many countries are putting enormous pressure on the entire energy sector to reduce carbon emission [94]. To encourage investment in cleaner forms of power like wind and solar, carbon tax (C_{tax}) is imposed on per unit amount of emitted greenhouse gases. The cost of emission (in \$/h) is represented as:

$$\text{Emission cost, } C_E = C_{tax} E \quad (3.34)$$

f) Objectives of optimization

The objective of OPF is formulated incorporating all the cost functions as discussed above. In first objective function, emission cost is not included. In second objective function, emission cost is added to study the effect of carbon tax on generation scheduling.

First objective: Minimize –

$$\begin{aligned} F_1 = C_T(P_{TG}) + \sum_{j=1}^{N_{WG}} [C_{W,j}(P_{ws,j}) + C_{RW,j}(P_{ws,j} - P_{wav,j}) + C_{PW,j}(P_{wav,j} - P_{ws,j})] \\ + \sum_{k=1}^{N_{SG}} [C_{S,k}(P_{ss,k}) + C_{RS,k}(P_{ss,k} - P_{sav,k}) + C_{PS,k}(P_{sav,k} - P_{ss,k})] \end{aligned} \quad (3.35)$$

where N_{WG} and N_{SG} are the numbers of wind generators and solar power generators in the network, respectively. All other cost components are computed using [Eqs. \(3.26\) - \(3.33\)](#).

Second objective: Minimize –

$$F_2 = F_1 + C_{tax} E \quad (3.36)$$

The OPF objectives are subject to system equality and inequality constraints.

i. Equality constraints

Equality constraints are the power balance equations where the generated active and reactive power in the network must be equal to the sum of respective demands and losses.

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{NB} V_j [G_{ij} \cos(\delta_{ij}) + B_{ij} \sin(\delta_{ij})] = 0 \quad \forall i \in NB \quad (3.37)$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} V_j [G_{ij} \sin(\delta_{ij}) - B_{ij} \cos(\delta_{ij})] = 0 \quad \forall i \in NB \quad (3.38)$$

where $\delta_{ij} = \delta_i - \delta_j$, is the difference in voltage angles of bus i and bus j , NB is the total number of buses, P_{Di} and Q_{Di} are active and reactive load demands, respectively at bus i . P_{Gi} and Q_{Gi} are active and reactive power generation respectively at bus i from any of the sources (conventional or renewable) as applicable. G_{ij} is the transfer conductance and B_{ij} is the susceptance between bus i and bus j , respectively.

ii. Inequality constraints

The inequality constraints are the operating limits of the equipment and components in power system, and security constraints on lines and load buses.

- Generator constraints: $P_{TGi}^{min} \leq P_{TGi} \leq P_{TGi}^{max} \quad \forall i \in N_{TG} \quad (3.39)$

$$P_{ws,j}^{min} \leq P_{ws,j} \leq P_{ws,j}^{max} \quad \forall j \in N_{WG} \quad (3.40)$$

$$P_{ss,k}^{min} \leq P_{ss,k} \leq P_{ss,k}^{max} \quad \forall k \in N_{SG} \quad (3.41)$$

$$Q_{TGi}^{min} \leq Q_{TGi} \leq Q_{TGi}^{max} \quad \forall i \in N_{TG} \quad (3.42)$$

$$Q_{ws,j}^{min} \leq Q_{ws,j} \leq Q_{ws,j}^{max} \quad \forall j \in N_{WG} \quad (3.43)$$

$$Q_{ss,k}^{min} \leq Q_{ss,k} \leq Q_{ss,k}^{max} \quad \forall k \in N_{SG} \quad (3.44)$$

$$V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{max} \quad \forall i \in NG \quad (3.45)$$

- Security constraints: $V_{Lp}^{min} \leq V_{Lp} \leq V_{Lp}^{max} \quad \forall p \in NL \quad (3.46)$

$$S_{lq} \leq S_{lq}^{max} \quad \forall q \in nl \quad (3.47)$$

Eqs. (3.39) - (3.41) represent the active power generation limits of thermal, wind and solar power generators, respectively. Eqs. (3.42) - (3.44) define the reactive power capabilities of the generators following same order of thermal, wind and solar. NG is the number of generators or generator buses (thermal and renewables). Eq. (3.45) is for the constraint on voltage of generator buses, while Eq. (3.46) defines the voltage limits imposed on load buses (PQ buses) with NL being the number of load buses. Line capacity constraints are given by Eq. (3.47) for total nl numbers of lines in the network.

It is worth mentioning that convergence of power flow to a solution ensures that the equality constraints of power balance equations are automatically satisfied. Among inequality constraints, generator active power (except slack or swing generator considered to be connected to bus 1) and generator bus voltages are termed as control variables which are self-limiting. For each such variable, the optimization algorithm selects a feasible value

within the range of that variable. Inequality constraints on slack generator power, reactive power output of the remaining generators, load bus voltage limits and line capabilities need special attention. Handling of inequality constraints consisting of these variables requires proper constraint handling technique.

Consideration of the generator reactive power capability is an important aspect in OPF study. For thermal generators, narrower ranges are implemented in the study than what have been provided in [136]. The reactive power capability of wind turbines has considerably been enhanced in recent years. Wind turbines (WTs) featuring full reactive power capability are already commercially available [152]. Ref. [153] discusses dependence of reactive power capability of a DFIG based WT on several factors for a certain active power. However, the reactive power range is found to be approximately between -0.8 p.u. and 0.8 p.u. in most conditions. The reactive power capability curve of Enercon FACTS-WT shows that throughout active power output range, the WT can deliver reactive power from -0.4 p.u. to 0.5 p.u. Delivery of negative reactive power signifies reactive power absorbing capability of the generator. Rooftop PVs can be modeled as load bus (PQ bus) with $Q=0$. However, utility scale PVs are equipped with converters for which complete modeling of generator capability (P-Q capability) becomes necessary owing to the dynamic behavior of the converters [154]. Ref. [155] analyses reactive power capability of PV including converter and controller models. Tobar *et. al.* [156] extends the study on PV converter capability considering variation in solar radiation and ambient temperature. For our study purpose, we consider that the reactive power capability of the solar power generator is approximately between -0.4 p.u. and 0.5 p.u. Active (P) and reactive (Q) power limits of generators are listed in the result section.

3.3.2 Stochastic wind / solar power and uncertainty models

It is well established that wind speed distribution follows Weibull probability density function (PDF) [50]-[53]. The probability of wind speed v m/s following Weibull PDF with scale factor (α) and shape factor (β) is given by:

$$f_v(v) = \left(\frac{\beta}{\alpha}\right) \left(\frac{v}{\alpha}\right)^{(\beta-1)} e^{-(v/\alpha)^\beta} \text{ for } 0 < v < \infty \quad (3.48)$$

Mean of Weibull distribution is defined as:

$$M_{wbl} = \alpha * \Gamma(1 + \beta^{-1}) \quad (3.49)$$

where gamma function $\Gamma(x)$ is described as:

$$\Gamma(x) = \int_0^{\infty} e^{-t} t^{x-1} dt \quad (3.50)$$

Fig. 3.32. Wind speed distribution (sample size 8000) for wind farm #1 at bus 5

Fig. 3.33. Wind speed distribution (sample size 8000) for wind farm #2 at bus 11

In our case studies of IEEE 30-bus system, conventional generators in bus 5 and bus 11 are replaced with wind power generators. Values of selected Weibull scale (α) and shape (β) parameters are provided in [Table 3.27](#). Unless mentioned otherwise for a specific case study, we follow these PDF parameters throughout. Weibull fitting and wind frequency distribution

in each of Fig. 3.32 and Fig. 3.33 are obtained after running 8000 Monte-Carlo scenarios. Standard [157] stipulates the design requirement of wind turbines and defines highest turbulent class IA of the turbine which is certified to perform for maximum annual average wind speed of 10 m/s at hub height. Care is taken in choosing scale (α) and shape (β) parameters for the windfarms such that maximum Weibull mean value remains around 10. Besides, different PDF parameters for the two windfarms characterize the realistic geographical diversity of the sites.

Table 3.27. PDF parameters for the sources of wind and PV power plants

Wind power generating plants					PV power plant		
Wind farm #	No. of turbines	Rated power, P_{wr} (MW)	Weibull PDF parameters	Weibull mean, M_{wbl}	Rated power, P_{sr} (MW)	Lognormal PDF parameters	Lognormal mean, M_{lgn}
1 (bus 5)	25	75	$\alpha = 9$ $\beta = 2$	$v = 7.976$ m/s	50	$\mu = 6$ $\sigma = 0.6$	$G_s = 483$ W/m ²
2 (bus 11)	20	60	$\alpha = 10$ $\beta = 2$	$v = 8.862$ m/s	(bus 13)

Fig. 3.34. Solar irradiance distribution (sample size 8000) for the PV plant at bus 13

Conventional generator at bus 13 of IEEE 30-bus system is replaced by a PV power generator. The output from the PV unit is dependent upon solar irradiance (G_s) which follows lognormal PDF [151]. The probability of solar irradiance (G_s) following lognormal PDF with mean μ and standard deviation σ is:

$$f_G(G_s) = \frac{1}{G_s \sigma \sqrt{2\pi}} \exp \left\{ \frac{-(\ln G_s - \mu)^2}{2\sigma^2} \right\} \text{ for } G_s > 0 \quad (3.51)$$

Mean of lognormal distribution is defined as:

$$M_{lgn} = \exp\left(\mu + \frac{\sigma^2}{2}\right) \quad (3.52)$$

Fig. 3.34 indicates frequency distribution and lognormal fitting of solar irradiance after running Monte Carlo simulation with a sample size of 8000. Table 3.27 summarizes the selected parameters for lognormal PDF. Unless mentioned otherwise for a specific case study, we follow these PDF parameters throughout.

a) Wind and photovoltaic power model

We consider wind power connected to bus 5 is the collective output of 25 wind turbines in the farm, and the output of a windfarm having 20 turbines is connected to bus 11. Each turbine has a rated power of 3 MW. Actual output from a wind turbine depends on the wind speed it encounters. Power output of a turbine as a function of wind speed (v) can be described as [57]:

$$p_w(v) = \begin{cases} 0, & \text{for } v < v_{in} \text{ and } v > v_{out} \\ p_{wr} \left(\frac{v - v_{in}}{v_r - v_{in}} \right) & \text{for } v_{in} \leq v \leq v_r \\ p_{wr} & \text{for } v_r < v \leq v_{out} \end{cases} \quad (3.53)$$

where v_{in} , v_r and v_{out} are the turbine cut-in, rated and cut-out wind speeds, respectively. p_{wr} is the rated output power of the wind turbine. For the 3-MW wind turbine, Enercon E82-E4 product datasheet is consulted. The various speed values are $v_{in} = 3$ m/s, $v_r = 16$ m/s and $v_{out} = 25$ m/s.

The solar irradiance (G_s) to energy conversion for the PV unit is given by [60]:

$$P_s(G_s) = \begin{cases} P_{sr} \left(\frac{G_s^2}{G_{std} R_c} \right) & \text{for } 0 < G_s < R_c \\ P_{sr} \left(\frac{G_s}{G_{std}} \right) & \text{for } G_s \geq R_c \end{cases} \quad (3.54)$$

where G_{std} is the solar irradiance in standard environment, set as 800 W/m². R_c is a certain irradiance point, set as 120 W/m². P_{sr} is the rated output of the PV power plant.

b) Calculation of wind power probabilities

Referring to Eq. (3.53), it may be observed that the wind power is discrete in a couple of regions of wind speed. When wind speed (v) is below cut-in speed (v_{in}) and above cut-out speed (v_{out}), the power output is zero. The turbine gives rated power output p_{wr} between

rated wind speed (v_r) and cut-out speed (v_{out}). For these discrete zones, probabilities are given by [57]:

$$f_w(p_w)\{p_w = 0\} = 1 - \exp\left[-\left(\frac{v_{in}}{\alpha}\right)^\beta\right] + \exp\left[-\left(\frac{v_{out}}{\alpha}\right)^\beta\right] \quad (3.55)$$

$$f_w(p_w)\{p_w = p_{wr}\} = \exp\left[-\left(\frac{v_r}{\alpha}\right)^\beta\right] - \exp\left[-\left(\frac{v_{out}}{\alpha}\right)^\beta\right] \quad (3.56)$$

The wind turbine power output is continuous between cut-in speed (v_{in}) and rated speed (v_r) of wind. The probability for the continuous region is calculated as [57]:

$$f_w(p_w) = \frac{\beta(v_r - v_{in})}{\alpha^\beta * p_{wr}} \left[v_{in} + \frac{p_w}{p_{wr}}(v_r - v_{in}) \right]^{\beta-1} \exp\left[-\left(\frac{v_{in} + \frac{p_w}{p_{wr}}(v_r - v_{in})}{\alpha}\right)^\beta\right] \quad (3.57)$$

c) Calculation of solar power over/under estimation cost

Histogram in Fig. 3.35 represents the available stochastic power for the PV plant. The maximum available real power from the plant is capped at rated power of the PV plant (i.e. 50 MW). The PV farm operator may not be qualified for penalty payment beyond the rated capacity of the plant, though the site has the potential to harness more solar energy. The magenta dotted line indicates the scheduled power the PV plant is supposed to deliver to the grid. As mentioned before, the scheduled power can be any amount of power mutually agreed between ISO and the solar firm owner. The overestimation cost in Eq. (3.31) can be calculated as (subscript ‘ k ’ in Eq. (3.31) is omitted here for single solar power plant):

$$C_{RS}(P_{ss} - P_{sav}) = K_{RS}(P_{ss} - P_{sav}) = K_{RS} \sum_{n=1}^{N_b^-} [P_{ss} - P_{sn-}] * f_{sn-} \quad (3.58)$$

where P_{sn-} is the available power which is less than the scheduled power P_{ss} , on left-half plane of P_{ss} in the histogram in Fig. 3.35. f_{sn-} is the relative frequency of occurrence of P_{sn-} . N_b^- is the number of discrete bins on left-half of P_{ss} or in other words, the number of pairs (P_{sn-}, f_{sn-}) generated for the PDF. To reduce computational burden in every iteration, the average (P_{sn}, f_{sn}) values of the bins (segments) are considered in calculation. Increasing number of segments does improve accuracy of results to an extent. For the problem in our study, a total (N_b) of 30 segments give fairly accurate results.

Fig. 3.35. Distribution of available real power (MW) from the PV plant at bus 13

Like overestimation, the underestimation cost in Eq. (3.32) can be calculated as:

$$C_{PS}(P_{sav} - P_{ss}) = K_{PS}(P_{sav} - P_{ss}) = K_{PS} \sum_{n=1}^{N_b^+} [P_{sn+} - P_{ss}] * f_{sn+} \quad (3.59)$$

where P_{sn+} is the available power which is more than the scheduled power P_{ss} , on right-half plane of P_{ss} in the histogram in Fig. 3.35. f_{sn+} is the relative frequency of occurrence of P_{sn+} . N_b^+ is the number of discrete bins on right-half of P_{ss} or in other words, the number of pairs (P_{sn+}, f_{sn+}) generated for the PDF.

3.3.3 Case studies and results for OPF with stochastic wind and solar power

Several case studies are performed for the adapted IEEE 30-bus system. Results of the case studies with application of SHADE-SF algorithm are tabulated and explanation are provided in this section. SHADE-SF algorithm can be referred in Chapter 2, section 2.1.4.1. The first two cases here are to examine variation of generation costs of wind and solar power with change in respective scheduled power and PDF parameters individually. The remaining case studies optimize the generation schedule from all sources. In each optimization case study, a maximum of 24000 function evaluations ($maxeval = 24000$) are performed for a population size of 30 (i.e. $Np = 30$) in a single complete run of the algorithm. Each case is run 5 times and the best value of the objective function thus found and corresponding settings of control variables are recorded.

a) *Case 1: Scheduled power vs cost (wind and solar power)*

The Weibull PDF parameters in this case are same as mentioned in Table 3.27. Relevant wind turbine parameters are provided in sub-section 3.3.2. Direct cost coefficients of wind power are $g_1 = 1.6$, $g_2 = 1.75$. Penalty cost coefficient for not utilizing full available wind power is assumed as $K_{PW,1} = K_{PW,2} = 1.5$ and reserve cost coefficient for overestimation is $K_{RW,1} = K_{RW,2} = 3$. Note that the direct cost of renewable energy is less than the average cost of thermal energy while the penalty cost for not using available wind power is less than the direct cost [158]. The scheduled power is varied from 0 to wind farm rated power and variations of reserve, penalty, direct and total costs are plotted in Fig. 3.36 and Fig. 3.37 for the two windfarms. Total cost is the sum of direct, reserve and penalty costs corresponding to the scheduled power. Direct cost follows linear relationship with scheduled power. As scheduled power increases, necessity of larger spinning reserve escalates the reserve cost and consequently the overall generation cost. The penalty cost rightly decreases, however at a lower rate, with the increase in scheduled power.

Fig. 3.36. Variation of wind power cost vs scheduled power for wind generator *WG1*

Fig. 3.37. Variation of wind power cost vs scheduled power for wind generator $WG2$

Fig. 3.38. Variation of solar power cost vs scheduled power for the PV plant

Similar to wind power, cost variations for over/under-estimation of solar power are plotted against scheduled power in Fig. 3.38. Yearly operation and maintenance cost of a PV power plant and an onshore wind power plant is in a similar range [159]. Therefore, the direct, penalty and reserve cost coefficients for solar power are assumed to be $h = 1.6$, $K_{ps} = 1.5$ and $K_{rs} = 3$, respectively. Other related PV plant parameters are discussed in sub-section 3.3.2. With the selected PDF parameters for solar irradiance, the total PV power cost is not monotonically increasing. Indeed, the minimum cost is reported somewhere around 18 MW of scheduled power.

b) Case 2: Probability density function parameter vs cost (wind and solar)

In this case study, scale parameter (α) of Weibull distribution is varied (with fixed shape parameter, $\beta = 2$) to observe change in costs of wind power for a fixed arbitrarily selected scheduled power. The scheduled power for $WG1$ is fixed at 25 MW and that of $WG2$ is at 20 MW, i.e. 1/3-rd of the installed capacity. The assumption of scheduled power is reasonable as practical wind farm has a capacity factor somewhere between 30% to 45% [159]. Cost coefficients are same as in Case 1.

Fig. 3.39. Variation of wind power cost vs Weibull scale parameter (α) for windfarm#1 (bus 5)

Fig. 3.40. Variation of wind power cost vs Weibull scale parameter (α) for windfarm#2 (bus 11)

Fig. 3.39 and Fig. 3.40 represent curves for cost vs Weibull scale parameter (α) for windfarm#1 and windfarm#2, respectively. The total minimum cost is at an intermediate value of scale parameter. As scale factor increases, higher wind speeds with certain probabilities prevail. With scheduled power remaining same, the penalty cost escalates raising the total power cost. The rate of decrement in reserve cost is not significant after a certain value of scale parameter.

For assessing the variation in solar power cost with change in lognormal PDF mean μ , value of μ is altered from 2 to 7 in steps of 0.5. Standard deviation σ is 0.6; scheduled power is fixed at 20 MW. Cost coefficients are same as in Case 1. Cost plots are given in Fig. 3.41. Total solar power cost is found to be gradually decreasing to the minimum value at $\mu=6$. At about $\mu=5.8$, penalty cost and reserve cost are same. Thereafter, the penalty cost takes a sharp upward turn, thus mounting the total generation cost of solar power. Solar irradiance is highly sensitive to mean μ of lognormal distribution, so is output power. At low values of μ , irradiance and output power are so low that almost full reserve is necessary. However, if irradiance follows frequency distribution with bigger μ values, output from the PV plant can be much higher. So, care must be taken in selecting appropriate value of scheduled solar power. If μ is low, a smaller value of scheduled power is recommended.

Fig. 3.41. Variation of PV power cost vs lognormal mean (μ) for the PV plant (bus 13)

c) *Case 3: Minimization of generation cost*

Case 3 performs optimization of the generation schedule for all thermal and renewable power generators to minimize total generation cost given by Eq. (3.35). Cost coefficients are same

as in Case 1, PDF parameters are provided in Table 3.27. The convergence of SHADE-SF algorithm is indicated in Fig. 3.42. As can be seen from the diagram, the optimum cost is achieved in less than 10000 function evaluations. Optimum settings of all control variables, generator reactive power (Q), total generation cost and other useful calculated parameters are summarized in Table 3.28. Voltage V_i in the table signifies the voltage at i -th bus; VD is calculated using Eq. (3.22). It may be noted that $P_{ws,1}$ signifies the scheduled power from wind generator $WG1$ and likewise. The emission is calculated based on the optimal schedule power from thermal generators. Reserve is assumed to be an alternate source that does not add to the emission. With the generation schedule listed in the table, minimum generation cost of **777.9552 \$/h** is achieved.

Table 3.28. Simulation results of optimization cases for the adapted IEEE 30-bus system

Control variables	Min	Max	Case 3	Case 6	Parameters	Min	Max	Case 3	Case 6
P_{TG2} (MW)	20	80	28.0385	32.8314	P_{TG1} (MW)	50	200	134.908	123.441
P_{TG3} (MW)	10	35	10	10	Q_{TG1} (MVar)	-20	150	1.7896	1.2674
P_{ws1} (MW)	0	75	43.5075	45.9056	Q_{TG2} (MVar)	-20	60	19.5649	18.2828
P_{ws2} (MW)	0	60	36.6637	38.6697	Q_{TG3} (MVar)	-15	40	39.8243	39.8857
P_{ss} (MW)	0	50	36.0901	37.8575	Q_{ws1} (MVar)	-30	35	25.759	25.5996
V_1 (p.u.)	0.95	1.10	1.0740	1.0724	Q_{ws2} (MVar)	-25	30	30	30
V_2 (p.u.)	0.95	1.10	1.0589	1.0586	Q_{ss} (MVar)	-20	25	18.7052	19.2344
V_5 (p.u.)	0.95	1.10	1.0365	1.0373	Total cost			777.9552	807.0834
V_8 (p.u.)	0.95	1.10	1.0412	1.0418	Emission (t/h)			1.7622	0.8871
V_{11} (p.u.)	0.95	1.10	1.0989	1.0989	Carbon tax			-	17.742
V_{13} (p.u.)	0.95	1.10	1.0589	1.0604	VD (p.u.)			0.4776	0.4869

Fig. 3.42. Convergence of SHADE-SF algorithm for Case 3 and Case 6 of OPF with stochastic sources

d) *Case 4: Optimized cost vs reserve cost*

This study case is similar to Case 3 with all parameters being same as in Case 3 except reserve cost coefficients. The reserve cost coefficients for both wind and solar power are varied from $K_{RW,1} = K_{RW,2} = K_{RS} = KR(\text{say}) = 4$ to $KR = 6$ in discrete steps of 1. The penalty cost coefficient for all the renewable sources, say $KP = 1.5$ as in Case 1 and Case 3. Optimized power schedule of generators is indicated by bar chart in Fig. 3.43. Notations of cases used - Case 4a ($KR = 4$), Case 4b ($KR = 5$) and Case 4c ($KR = 6$). As reserve cost coefficient increases, the optimum power scheduled from wind generator and PV power generator decreases as lowering the scheduled power requires a lesser spinning reserve. Lower outputs from the renewable sources are compensated by thermal generators. Therefore, thermal generator cost increases as can be observed from ‘TG cost’ profile in Fig. 3.44. Costs of both wind (‘WG cost’) and PV (‘PV cost’) power gradually decrease to an extent. ‘WG cost’ accounts for power costs of both the wind generators. Overall cost (‘Total cost’) rises with the increase in reserve cost coefficient.

Fig. 3.43. Optimal scheduled real power (MW) vs reserve cost coefficient (KR)

Fig. 3.44. Cost curves for change in reserve cost coefficient (KR)

e) Case 5: Optimized cost vs penalty cost

All parameters of this case study are same as in Case 3 except penalty cost coefficients. The penalty cost coefficients for both wind and solar power are varied from $K_{PW,1} = K_{PW,2} = K_{PS} = KP(\text{say}) = 1.5$ to $KP = 3$ (Case 5a), $KP = 4$ (Case 5b) and $KP = 5$ (Case 5c). The reserve cost coefficient for all the renewable sources is, $KR = 3$ as in Case 1 and Case 3. Optimized schedule of generators is specified by bar chart in Fig. 3.45. As the penalty cost coefficient increases, scheduled outputs from renewable sources tend to increase as raising the scheduled power would help to bring down the penalty cost when wind speed or solar irradiance is high. However, unlike Case 4 where both wind and PV power monotonically decrease, here, the increment is not uniform across all renewable sources. Indeed, output from the PV plant occasionally decreases with increase in value of KP . This can be attributed to highly non-linear relationships between probability distribution and penalty/reserve costs associated with both wind and solar power. Wind power cost ('WG cost') is found progressively increasing in Fig. 3.46. The cost of solar power ('PV cost') increases at a moderate rate initially, thereafter, remains nearly unchanged. Thermal generation cost ('TG cost') remains almost constant after initial decay and overall cost ('Total cost') rightly shows steady rise.

Fig. 3.45. Optimal scheduled real power (MW) vs penalty cost coefficient

Voltages of generator buses are combined in Fig. 3.47 for all scenarios of changing reserve and penalty costs performed under Case 4 and Case 5. The generator bus voltages are all within specified range of 0.95 and 1.10 p.u. The voltages remain quite steady for changing values of cost coefficients. The little variation observed is due to change in generator reactive power for different case studies.

Fig. 3.46. Cost curves for change in penalty cost coefficient (KP)

Fig. 3.47. Generator bus voltages for Case 4 and Case 5 of OPF with stochastic sources

Fig. 3.48. Generator reactive power schedule for Case 4 and Case 5 of OPF with stochastic sources

Generator reactive power is a state or dependent variable in OPF problem. The constraint on reactive power must be satisfied during optimization. Fig. 3.48 represents schedule of all generator reactive power. Looking at the limits given in Table 3.28, the operation of generators *TG3* and *WG2* is at their limits of reactive power capability for many cases. So, care must be taken in dealing with the constraint on reactive power during optimization by an algorithm. The superiority of a proper constraint handling method lies in the fact that it allows the network components to operate close to the limits without violating those.

Therefore, such criteria justify the application of SF constraint handling method in the non-linear, constrained OPF problem.

f) Case 6: Minimization of generation cost with carbon tax

This case minimizes the total generation cost that includes carbon tax imposed on the emission from conventional thermal power generators. The aggregate cost, given by Eq. (3.36), is to be minimized. Carbon tax rate, C_{tax} is assumed to be \$20/tonne [94]. As wind and solar power are clean forms of energy, the penetration of these sources is expected to increase due to carbon tax component. Optimum generation schedule, generator reactive power, total generation cost (including carbon tax) and other calculated parameters are listed in Table 3.28. It is observed that penetration of both wind and solar energy is higher in Case 6 (when carbon tax is levied) than in Case 3 (with no penalty on emission). As an obvious fact, the extent of increase in optimum generation of the renewable sources depends on the emission volume and the rate of carbon tax imposed.

In OPF problem, constraint on load bus voltage is also critical as optimum operating voltages of load buses are often found be close to their limits. In this study, the load bus voltage must be maintained between 0.95 p.u. and 1.05 p.u. The voltage profiles of load buses are drawn in Fig. 3.49 for optimization Case 3 and Case 6. For other remaining optimization cases, the voltage profiles follow similar pattern, therefore, not included in the diagram for clarity. Clearly, bus voltages are all within specified limits.

Fig. 3.49. Load bus voltage profiles for Case 3 and Case 6 of OPF with stochastic sources

3.3.4 Conclusion: OPF study with stochastic wind and solar power

This section of the chapter proposes a solution approach to optimal power flow (OPF) problem incorporating stochastic wind and solar power. Uncertainties of the intermittent renewable sources are modeled with different probability density functions (PDFs). The integration method of all the sources is discussed in detail. Generation cost incorporating all sources is optimized and the variation in generation cost with the change in cost coefficients (reserve and penalty cost coefficients) is studied. The change in PDF parameters of uncertain sources also alters the generation cost following a pattern dictated by the selected PDF functions and the associated parameters. Inclusion of carbon tax in a case study rightly raises the optimum contributions from the clean energy sources (i.e. renewable sources). Further, power system constraints are duly satisfied by SF constraint handling method for all the case studies performed for the highly non-linear model of OPF with stochastic sources. The conclusions of this section of the chapter can be summarized as below:

- Generation cost is dependent upon the selected probability density functions (PDF) and their parameters for the stochastic renewable energy sources.
- Changes in penalty and reserve cost coefficients alter the optimal scheduled power from the generators.
- Inclusion of carbon tax in total cost objective function reduces output from thermal generators while it increases the contribution from clean energy sources.

Chapter 4

4. Optimal reactive power dispatch

4.1. Introduction to optimal reactive power dispatch (ORPD)

Optimizing reactive power flow in electrical network is an important aspect of system study as the reactive power supports network voltage which needs to be maintained within desirable limits for system reliability. A network consisting of only conventional thermal generators has been extensively studied for optimal active and reactive power dispatch. However, increasing penetration of renewable sources into the grid necessitates power flow studies incorporating these sources. This chapter presents a formulation and solution procedure for stochastic optimal reactive power dispatch (ORPD) problem with uncertainties in load demand, wind and solar power. Appropriate probability density functions (PDFs) are considered to model the stochastic load demand and the power generated from the renewable energy sources. Numerous scenarios are created running Monte-Carlo simulation and scenario reduction technique is implemented to deal with reduced number of scenarios. Real power loss and steady state voltage deviation of load buses in the network are independently set as the objectives of optimization. The constraints in ORPD problem are handled using epsilon constraint (EC) handling technique. As observed in Chapter 3, superiority of feasible solutions (SF) and epsilon constraint (EC) handling techniques perform equally well for OPF problem. ORPD being a sub-problem of OPF, we employ the EC constraint handling method in this study. Like OPF, application of a proper constraint handling method can hardly be traced in the literature. Mallipeddi *et. al.* [160] assessed performance of several constraint handling techniques like superiority of feasible solutions (SF), self-adaptive penalty (SP), epsilon constraint (EC) and stochastic ranking (SR) on classical ORPD problem considering thermal generators and DE was used as the basic search algorithm. We adopt SHADE as the search algorithm in this study and the integration of EC technique with SHDAE has been discussed in Chapter 2, section 2.1.4.1. Simulations results of SHADE-EC algorithm are analyzed in detail for cases with and without stochastic load demand and renewable power.

In organizing rest of the chapter, section 4.2 includes details of mathematical modeling for ORPD problem with the constraints involved. Section 4.3 explains the uncertainty modeling of load demand, wind and solar power followed by scenario generation and scenario reduction techniques. Detailed analyses of results and comparison are performed in section 4.4. The chapter ends with conclusion in section 4.5.

4.2. Mathematical models for ORPD study

The ORPD problem is non-convex and non-linear. The optimization is subject to many equality and inequality constraints. Mathematically, the general form of ORPD is:

$$\begin{aligned} &\text{Minimize: } f(x, u) \\ &\text{subject to: } \begin{cases} h(x, u) \leq 0 \\ z(x, u) = 0 \end{cases} \end{aligned} \quad (4.1)$$

where, x is the vector of control or independent variables, u is the vector of state or dependent variables. $f(x, u)$: the objective function of ORPD, $h(x, u)$: set of inequality constraints, $z(x, u)$: set of equality constraints.

4.2.1. Objective functions

A sub-problem of optimal power flow (OPF) is ORPD where values of active power generation from all generators except swing (or slack) generator are fixed and known [161]. In power flow study, total generation must be equal to the sum of demands and losses in the network. Swing generator balances the active power as well as the reactive power flow in the network. In ORPD, control variables which manage reactive power are the generator terminal voltages, settings of shunt VAR compensators and transformer taps. The two commonly used optimization objectives for ORPD are minimization of real power loss and minimization of voltage deviation of the network from desired value of 1 p.u.

a) Real power loss

The objective function of real power loss in the network, same as mentioned in Chapter 3 Eq. (3.20), is calculated as:

$$\text{Minimize, Loss} = \sum_{k=1}^{nl} G_{k(ij)} [V_i^2 + V_j^2 - 2V_i V_j \cos(\delta_{ij})] \quad (4.2)$$

where power loss is usually expressed in MW, V_i and δ_i are the voltage magnitude and voltage angle, respectively at i -th bus; $\delta_{ij} = \delta_i - \delta_j$, is the difference in voltage angles of bus i and bus j , $G_{k(ij)}$ is the transfer conductance of branch k connecting buses i and j and nl is the number of branches (i.e. transmission lines) in the network.

b) Aggregate voltage deviation

The index of voltage deviation is a measure of voltage quality in the network. It is important from security aspect also. The index is formulated as the summation of voltage deviations at all load buses (PQ buses) in the network from the ideal value of 1 p.u. Mathematically, the minimization of the objective is expressed as (same as in Chapter 3, Eq. (3.22)):

$$\text{Minimize, } VD = \left(\sum_{p=1}^{NL} |V_{Lp} - 1| \right) \quad (4.3)$$

where V_{Lp} is the bus voltage of p -th load bus (PQ bus) and NL is the number of load buses.

4.2.2. Control or independent variables

The control variables are represented in vector form as:

$$x = [V_{G1} \dots V_{GNG}, Q_{C1} \dots Q_{CNC}, T_1 \dots T_{NT}] \quad (4.4)$$

where V_{Gi} is the voltage magnitude at i -th PV bus (generator bus), Q_{Ck} is the shunt compensation at k -th bus and T_j is the j -th branch transformer tap. NG, NC and NT are the number of generators, VAR compensators and transformers, respectively. Majority of the study cases in our work consider transformer tap settings and shunt VAR compensator ratings as discrete variables. Only selected few cases, as mentioned in result section, consider these as continuous variables. Remaining all other variables are continuous.

4.2.3. State or dependent variables

The state variables in vector form can be represented as:

$$u = [V_{L1} \dots V_{LNL}, Q_{G1} \dots Q_{GNG}, S_{l1} \dots S_{lnl}] \quad (4.5)$$

where Q_{Gi} is the reactive power of the generator connected to bus i , V_{Lp} is the bus voltage of p -th load bus (PQ bus) and S_{lq} is the line loading of q -th line. NL is the number of load buses, while nl is the number of transmission lines in the network.

4.2.4. Constraints

The equality and inequality constraints pertaining to ORPD problem are segregated and provided herein.

a) Equality constraints

The equality constraints are the power balance equations given by:

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{NB} V_j [G_{ij} \cos(\delta_{ij}) + B_{ij} \sin(\delta_{ij})] = 0 \quad \forall i \in NB \quad (4.6)$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} V_j [G_{ij} \sin(\delta_{ij}) - B_{ij} \cos(\delta_{ij})] = 0 \quad \forall i \in NB \quad (4.7)$$

where $\delta_{ij} = \delta_i - \delta_j$, is the difference in voltage angles of bus i and bus j , NB is the number of buses, P_D and Q_D are active and reactive load demands respectively. G_{ij} is the transfer conductance and B_{ij} is the susceptance between buses i and j , respectively.

b) Inequality constraints

The inequality constraints are for the operational limits of the equipment and the security constraints associated with the network.

- Generator constraints: $V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{max} \forall i \in NG$ (4.8)

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max} \forall i \in NG \quad (4.9)$$

- Transformer constraints: $T_j^{min} \leq T_j \leq T_j^{max} \forall j \in NT$ (4.10)

- Shunt compensator constraints: $Q_{Ck}^{min} \leq Q_{Ck} \leq Q_{Ck}^{max} \forall k \in NC$ (4.11)

- Security constraints: $V_{Lp}^{min} \leq V_{Lp} \leq V_{Lp}^{max} \forall p \in NL$ (4.12)

$$S_{lq} \leq S_{lq}^{max} \forall q \in nl \quad (4.13)$$

As mentioned before in Chapter 3, the control variables are self-limiting. During optimization, the algorithm picks a feasible value for each control variable. The state or dependent variables are handled by the EC technique.

4.2.5. Bus test system

This chapter considers base configurations of IEEE 30 and IEEE 57-bus systems to perform selected cases of deterministic ORPD and compare the results of those cases with previously reported results. The base configurations have all thermal generators. The details of base configuration have been provided in Table 3.1 in Chapter 3. The only difference is in number of control variables. In ORPD study, generator active power is fixed (except for swing generator). Total control variables for IEEE 30-bus system and IEEE 57-bus system are 19 and 27, respectively, for ORPD study. To execute stochastic ORPD including a wind generator and a PV unit, the IEEE 30-bus system is modified. The thermal generator at bus 5 is replaced with a wind power generating source. A photovoltaic (PV) power unit substitutes the thermal generator at bus 8. The diagram of the modified system is presented in Fig. 4.1.

Fig. 4.1. The adapted IEEE 30-bus system with wind and PV units for stochastic ORPD study

4.3. Scenario generation and reduction techniques of uncertain load demand, wind and solar power

This section applies to the modified IEEE 30-bus system incorporating the renewable sources. While base case considers 100% loading (fixed) of the network, uncertainty in load demand is considered for the adapted network. This section discusses the uncertainty modeling of load demand and renewable power sources, followed by the techniques of scenario generation and scenario reduction.

4.3.1. Scenario generation of uncertain load demand, wind and solar power

Load uncertainty is modeled using normal probability density function (PDF) as in [82] with known mean (μ_d) and standard deviation (σ_d). The probability density of normal distribution of load (P_d) is given by:

$$\Delta_d(P_d) = \frac{1}{\sigma_d \sqrt{2\pi}} \exp \left[-\frac{(P_d - \mu_d)^2}{2\sigma_d^2} \right] \quad (4.14)$$

Fig. 4.2 shows 1000 Monte Carlo scenarios of load demand generated using normal PDF with $\mu_d = 70$ and $\sigma_d = 10$. The horizontal axis denotes the percentage loading of the network.

Fig. 4.2. Load demand scenarios (sample size 1000) using normal PDF

Fig. 4.3. Wind speed scenarios (sample size 1000) for the wind generator (bus 5) using Weibull PDF

Wind speed distribution is popularly represented with Weibull PDF [50]-[53]. The probability density of wind speed (v_w) following Weibull PDF is expressed as:

$$\Delta_v(v_w) = \left(\frac{\beta}{\alpha}\right) \left(\frac{v_w}{\alpha}\right)^{(\beta-1)} \exp \left[-\left(\frac{v_w}{\alpha}\right)^\beta \right] \quad \text{for } 0 < v_w < \infty \quad (4.15)$$

where α is the scale parameter and β is the shape parameter for Weibull PDF. The 1000 Monte Carlo scenarios of wind speed distribution following Weibull PDF with $\alpha = 9, \beta = 2$ are exhibited in Fig. 4.3.

Fig. 4.4. Solar irradiance scenarios (sample size 1000) for the PV (bus 8) using lognormal PDF

Fig. 4.5. Solar irradiance scenarios (without zero irradiance) for the photovoltaic (PV)

Solar irradiance (G_s) is well-known to trail lognormal distribution [151]. The lognormal probability density with mean (μ_s) and standard deviation (σ_s) of solar irradiance (G_s) is represented as:

$$\Delta_G(G_s) = \frac{1}{G_s \sigma_s \sqrt{2\pi}} \exp \left[\frac{-(\ln G_s - \mu_s)^2}{2\sigma_s^2} \right] \quad \text{for } G_s > 0 \quad (4.16)$$

It is worthwhile to note that lognormal distribution for solar irradiance considers the duration when sunlight is available (daytime). In general, as the sun is not available almost half of the

time (in a whole day of 24 hours), the solar irradiance (and hence PV output) for that duration would be zero. The scenarios created for solar irradiance using Monte-Carlo method are presented in Fig. 4.4. Zero irradiance is initialized with 50% probability and the remaining 50% probability covers the scenarios of solar irradiance generated using lognormal distribution mean $\mu_s = 5.5$ and standard deviation $\sigma_s = 0.5$. For clarity, the solar irradiance distribution is reproduced in Fig. 4.5 after removing the zero irradiance.

Refs. [82]-[84] adopted a simplistic approach of scenario creation. Five values of load demand and equal number of wind power values were arbitrarily chosen and a total of 25 scenarios were created with all possible combinations of these scenarios. If similar method is followed, addition of a solar power source will raise the number of scenarios to 125 (i.e. $5 \times 5 \times 5$). As it is impractical to handle so many scenarios, an appropriate scenario reduction method is necessary.

In this work, a more logical approach to scenario creation and scenario reduction is taken. The 1000 Monte-Carlo scenarios of each of load demand, wind speed and solar irradiance are combined to form a set of 1000 scenarios with each scenario representing a vector of 3 elements (demand, wind speed and solar irradiance). The i -th scenario is written as:

$$Y_i = [P_{d,i}, v_{w,i}, G_{s,i}] \quad (4.17)$$

The 1000 scenarios are reduced to a representative set of 25 scenarios by applying backward reduction technique [162] of stochastic programming. Increasing number of selected scenarios might improve the accuracy of results marginally, however, optimization based on 25 scenarios is good for all practical purposes.

4.3.2. Scenario reduction method

The method of scenario reduction using backward reduction algorithm (BRA) [162] is lucidly explained in Table 4.1. One scenario is removed at a time with one loop of operation of the algorithm. The operation starts with N_0 scenarios. Initially, all scenarios have equal probability (say, $\Delta_0 = 1/N_0$) of occurrence.

Table 4.1. Backward reduction algorithm

Steps in scenario reduction	
INITIALIZATION	<ul style="list-style-type: none"> • Create N_0 scenarios with vectors Y_i in eq. (4.17) for $i = 1, 2, \dots, N_0$. In this problem, we consider $N_0 = 1000$. • Initially, all scenarios have equal probability: $\Delta_0 = 1/N_0$. • Compute distance between each pair of scenarios by calculating the norm. Distance between scenarios Y_i and Y_j is $d_{ij} = \ Y_i - Y_j\$. • Formulate the distance matrix D including elements of self-distance (which is 0).

Steps in scenario reduction	
	<ul style="list-style-type: none"> Construct distance matrix D in such a way that all diagonal elements of the matrix are 0 and $d_{ij} = d_{ji}$. Initially, D matrix will be a square matrix of dimension $N_0 \times N_0$. Now, set $N_{dyn} = N_0$ and a stopping criterion N_{sc}, the number of final selected scenarios.
LOOP OPERATION:	
STEP 1	<ul style="list-style-type: none"> Find minimum distance value (excluding the elements of self-distance d_{ii}) from the distance matrix D. Two rows will contain same minimum value (as $d_{ij} = d_{ji}$). Suppose, the two rows are scenario m (row m) and scenario n (row n) with probabilities Δ_m and Δ_n, respectively.
STEP 2	<ul style="list-style-type: none"> If $\Delta_m \geq \Delta_n$, remove scenario n. Update probability $\Delta_m = \Delta_m + \Delta_n$. Else, remove scenario m. Update probability $\Delta_n = \Delta_n + \Delta_m$.
STEP 3	<ul style="list-style-type: none"> $N_{dyn} = N_{dyn} - 1$. Recalculate the distance between each pair of scenarios for the remaining scenarios and update distance matrix D.
STEP 4	<ul style="list-style-type: none"> Is $N_{dyn} > N_{sc}$? If yes, go to STEP 1 of loop operation. Else, STOP.

4.3.3. Selected scenarios, their probabilities and calculated power

The selected representative scenarios and their probabilities are listed in [Table 4.2](#). The row corresponding to a scenario also provides data on percentage load demand, wind speed and solar irradiance for that scenario. It is worth mentioning that load data provided in [Table A.1](#) in the Appendix are for 100% loading of the network. While considering a particular scenario, the demands (loading) in all buses are multiplied by the % loading of that scenario. The methods for calculation of wind power and solar power are discussed herein from wind speed and solar irradiance, respectively.

The output of a windfarm consisting of 25 turbines of 3 MW each is connected to bus 5. A wind turbine generates power output according to the wind speed it encounters. The relationship between output power and wind speed (v_w) is expressed as:

$$p_w(v_w) = \begin{cases} 0 & \text{for } v_w < v_{w,in} \text{ and } v_w > v_{w,out} \\ p_{wr} \left(\frac{v_w - v_{w,in}}{v_{w,r} - v_{w,in}} \right) & \text{for } v_{w,in} \leq v_w \leq v_{w,r} \\ p_{wr} & \text{for } v_{w,r} < v_w \leq v_{w,out} \end{cases} \quad (4.18)$$

where p_{wr} is the rated output power of a single wind turbine. Cut-in, rated and cut-out wind speeds of the turbine are $v_{w,in}$, $v_{w,r}$ and $v_{w,out}$, respectively. The numerical values of the speed considered are: $v_{w,in} = 3$ m/s, $v_{w,r} = 16$ m/s and $v_{w,out} = 25$ m/s, same as the data

of 3-MW turbine model Enercon E82-E4. The calculated values of wind power for different wind speeds are provided in [Table 4.2](#).

The solar irradiance (G_s) to energy conversion is given by following relationship with maximum output power limited to the PV unit rated power, P_{sr} . The rated power (P_{sr}) of the PV unit is assumed to be 50 MW.

$$P_s(G_s) = \begin{cases} P_{sr} \left(\frac{G_s^2}{G_{std} R_c} \right) & \text{for } 0 < G_s < R_c \\ P_{sr} \left(\frac{G_s}{G_{std}} \right) & \text{for } G_s \geq R_c \end{cases} \quad (4.19)$$

where G_{std} is the solar irradiance in standard environment, set as 1000 W/m². R_c is a certain irradiance point, set as 120 W/m². The calculated values of solar power at different levels of solar irradiance are provided in [Table 4.2](#).

Table 4.2. Selected scenarios and relevant parameters for the scenarios

Scenario number	% Loading P_d	Wind speed v_w (m/s)	Irradiance, G_s (W/m ²)	Wind power (MW)	PV power (MW)	Scenario probability, Δ_{sc}
1	105.784	1.702	1115.95	0	50	0.001
2	55.714	7.605	726.973	26.566	36.349	0.001
3	73.165	10.414	476.090	42.772	23.805	0.007
4	77.665	2.377	803.282	0	40.164	0.001
5	99.491	9.182	935.904	35.666	46.795	0.001
6	60.573	3.158	607.269	0.912	30.363	0.004
7	97.292	5.712	365.655	15.645	18.283	0.001
8	58.378	9.221	326.471	35.892	16.324	0.038
9	98.092	8.166	0	29.805	0	0.006
10	77.942	5.470	751.597	14.248	37.580	0.002
11	41.386	4.661	181.466	9.580	9.073	0.004
12	65.615	5.871	869.125	16.561	43.456	0.001
13	90.475	8.806	441.341	33.496	22.067	0.003
14	66.773	10.001	1103.501	40.393	50	0.001
15	61.498	8.628	551.278	32.470	27.564	0.009
16	68.935	6.229	0	18.629	0	0.478
17	67.603	9.084	138.834	35.103	6.942	0.093
18	71.770	9.678	379.832	38.528	18.992	0.044
19	79.921	5.271	672.788	13.102	33.639	0.004
20	72.351	7.880	411.201	28.152	20.560	0.037
21	78.322	4.813	201.152	10.458	10.058	0.048
22	66.073	11.743	95.657	50.441	3.813	0.027
23	74.465	2.538	229.271	0	11.464	0.071
24	63.754	3.245	518.084	1.416	25.904	0.012
25	67.487	14.439	275.124	65.994	13.756	0.106

A further review of [Table 4.2](#) reveals that the probabilities of various scenarios are realistic. PV plant produces almost zero output power with about 50% probability (scenario 16). The

probability of power output from both sources being simultaneously high is very small (e.g. scenario 14 in the order of 0.1%). The maximum and minimum possible outputs from both the sources are included in the set of selected scenarios. As the mean of normal PDF (for network loading) is considered as 70%, probability of network being overloaded is very low (scenario 1). A representative scenario (scenario 9) of high network loading and low output from renewable sources is also selected by the adopted scenario reduction technique. In summary, the set of selected 25 scenarios with the assigned probabilities represents a good approximation of original 1000 scenarios.

Now, the optimization algorithm is run for each scenario independently to minimize the objective functions of power loss and voltage deviation. The results and calculations of final objective values considering all the scenarios are presented in subsequent section.

4.4. Simulation results, analyses and comparisons for ORPD cases

The user-defined input parameters for the algorithm are listed in Table 4.3. The population sizes are selected after several trials. Simulations are run on MATLAB platform on a computer with Intel Core i5 CPU @2.7GHz and 4GB RAM. Simulation results, detailed analyses and comparisons are included in this section for the two standard test systems and one adapted system. The deterministic ORPD cases for base configurations (only thermal generators) are discussed first, followed by stochastic ORPD solutions with renewable energy sources adopting scenario-based approach.

Table 4.3. Input parameters for SHADE-EC algorithm in ORPD study

Parameter	IEEE 30-bus	IEEE 57-bus
Dimension of optimization problem, d	19	27
Population size, Np	40	60
Constant, cp	5	5
Maximum no. of function evaluations, $maxeval$	30,000	36,000
Decision variable range $[x_{min}, x_{max}]$	Refer to the tabulated results	

4.4.1. System 1: IEEE 30-bus test system (base case)

Case 1 and **Case 2** are for minimization of real power loss (Loss) and aggregate voltage deviation (VD), respectively, for 30-bus system with all thermal generators. These two study cases consider more realistic mixed integer optimization problems where shunt VAR compensator ratings (capacitor banks) and transformer taps are treated as discrete variables. Capacitor can be switched in at discrete steps of 200 kVAr (i.e. 0.2 MVar) and transformer tap settings can be adjusted in steps of 0.02 p.u. Therefore, possible transformer taps are

[0.90-0.92-0.94-...-1.08-1.10] p.u. To handle discrete variables, the algorithm performs rounding operation. During evolution, the control variables on shunt capacitor ratings and transformer taps are rounded off (upto required decimal points) to the nearest multiples of 0.2 (MVar) and 0.02 (p.u.), respectively. Further, as active power settings of generators (except swing generator) are vital for the optimization problem, the values are judiciously chosen within the defined ranges of the generators. The values of fixed active controls (i.e. active power of generators) are provided in [Table 4.4](#). **Case 1a** and **Case 2a** are additional study cases with objectives of minimization of real power loss (*Loss*) and aggregate voltage deviation (*VD*), respectively and performed here for a valid comparison with past studies. These cases consider all continuous variables with distribution of generation (except swing) fixed at the values given in [\[69\]](#) and also provided in [Table 4.4](#).

Table 4.4. Generator data for IEEE 30-bus system (base case) in ORPD study

Bus no.	P_G^{min} (MW)	P_G^{max} (MW)	Q_G^{min} (MVar)	Q_G^{max} (MVar)	Settings of thermal units, P_G (MW)	
					Case 1, 2	Case 1a, 2a
1	50	200	-20	150	Swing	Swing
2	20	80	-20	60	75	80
5	15	50	-15	62.5	40	50
8	10	35	-15	48.7	30	20
11	10	30	-10	40	25	20
13	12	40	-15	44.7	30	20

[Table 4.5](#) lists the optimum settings of all control variables and calculated state variables with their allowable ranges to minimize the respective objective functions of case studies related to IEEE 30-bus system. The state variables on generator reactive power are listed here to show compliance with the limits of these constraining variables. The negative reactive power signifies absorption of reactive power (i.e. VAR consumption) by the generator. As it transpires, some of the values of reactive power are at the limits (either upper or lower). So, the designer must be careful of this constraint while performing the optimization study. The constraint on load bus voltage is also critical as the allowable operating range for the bus voltage is narrow and the buses are often found to be operating near to the limits. The voltage profiles of load buses for the study cases are presented in [Fig. 4.6](#). In order to attain minimum power loss, voltages of few load buses are pushed to the upper limit.

Case 2 (and **Case 2a**) of minimizing voltage deviation (*VD*) will not lead to overvoltage as the objective is to maintain system voltage around 1 p.u. However, this objective may influence the generators to an extent to breach the reactive power limits. The reduced voltage

level (in **Case 2** and **Case 2a**) throughout the system escalates the currents and losses. Further, change in reactive power demand may entice the nearby generators to deliver/absorb additional VAR. Power flow is a complex phenomenon in the electrical network, and supply and consumption of VAR depend on many factors such as locations of loads, types of loads, voltages of buses, parameters of lines, etc. However, the facts and observations in the study cases presented here reiterate the need of verifying state of the constraints in a constrained optimization problem such as ORPD. The superiority of a proper constraint handling (CH) technique like EC lies in the fact that the search process is systematically guided towards the feasible region of solutions. In general, no additional measures are needed to look for or check feasibility of the optimal solutions. Fig. 4.7 shows convergence characteristics of SHADE-EC algorithm for the study Cases 1 and 2. The algorithm converges to optimal solution within 12000 function evaluations. The minimum loss achieved in **Case 1** is **4.4128 MW**, while the optimal value of voltage deviation in **Case 2** is **0.09080 p.u.**

Table 4.5. Simulation results for ORPD case studies of IEEE30-bus system

Parameters	Min	Max	Case 1 (Min. Loss)	Case 1a (Min. Loss)	Case 2 (Min. VD)	Case 2a (Min. VD)
V ₁ (p.u.)	0.95	1.10	1.0691	1.0720	1.0132	1.0031
V ₂ (p.u.)	0.95	1.10	1.0607	1.0628	1.0134	0.9986
V ₅ (p.u.)	0.95	1.10	1.0373	1.0405	1.0153	1.0162
V ₈ (p.u.)	0.95	1.10	1.0432	1.0406	1.0097	1.0084
V ₁₁ (p.u.)	0.95	1.10	1.0932	1.0923	1.0582	1.0674
V ₁₃ (p.u.)	0.95	1.10	1.0511	1.0526	0.9876	1.0206
T ₁₁ (p.u.)	0.90	1.10	1.08	1.0624	1.08	1.0918
T ₁₂ (p.u.)	0.90	1.10	0.92	0.9153	0.90	0.90
T ₁₅ (p.u.)	0.90	1.10	0.98	0.9873	0.94	1.0067
T ₃₆ (p.u.)	0.90	1.10	0.98	0.9752	0.96	0.9697
QC ₁₀ (MVar)	0.0	5.0	2.2	0	5	5
QC ₁₂ (MVar)	0.0	5.0	0.4	2.8322	0	4.1036
QC ₁₅ (MVar)	0.0	5.0	4.2	4.0992	5	5
QC ₁₇ (MVar)	0.0	5.0	5	5	0	0
QC ₂₀ (MVar)	0.0	5.0	3.8	3.9847	5	5
QC ₂₁ (MVar)	0.0	5.0	5	5	4.8	5
QC ₂₃ (MVar)	0.0	5.0	3	2.7884	5	5
QC ₂₄ (MVar)	0.0	5.0	5	5	5	5
QC ₂₉ (MVar)	0.0	5.0	2.6	2.4367	1.6	2.62
Loss (MW)			4.4128	4.8612	5.2083	6.0099
VD (p.u.)			0.8887	0.9205	0.09080	0.08724
Q _{G1} (MVar)	-20	150	-0.5058	0.0754	-20	-20
Q _{G2} (MVar)	-20	60	15.4055	16.4707	15.1624	-20
Q _{G5} (MVar)	-15	62.5	24.8254	24.3843	48.3673	53.4571
Q _{G8} (MVar)	-15	48.7	28.0250	29.6861	48.7	48.7
Q _{G11} (MVar)	-10	40	30.3954	27.2998	30.2106	34.9661
Q _{G13} (MVar)	-15	44.7	1.4150	2.2413	-14.2175	8.8982
CPU Time (s)			149.9	151.2	147.8	146.7

Fig. 4.6. Load bus voltage profiles for ORPD case studies of IEEE 30-bus system

Fig. 4.7. Convergence curves of SHADE-EC algorithm for ORPD Case 1 and Case 2

Table 4.6 presents the comparison of results obtained in present study by SHADE-EC with some recently reported results on ORPD. It is worthwhile to mention that barring ref. [69] no other reference papers in the table explicitly mentioned about active power settings of individual generators. It is assumed that all have followed the data given in [69]. While active control settings in **Case 1** lead to the lowest loss (by SHADE-EC), the loss achieved by the algorithm with settings of **Case 1a** is apparently bettered by quite a few algorithms. However, a more detailed and in-depth analysis is necessary in this regard. In comparison of objective of power loss minimization, the reported VD values in [65], [67] and [73] render the solutions infeasible. As mentioned in Chapter 3, under no circumstances the VD value

shall be higher than 1.2 p.u. for the 30-bus system to maintain its load bus voltages within [0.95 p.u.-1.05 p.u.]. Among the references listed in comparison table, except ref. [70], all have used penalty function method to handle system constraints. As mentioned before, the static penalty function approach is sensitive to selection of penalty coefficient and inconsiderate selection may lead to violation of system constraints, possibly without the cognizance of the designer. Refs. [68] and [75] did not report the voltage profile or VD value. The control variable settings, specifically, the generator voltages in [68] and [69] (not listed here) are all near to 1.1 p.u. While the condition helps minimize the current (hence loss) in the network, it makes impossible for the system to maintain all load bus voltages (especially the load buses near to the generators) below 1.05 p.u. The shunt compensation in [76] is very low (total about only 0.2 MVar). To minimize loss, voltage in the network should be maintained high enough to reduce current (and hence loss). With compensation being so low, it is not possible to achieve minimum loss. A different approach to constraint handling (CH) is noted in [70]. It adopted a concept similar to superiority of feasible solutions (SF) to handle the system constraints. However, the range of load bus voltage used in the study (0.94 p.u. to 1.06 p.u.) is different from others.

Table 4.6. Comparison of results of ORPD case studies for IEEE 30-bus system

Case no.	Algorithm	Loss (MW)	VD (p.u.)
Case 1	SHADE-EC	4.4128	0.8887
Case 1a	SHADE-EC	4.8612	0.9205
	DE [65]	4.5550	1.9589 ^b
	QOTLBO [67]	4.5594	1.9057 ^b
	MFO [68]	4.5128	-
	EMA [69]	4.4978	0.8123
	IGSA-CSS [70]	4.7660 ^a	-
	OGSA [71]	4.4984	0.8085
	HFA [73]	4.529	1.625 ^b
	FAHCLPSO [75]	4.4877	-
	NGBWCA [76]	4.4801	0.8413
Case 2	SHADE-EC	5.2083	0.09080
Case 2a	SHADE-EC	6.0099	0.08724
	QOTLBO [67]	6.4962	0.0856
	MFO [68]	-	0.12154
	EMA [69]	6.241	0.06131
	IGSA-CSS [70]	-	0.08968 ^a
	OGSA [71]	6.9044	0.0640
	HFA [73]	5.75	0.0980
	FAHCLPSO [75]	-	0.04315
	NGBWCA [76]	6.3142	0.0458

^aHigher ranges for load bus voltage and generator reactive power considered

^bInfeasible solution, constraint on load bus voltage is violated

In comparison of study **Case 2** (and **Case 2a**), many algorithms reported much lower VD values. Unfortunately, no publication listed here verified the status of the actual reactive power generation or voltage profile of load buses. We investigate the control variables listed in [75] and [76]. Almost zero compensation (about 0.14 MVar) and generator voltage settings of about 1 p.u. in [76] lead to undervoltage in many load buses. In comparison between refs. [75] and [76], ref. [75] proposed a total shunt compensation of about 21.5 MVar against 0.14 MVar in [76]. With so much difference in compensation, the VD values cannot be similar as reported. Further, verification of actual reactive power generation is also desirable. In summary, the performance comparison between a pair of algorithms merely on numerical values is invalid and unjustified for a constrained optimization problem. The effectiveness of the adopted constraint handling techniques must be assessed, moreover, the feasibility of the solutions must be checked.

4.4.2. System 2: IEEE 57-bus test system (base case)

The minimization of real power loss (Loss) and aggregate voltage deviation (VD) for IEEE 57-bus system are formulated in **Case 11** and **Case 12**. The rationale behind the study cases is about giving due consideration to discrete steps of shunt VAR compensators and transformer taps in real-world applications. The discrete steps are same as mentioned for the equipment in 30-bus system. These cases also consider more practical settings of active power for the generators (except swing generator). Table 4.7 lists the generator active power used for the case studies of 57-bus system. In **Case 11** and **Case 12**, no generator real power is set to zero unlike **Case 11a** and **Case 12a**. **Case 11a** and **Case 12a** are performed with same data set as in reference papers and with all continuous (control) variables. The real power settings of 3-generators are zero in **Case 11a** and **Case 12a**. This signifies that these generators are not producing any real power; they are either consuming VAR or delivering VAR (as synchronous condenser). Though theoretically it is very much possible by controlling excitation of the generators, the practice is not so common. Hence, more practical case studies - **Case 11** and **Case 12** are performed in our work. Like 30-bus system, all control variables and state variables on generator reactive power alongwith their operating ranges are provided in Table 4.8 for the case studies of 57-bus system. The load bus voltage profiles are exhibited in Fig. 4.8. Clearly all constraints are diligently satisfied by the epsilon constraint (EC) handling method. The convergence curves of SHADE-EC algorithm are drawn in Fig. 4.9 for **Case 11** and **Case 12**. The algorithm converges to an optimal solution within 20000 function evaluations.

Table 4.7. Generator data for IEEE 57-bus system in ORDP study

Bus no.	P_G^{min} (MW)	P_G^{max} (MW)	Q_G^{min} (MVar)	Q_G^{max} (MVar)	Settings of thermal units, P_G (MW)	
					Case 11, 12	Case 11a, 12a
1	0	576	-140	200	Swing	Swing
2	30	100	-17	50	50	0
3	40	140	-10	60	60	40
6	30	100	-8	25	50	0
8	100	550	-140	200	400	450
9	30	100	-3	9	50	0
12	100	410	-150	155	300	310

Table 4.8. Simulation results for ORPD case studies of IEEE 57-bus system

Parameters	Min	Max	Case 11 (Min. Loss)	Case 11a (Min. Loss)	Case 12 (Min. VD)	Case 12a (Min. VD)
V ₁ (p.u.)	0.95	1.10	1.0848	1.0875	1.0210	1.0200
V ₂ (p.u.)	0.95	1.10	1.0782	1.0768	1.0172	1.0116
V ₃ (p.u.)	0.95	1.10	1.0661	1.0653	1.0158	1.0107
V ₆ (p.u.)	0.95	1.10	1.0584	1.0562	1.0005	1.0034
V ₈ (p.u.)	0.95	1.10	1.0731	1.0746	1.0064	1.0297
V ₉ (p.u.)	0.95	1.10	1.0464	1.0428	0.9945	1.0070
V ₁₂ (p.u.)	0.95	1.10	1.0480	1.0455	1.0246	1.0360
T ₁₉ (p.u.)	0.90	1.10	1.06	0.9729	0.96	0.9653
T ₂₀ (p.u.)	0.90	1.10	0.94	1.0085	1.04	0.9942
T ₃₁ (p.u.)	0.90	1.10	1	1.0054	0.98	0.9714
T ₃₅ (p.u.)	0.90	1.10	0.96	1.0302	1.04	1.0541
T ₃₆ (p.u.)	0.90	1.10	1.04	0.989	0.98	1.0876
T ₃₇ (p.u.)	0.90	1.10	1	1.0044	1	1.0039
T ₄₁ (p.u.)	0.90	1.10	1	0.9968	0.98	1.0017
T ₄₆ (p.u.)	0.90	1.10	0.96	0.9524	0.94	0.9180
T ₅₄ (p.u.)	0.90	1.10	0.94	0.9094	0.9	0.9001
T ₅₈ (p.u.)	0.90	1.10	1	0.9894	0.94	0.9303
T ₅₉ (p.u.)	0.90	1.10	0.98	0.9712	0.96	0.9849
T ₆₅ (p.u.)	0.90	1.10	0.98	0.9749	1	1.0072
T ₆₆ (p.u.)	0.90	1.10	0.94	0.9416	0.9	0.9
T ₇₁ (p.u.)	0.90	1.10	0.98	0.9710	0.98	0.9589
T ₇₃ (p.u.)	0.90	1.10	1	0.9848	0.98	1.0082
T ₇₆ (p.u.)	0.90	1.10	0.98	0.9590	0.9	0.9
T ₈₀ (p.u.)	0.90	1.10	1	0.9845	0.98	0.9870
Q _{C18} (MVar)	0	20	5.2	8.1480	13.8	0.0075
Q _{C25} (MVar)	0	20	14.2	14.4048	18.4	19.9909
Q _{C53} (MVar)	0	20	13.6	13.2747	20	19.9974
Loss (MW)			18.4000	23.3031	21.6013	27.7317
VD (p.u.)			1.5207	1.7322	0.62632	0.59673
Q _{G1} (MVar)	-140	200	51.2244	52.0795	0.5534	-14.9401
Q _{G2} (MVar)	-17	50	50	50	50	49.9403
Q _{G3} (MVar)	-10	60	41.9006	48.3738	60	59.9930
Q _{G6} (MVar)	-8	25	-8	-1.2067	-8	-7.9852
Q _{G8} (MVar)	-140	200	58.7302	67.037	12.4105	51.2724
Q _{G9} (MVar)	-3	9	9	8.9997	9	8.9798
Q _{G12} (MVar)	-150	155	52.9306	46.6327	138.7671	154.8363
CPU Time (s)			209.9	215.6	208.7	212.3

Fig. 4.8. Load bus voltage profiles for ORPD case studies of IEEE 57-bus system

Fig. 4.9. Convergence curves of SHADE-EC algorithm for ORPD Case 11 and Case 12

The comparison of results of study cases related to IEEE 57-bus system with some recently reported results is provided in [Table 4.9](#). SHADE-EC algorithm achieves the best results among the results of all algorithms listed in the table. The algorithm duly satisfies all constraints. The optimum real power loss in **Case 11a** is **23.3031 MW** and the minimum VD attained in **Case 12a** is **0.59673 p.u.** However, as already mentioned, comparison on apparent numerical results of a constrained optimization problem is flawed. One must verify the feasibility of the solutions. The proper constraint handling technique like EC initially guides the search process towards feasible region, thereafter, improves the solution with the aid of a compatible evolutionary algorithm.

Table 4.9. Comparison of results of ORPD case studies for IEEE 57-bus system

Case no.	Algorithm	Loss (MW)	VD (p.u.)
Case 11	SHADE-EC	18.4000	1.5207
Case 11a	SHADE-EC	23.3031	1.7322
	MFO [68]	24.2529	-
	IGSA-CSS [70]	22.2718 ^a	-
	OGSA [71]	23.43	1.1907
	ICA [72]	24.1607	-
	PSO-ICA [72]	24.1386	-
	MICA-IWO [74]	24.2568	-
Case 12	SHADE-EC	21.6013	0.62632
Case 12a	SHADE-EC	27.7317	0.59673
	IGSA-CSS [70]	-	0.60347 ^a
	OGSA [71]	32.34	0.6982
	ICA [72]	-	0.6137
	PSO-ICA [72]	-	0.6031

^aDifferent ranges for generator reactive power are used

4.4.3. System 3: Adapted IEEE 30-bus test system

This section deals with the modified IEEE 30-bus system where the thermal generators at bus 5 and bus 8 are replaced with a wind generator and a PV unit, respectively. The load is variable based on the scenario. Shunt VAR compensators and transformer taps are considered discrete as in Cases 1 and 2. Thermal generator settings (except swing generator) are provided in Table 4.10. The wind generator power and PV output are variables under different scenarios as discussed in section 4.3. Therefore, the swing generator must be capable of delivering the balance active power if there is a deficit in supply of active power from these renewable energy units. The maximum real power output of swing generator is considered high enough (200 MW) in this study so that the generator can mitigate the load demand even if the real power output from both the renewable energy sources is zero. The reactive power output range of the wind generator and the PV unit is considered approximately between -0.4 p.u. to 0.5 p.u. throughout their active power output range. The justification for such assumption is provided in Chapter 3, sub-section 3.3.1 (f).

Table 4.10. Generator data for the adapted IEEE 30-bus system for ORPD study

Bus no.	P_G^{min}	P_G^{max}	Q_G^{min}	Q_G^{max}	Settings of thermal units, P_G (MW)
	(MW)	(MW)	(MVar)	(MVar)	Case 21, 22
1	50	200	-20	150	Swing
2	20	80	-20	60	75
5 (wind)	0	75	-30	35	Variable
8 (PV)	0	50	-20	25	Variable
11	10	30	-10	40	25
13	12	40	-15	44.7	30

The scenario-based approach with uncertain wind power was proposed in [82]-[84]. The authors took same approach in calculating expected power loss (*EPL*) and expected voltage deviation (*EVD*) in all these reference papers. The control variables on generator bus voltages and transformer tap settings (termed as ‘*here and now*’ control variables) are consider same and fixed for all scenarios. Uncertain wind generator active power is variable (for different scenarios) and power loss is optimized for different scenarios by adjusting shunt VAR compensation (termed as ‘*wait and see*’ control variable). However, the authors did not provide explanation on why the control variables were segregated. One possible reason is that the optimal settings of ‘*here and now*’ control variables are not hugely different across the scenarios. But, if shunt VAR compensation and slack generator active power are adjusted, generator bus voltage can also be adjusted by changing excitation of the generator. Online alteration of tap changer is also plausible. Therefore, we consider optimization of all control variables to minimize power loss under all scenarios with respective values of load demand and renewable power (i.e. active power at bus 5 and bus 8). In reality, OPF is run at certain time intervals to optimize various objectives in the network. Hence, running ORPD to optimize settings of all control variables for different scenarios is a realistic proposition in calculating probabilistic loss and voltage deviation. To elaborate further, the minimization of *EPL* in **Case 21** requires running the optimization algorithm 25 times for 25 scenarios. For each scenario, the optimized value of power loss ($Loss_{sc}$) is provided in Table 4.11. If probability of the scenario is Δ_{sc} and optimized power loss for the scenario is $Loss_{sc}$, the expected power loss (*EPL*) is calculated over all scenarios as:

$$EPL: \sum_{sc=1}^{N_{sc}} \Delta_{sc} \times Loss_{sc} \quad (4.20)$$

where N_{sc} is the total number of selected scenarios. In similar manner, voltage deviation (*VD*) for each scenario is optimized in **Case 22** and the optimal values of voltage deviations for all scenarios (VD_{sc}) are presented in Table 4.11. The expected value of voltage deviation (*EVD*) over all scenarios is expressed as:

$$EVD: \sum_{sc=1}^{N_{sc}} \Delta_{sc} \times VD_{sc} \quad (4.21)$$

Table 4.11. Expected power loss and voltage deviation with uncertain demand and renewable power

Scenario number	% Loading	Wind power (MW)	PV power (MW)	Scenario probability, Δ_{sc}	Scenario based $Loss_{sc}$ (MW)	Scenario based VD_{sc} (p.u.)
1	105.784	0	50	0.001	7.9319	0.12220
2	55.714	26.566	36.349	0.001	0.9004	0.04330
3	73.165	42.772	23.805	0.007	1.3633	0.05884
4	77.665	0	40.164	0.001	3.3351	0.07177
5	99.491	35.666	46.795	0.001	3.8883	0.09801
6	60.573	0.912	30.363	0.004	1.7466	0.04863
7	97.292	15.645	18.283	0.001	6.4390	0.10849
8	58.378	35.892	16.324	0.038	0.8527	0.04432
9	98.092	29.805	0	0.006	6.6330	0.10172
10	77.942	14.248	37.580	0.002	2.5992	0.06973
11	41.386	9.580	9.073	0.004	0.7832	0.03318
12	65.615	16.561	43.456	0.001	1.4177	0.05160
13	90.475	33.496	22.067	0.003	3.6836	0.08605
14	66.773	40.393	50	0.001	1.0216	0.05144
15	61.498	32.470	27.564	0.009	0.9400	0.04610
16	68.935	18.629	0	0.478	2.5207	0.05619
17	67.603	35.103	6.942	0.093	1.5320	0.05284
18	71.770	38.528	18.992	0.044	1.4708	0.06316
19	79.921	13.102	33.639	0.004	3.0025	0.07099
20	72.351	28.152	20.560	0.037	1.8219	0.05902
21	78.322	10.458	10.058	0.048	3.8375	0.07098
22	66.073	50.441	3.813	0.027	1.1676	0.05110
23	74.465	0	11.464	0.071	3.8974	0.07095
24	63.754	1.416	25.904	0.012	2.0554	0.05748
25	67.487	65.994	13.756	0.106	0.9567	0.05678
				Case 21 - EPL: $\sum \Delta_{sc} \times Loss_{sc} = 2.2515$ MW		
				Case 22 - EVD: $\sum \Delta_{sc} \times VD_{sc} = 0.05794$ p.u.		

The *EPL* achieved in **Case 21** is **2.2515 MW** and *EVD* in **Case 22** is **0.05794 p.u.** In [Table 4.11](#), the scenario based optimal losses ($Loss_{sc}$) can be easily interpreted. The lowest value of loss is realized when network loading is minimum (scenario 11). Minimum loading signifies lowest current (hence low loss) in the network. On contrary, the loss is the highest when network loading is maximum with no available wind power (scenario 1). The non-availability of wind power requires the swing generator to supply additional power to relatively remote load points. The voltage in some section of the network is also not well supported. The combined effect of high load current and low voltage level raises the network losses. Results of voltage deviation can also be analyzed in similar way. With minimum loading (scenario 11), the voltage profile of the network can be maintained throughout very close to the desired 1 p.u. Again, low current (for minimum loading condition) means small voltage drop. Hence, scenario 11 leads to the minimum aggregate voltage deviation. On the other hand, maximum loading and zero wind power (scenario 1) results in the highest

aggregate voltage deviation of the system. The control variables for these extreme scenarios are provided in Table 4.12 for both the cases.

Table 4.12. Control variables under extreme scenarios in ORPD Case 21 and Case 22

Parameters	Min	Max	Case 21 (min. <i>EPL</i>)		Case 22 (min. <i>EVD</i>)	
			(scenario 1)	(scenario 11)	(scenario 1)	(scenario 11)
V ₁ (p.u.)	0.95	1.10	1.0742	1.0483	1.0314	0.9952
V ₂ (p.u.)	0.95	1.10	1.0612	1.0535	1.0291	0.9981
V ₅ (p.u.)	0.95	1.10	1.0265	1.0424	0.9895	1.0048
V ₈ (p.u.)	0.95	1.10	1.0413	1.0482	0.9993	0.9930
V ₁₁ (p.u.)	0.95	1.10	1.0999	1.0266	1.0677	1.0525
V ₁₃ (p.u.)	0.95	1.10	1.0476	1.0477	1	0.9947
T ₁₁ (p.u.)	0.90	1.10	1.10	1.02	1.08	1.06
T ₁₂ (p.u.)	0.90	1.10	0.90	0.98	0.90	1
T ₁₅ (p.u.)	0.90	1.10	0.98	1	0.96	1
T ₃₆ (p.u.)	0.90	1.10	0.98	1	0.96	1
Q _{C10} (MVar)	0.0	5.0	3.2	5	5	3.8
Q _{C12} (MVar)	0.0	5.0	3.8	4.4	0.4	4.8
Q _{C15} (MVar)	0.0	5.0	3.4	1.6	5	3
Q _{C17} (MVar)	0.0	5.0	5	2.6	1.4	1.6
Q _{C20} (MVar)	0.0	5.0	4.6	1.6	5	4.6
Q _{C21} (MVar)	0.0	5.0	5	4.4	5	3.4
Q _{C23} (MVar)	0.0	5.0	3.8	0.6	5	1.2
Q _{C24} (MVar)	0.0	5.0	5	3	5	5
Q _{C29} (MVar)	0.0	5.0	3	1	2.6	3.8

Fig. 4.10. Optimal settings of generator bus voltages for all scenarios in ORPD Case 21

The control variables on generator bus voltages for different scenarios are presented in Fig. 4.10 and Fig. 4.11 for all scenarios in **Case 21** and **Case 22**, respectively. In general, the voltage levels of generator buses in **Case 21** are higher than those in **Case 22**. In the former case, power loss is minimized. Hence, bus voltages are to be maintained at a higher level to

reduce load current that incurs power loss. Voltage setting of generator bus 11 is higher than the other generator buses, especially in **Case 22**. Bus 11 is connected to neighboring load buses without any shunt compensation. A little higher voltage setting of this generator bus facilitates sustainment of steady voltage at the load buses in the proximity. The settings of other control variables on transformer taps and shunt VAR compensators are provided in stacked column charts in [Fig. A.1](#), [Fig. A.2](#), [Fig. A.3](#) and [Fig. A.4](#) in the Appendix.

Fig. 4.11. Optimal settings of generator bus voltages for all scenarios in ORPD Case 22

Due to highly non-linear nature of ORPD problem, it is difficult to decipher any specific pattern of change in control variables under different scenarios of network loading, wind and solar power. However, in no scenario of a case study, the voltage levels of load buses violate the allowable limits. This is insured by the CH technique in optimization algorithm. It is not practical to indicate voltage profiles for all scenarios here. The profiles of extreme scenarios (scenario 1 and scenario 11) are drawn in [Fig. 4.12](#) for both the cases. Load bus voltage levels are justifiably nearest to the peak to lower load current (hence loss) in scenario 11 of **Case 21** when the network loss is minimum. The load bus voltage profile is closest to 1 p.u. in scenario 11 of **Case 22** when the aggregate voltage deviation (VD) is the least. [Fig. 4.13](#) shows maximum and minimum reactive power contributions of all the generators across all scenarios for **Case 21** of minimum EPL . Similar bar chart is drawn for **Case 22** (of minimum EVD) in [Fig. 4.14](#). ‘Allow Max’ and ‘Allow Min’ are the maximum and minimum allowable values of generator reactive power, respectively. The actual values of maximum and minimum reactive power superimposed in these diagrams confirm compliance to reactive power limits under all scenarios.

Fig. 4.12. Load bus voltage profiles under extreme scenarios for ORPD Case 21 and Case 22

Fig. 4.13. Minimum and maximum reactive power of generators over all scenarios in ORPD Case 21

Fig. 4.14. Minimum and maximum reactive power of generators over all scenarios in ORPD Case 22

4.5. Conclusion: optimal reactive power dispatch study

In first section of this chapter, deterministic optimal reactive power dispatch (ORPD) studies for two standard bus systems with only thermal generators are performed. Subsequently, stochastic ORPD formulation and solution incorporating uncertain load demand and solar power adopting scenario-based approach are presented. SHADE-EC algorithm is implemented for the optimization task in all cases. The usefulness of a proper constraint handling (CH) technique such as EC is established with the case studies using basic configurations of the two test systems. The status of all network constraints is verified, and results are critically analyzed against constraint violation in comparison with past studies. In ORPD study with stochastic load demand, wind and solar power, the uncertainties are appropriately modeled with suitable probability density functions (PDFs). Numerous scenarios are created running Monte Carlo simulations. A representative set of scenarios is selected employing appropriate scenario reduction method of stochastic programming. Expected power loss (*EPL*) and expected voltage deviation (*EVD*) values are calculated with optimization of network parameters under various scenarios of load demands, available wind and solar power. The conclusions of the chapter can be summarized as below:

- Like OPF, epsilon constraint (EC) handling method together with SHADE algorithm shows promising results for ORPD problem satisfying all constraints.
- The stochastic ORPD problem incorporating the intermittent renewable energy sources can be dealt with scenario-based approach.
- Numerous scenarios of load demand, wind and solar power can be reduced to some representative scenarios with scenario reduction techniques. Optimization is required to be performed for reduced number of scenarios to come up with ORPD solutions.

Chapter 5

5. Economic-environmental dispatch with stochastic wind-solar-small hydro power

5.1. Introduction to multi-objective economic environmental dispatch (MOEED)

Economic-environmental power dispatch is one of the most popular bi-objective non-linear optimization problems in power system. Classical economic power dispatch problem is formulated with only thermal generators, often ignoring security constraints of the network. But importance of reduction in emission is paramount from the perspective of environmental sustainability and hence penetration of more and more renewable sources into the electrical grid is encouraged. However, most common forms of renewable energy are intermittent and uncertain. This chapter proposes multi-objective economic emission power dispatch problem formulation and solution incorporating stochastic wind, solar and small-hydro (run-of-river) power. Weibull, lognormal and Gumbel probability density functions are used to calculate available wind, solar and small-hydro power, respectively. Penalty cost for underestimation and reserve cost for overestimation of these intermittent sources are suitably added to the generation cost. Till date, no literature performed even the single-objective economic dispatch (ED) with all these renewable sources together. For study purpose, some conventional generators of the standard IEEE 30-bus system are replaced with renewable power sources. Decomposition based multi-objective evolutionary algorithm (MOEA/D) and summation based multi-objective differential evolution (SMODE) algorithm are applied to the multi-objective economic-environmental (MOEED) power dispatch problem to obtain the sets of Pareto solutions. An important aspect of EED problem is compliance with system constraints. Most of the works on EED did not consider network security constraints in the problem formulation and solution. However, network buses have a certain operating range and transmission line capacities are also defined. The present work considers network security constraints together with constraints on generator capability and prohibited operating zones (POZs). Furthermore, in the literature, system constraints have been handled by penalty function approach where the penalty coefficient is decided largely by trial and error method. As discussed in previous chapter on OPF, inconsiderate selection of penalty coefficient may lead to violation of system constraints. We adopt an effective constraint handling technique, superiority of feasible solutions (SF) to handle constraints in the problem. The integration methods of SF technique separately with MOEA/D and SMODE

are provided in Chapter 2, sections 2.1.4.2 and 2.1.4.3. The algorithms MOEA/D-SF and SMODE-SF can successfully perform the task of multi-objective optimization for MOEED satisfying all the system constraints.

The remainder of the chapter is organized in following manner. Mathematical model of MOEED problem alongwith constraints is included in section 5.2. Wind, solar and small-hydro power uncertainties are modeled in section 5.3. Case studies and simulation results are discussed in section 5.4. The chapter ends with concluding remarks in section 5.5.

5.2. Mathematical models for MOEED study

Basic parameters of the modified IEEE 30-bus network are provided in [Table 5.1](#). The single line diagram of the adapted network is depicted in [Fig. 5.1](#). The network has 3 thermal generators at buses 1, 2 and 8. Output of a windfarm is connected to bus 5 while a photovoltaic (PV) power unit is supplying power to bus 11.

Table 5.1. A summary of the adapted IEEE 30-bus system for MOEED study

Items	Quantity	Details
Buses	30	Table A.1 (Appendix)
Branches	41	Table A.3 (Appendix)
Thermal generators ($TG1, TG2, TG3$)	3	Buses: 1 (swing), 2 and 8
Wind generator (WG)	1	Bus: 5
Solar (PV) unit (PV)	1	Bus: 11
Solar + small-hydro (PVH)	1	Bus: 13
Control parameters	11	Scheduled real power of 5 generators: $TG2, TG3, WG, PV$ and PVH ; bus voltages of all 6 generator buses
Connected load	-	283.4 MW, 126.2 MVar
Allowable range for load bus voltage	24	[0.95 – 1.05] p.u.

The small-hydro power in most cases is a ‘run-of-river’, where usually little or no storage is needed [\[163\]](#). Natural flow of a river to downhill is diverted by a weir and the controlled water is channelized to the turbine before the water is released back to downstream of the river. A small-hydro unit can generate a maximum output in the range of only few megawatts [\[163\]](#). Hence, a PV unit is considered to be connected together with the small-hydro power unit at bus 13. As an obvious fact, outputs from wind, solar and small-hydro are all variables and any deficit in total output from these units must be mitigated by the spinning reserve. As listed in [Table 5.1](#), the network has 11 control variables that can be optimized for efficient and economical operation of the network. The control variables include scheduled real power of all generators (except swing generator $TG1$ connected to bus 1) and all generator bus voltages. Transformer tap settings are considered fixed at 1 p.u.

5.2.1 Generation cost of thermal power units

Fuel or generation cost (in \$/h) of thermal generators follows a quadratic relationship with the generated output power (in MW). The same can be expressed as:

$$C_{T0}(P_{TG}) = \sum_{i=1}^{N_{TG}} a_i + b_i P_{TGi} + c_i P_{TGi}^2 \quad (5.1)$$

where a_i, b_i, c_i represent the cost coefficients of the i -th thermal power unit generating power P_{TGi} . Total number of thermal generators in the network is N_{TG} .

Fig. 5.1. The adapted IEEE 30-bus system with wind-solar-small hydro units for MOEED study

Thermal generation cost increases with consideration of valve-point loading effect for the steam turbines. The cost curve becomes non-smooth with many ripples. The additional cost due to valve-point effect is accounted for in modulus of a sinusoidal function given in Eq. (3.21) in Chapter 3 and re-written here:

$$C_T(P_{TG}) = \sum_{i=1}^{N_{TG}} a_i + b_i P_{TGi} + c_i P_{TGi}^2 + \left| d_i \times \sin \left(e_i \times (P_{TGi}^{min} - P_{TGi}) \right) \right| \quad (5.2)$$

where d_i and e_i are the coefficients for the valve-point loading effect. Minimum power of the i -th thermal unit when in operation is P_{TGi}^{min} . All cost coefficients pertaining to thermal power generators are provided in Table 5.2 and except for cost coefficient a , these are same as mentioned in Table 3.26 in Chapter 3.

Table 5.2. Cost and emission coefficients of thermal power generators in MOEED study

Gen #	Bus	a (\$/h)	b (\$/MWh)	c (\$/MW ² h)	d (\$/h)	e (rad/ MW)	φ	ψ	ω	τ	ζ
TG1	1	30	2	0.00375	18	0.037	4.091	-5.554	6.490	0.0002	6.667
TG2	2	25	1.75	0.01750	16	0.038	2.543	-6.047	5.638	0.0005	3.333
TG3	8	20	3.25	0.00834	12	0.045	5.326	-3.550	3.380	0.0020	2

5.2.2 Cost of uncertain and intermittent renewable sources

The difficult part in integrating the renewable sources into the grid is the intermittent and uncertain nature of these sources. Usually windfarm, solar farm, etc. are owned by the private operator, an entity that undergoes a purchase agreement for a certain amount of scheduled power with the grid/independent system operator (ISO). If these farms do not produce the scheduled power due to non-availability or insufficiency of renewable sources, the ISO is liable to mitigate the deficit amount, if demand arises, by keeping a spinning reserve. Such a scenario is termed as the overestimation of renewable power and for which maintaining a spinning reserve adds to the generation cost. On contrary, a situation may arise when the generated power from renewable sources is more than the scheduled power. In such a case of underestimation, the surplus power is wasted, and ISO should bear the penalty cost. The total cost of the renewable sources thus consists of direct cost associated with the scheduled power, penalty cost for underestimation and reserve cost for overestimation.

a) Direct cost of wind, solar photovoltaic and small-hydro power

Wind, solar and small-hydro power generators do not require any fossil fuel. In the case where these plants are owned by the independent system operator (ISO), this cost function may not exist unless ISO wants to assign some payback cost for initial setup for the plants or to assign this as a maintenance cost. However, when these plants are owned by private operators, ISO needs to pay a price proportional to the scheduled power mutually contracted.

Direct cost of wind power from the windfarm as a function of scheduled power can be represented as:

$$C_w(P_{ws}) = g_w P_{ws} \quad (5.3)$$

where P_{ws} is the scheduled power as agreed from the wind power plant and g_w is the direct cost coefficient pertaining to the same plant.

Like wind power plant, direct cost associated with the PV power plant is:

$$C_s(P_{ss}) = h_s P_{ss} \quad (5.4)$$

where P_{ss} is the scheduled power from the PV power plant and h_s is the direct cost coefficient of the same plant.

The third renewable plant considered in this study is a combination of a PV unit and a small-hydro unit, owned by a single private operator. The direct cost coefficients of both these units are different. However, scheduled output power agreed by ISO is a fixed amount and this power is delivered jointly by the solar (PV) and small-hydro units. Output of the hydropower unit varies according to the flow rate of the river assuming constant head for run-of-river arrangement [164]. However, as capacity of the small-hydro unit is insignificant compared to the load demand of the system, the unit is usually run flat out. Therefore, available amount (depending upon the river flow rate) of hydro power and the output from PV unit constitute the scheduled power.

Direct cost associated with the combined PV and small-hydro unit is:

$$C_{sh}(P_{ssh}) = C_{sh}(P_{ssh,s} + P_{ssh,h}) = h_s P_{ssh,s} + m_h P_{ssh,h} \quad (5.5)$$

where P_{ssh} is the scheduled power from the combined plant. The contribution from PV power plant is $P_{ssh,s}$ and that from small-hydro unit is $P_{ssh,h}$. Direct cost coefficient of PV power is considered same as earlier (h_s) and that of small-hydro unit is m_h .

b) Uncertain wind power cost evaluation

As mentioned earlier, due to uncertain nature of wind energy, the windfarm may produce less than the scheduled amount. ISO needs to have an adequate spinning reserve to mitigate the demand if such a situation arises. Reserve cost for the wind power plant is defined as:

$$C_{Rw}(P_{ws} - P_{wav}) = K_{Rw}(P_{ws} - P_{wav}) = K_{Rw} \int_0^{P_{ws}} (P_{ws} - p_w) f_w(p_w) dp_w \quad (5.6)$$

where K_{Rw} is the reserve cost coefficient for the wind power plant, P_{wav} is the actual available power from the same plant. $f_w(p_w)$ is the wind power probability density function.

In the case of underestimation, actual available output power from the windfarm is more than the scheduled output. This power is wasted if it is not utilized by reducing the power output from conventional generators. In such a case, a penalty cost is paid by the ISO. Penalty cost for the wind power plant is given by:

$$C_{PW}(P_{wav} - P_{ws}) = K_{PW}(P_{wav} - P_{ws}) = K_{PW} \int_{P_{ws}}^{P_{wr}} (p_w - P_{ws}) f_w(p_w) dp_w \quad (5.7)$$

where K_{PW} is the penalty cost coefficient for the wind power plant, P_{wr} is the rated power output from the plant.

c) Uncertain photovoltaic (PV) power cost evaluation

The approach for cost evaluation of uncertain and intermittent PV power is fundamentally same as wind power. However, solar radiation is well known to trail lognormal PDF [151]. For mathematical convenience, reserve and penalty cost models are constructed in line with the method already presented in Chapter 3. Reserve cost for overestimation of the solar power is:

$$C_{RS}(P_{ss} - P_{sav}) = K_{RS}(P_{ss} - P_{sav}) = K_{RS} * f_s(P_{sav} < P_{ss}) * [P_{ss} - E(P_{sav} < P_{ss})] \quad (5.8)$$

where K_{RS} is the reserve cost coefficient associated with the PV power plant, P_{sav} is the actual available power from the plant. The probability of occurrence of solar power shortage, i.e. actual power below the scheduled power (P_{ss}), is defined by $f_s(P_{sav} < P_{ss})$ and the expectation of PV output power below P_{ss} is $E(P_{sav} < P_{ss})$.

On contrary to overestimation, penalty cost for underestimation of the solar power is:

$$C_{PS}(P_{sav} - P_{ss}) = K_{PS}(P_{sav} - P_{ss}) = K_{PS} * f_s(P_{sav} > P_{ss}) * [E(P_{sav} > P_{ss}) - P_{ss}] \quad (5.9)$$

where K_{PS} is the penalty cost coefficient for the PV power plant, $f_s(P_{sav} > P_{ss})$ is the probability of solar power being excess of the scheduled power (P_{ss}), $E(P_{sav} > P_{ss})$ is the expectation of PV power above P_{ss} .

d) Cost evaluation of uncertain combined photovoltaic and small-hydro power

Large hydro power plants have huge reservoirs, turning those plants into ideal sources for spinning reserve. However, the capacity being insignificant for the small-hydro compared to the system generation and demand, the ISO may not be bothered about its spinning reserve capacity. In reality, private operators of small-hydro units may not qualify for any reserve or penalty payment. In our case, the 3rd generation system is a combination of a PV unit and a small-hydro unit. Output from the small-hydro unit depends on river flow rate which is well

known for following Gumbel distribution [165]-[166]. Now, the PV power plant qualifies for the reserve and penalty payments like the one discussed in previous section. As contribution of small-hydro is only about 10-20% of total contribution from the combined system, for calculation purpose, we consider reserve and penalty payments for overestimated and underestimated total amounts of power out of the combined system.

Following Eq. (5.8), reserve cost for overestimation of the power from combined generation system is:

$$\begin{aligned} C_{Rsh}(P_{ssh} - P_{shav}) &= K_{Rsh}(P_{ssh} - P_{shav}) \\ &= K_{Rsh} * f_{sh}(P_{shav} < P_{ssh}) * [P_{ssh} - E(P_{shav} < P_{ssh})] \end{aligned} \quad (5.10)$$

where K_{Rsh} is the reserve cost coefficient associated with the combined system, P_{shav} is the actual available power from the plant. The probability of occurrence of combined system power deficit from the scheduled power (P_{ssh}) is given by $f_{sh}(P_{shav} < P_{ssh})$ and the expectation of delivered power below P_{ssh} is $E(P_{shav} < P_{ssh})$.

Following Eq. (5.9), penalty cost for underestimation of the power from combined generation system is:

$$\begin{aligned} C_{Psh}(P_{shav} - P_{ssh}) &= K_{Psh}(P_{shav} - P_{ssh}) \\ &= K_{Psh} * f_{sh}(P_{shav} > P_{ssh}) * [E(P_{shav} > P_{ssh}) - P_{ssh}] \end{aligned} \quad (5.11)$$

where K_{Psh} is the penalty cost coefficient associated with the combined system, $f_{sh}(P_{shav} > P_{ssh})$ is the probability of combined system power being excess of the scheduled power (P_{ssh}), $E(P_{shav} > P_{ssh})$ is the expectation of the combined system power above P_{ssh} .

5.2.3 Emission

Thermal generators which run on fossil fuels emit harmful gases into the environment. The amount of emission of greenhouse gases such as SO_x and NO_x varies with the generated output power (in p.u. MW on 100 MW base) following Eq. (5.12). Emission in tonnes per hour (t/h) is computed by:

$$Emission, E_{Tot} = \sum_{i=1}^{N_{TG}} [(\varphi_i + \psi_i P_{TGi} + \omega_i P_{TGi}^2) \times 0.01 + \tau_i \exp(\zeta_i P_{TGi})] \quad (5.12)$$

where $\varphi_i, \psi_i, \omega_i, \tau_i$ and ζ_i are all emission coefficients associated with the i -th thermal generator. These coefficients are provided in Table 5.2. It is worth mentioning that the study does not consider emission from the spinning reserve.

5.2.4 Objectives of optimization

The objectives of EED problem are minimization of both generation cost and emission. Total cost of generation is the summation of thermal generator cost and direct, reserve and penalty costs for the renewable power. Thus, total cost for 3 thermal units, one wind power unit, one PV power unit and one combined PV and small-hydro unit can be represented as the summation of Eqs. (5.2) - (5.11):

$$\begin{aligned} C_{Tot} = & C_T(P_{TG}) + [C_w(P_{ws}) + C_{Rw}(P_{ws} - P_{wav}) + C_{Pw}(P_{wav} - P_{ws})] \\ & + [C_s(P_{ss}) + C_{Rs}(P_{ss} - P_{sav}) + C_{Ps}(P_{sav} - P_{ss})] \\ & + [C_{sh}(P_{ssh}) + C_{Rsh}(P_{ssh} - P_{shav}) + C_{Psh}(P_{shav} - P_{ssh})] \end{aligned} \quad (5.13)$$

Objectives of multi-objective optimization:

$$\text{Minimize } [C_{Tot}, E_{Tot}] \quad (5.14)$$

The EED objective is subject to many system equality and inequality constraints.

a) Equality constraints

Equality constraints are for instantaneous power balance for which the generated active and reactive power must be equal to the sum of respective demands and losses in the network.

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{NB} V_j [G_{ij} \cos(\delta_{ij}) + B_{ij} \sin(\delta_{ij})] = 0 \quad \forall i \in NB \quad (5.15)$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} V_j [G_{ij} \sin(\delta_{ij}) - B_{ij} \cos(\delta_{ij})] = 0 \quad \forall i \in NB \quad (5.16)$$

where $\delta_{ij} = \delta_i - \delta_j$, is the voltage angle difference of buses i and j . Active and reactive load demands at bus i are P_{Di} and Q_{Di} , respectively, while active and reactive power generation from a source (conventional or renewable) connected at bus i are P_{Gi} and Q_{Gi} , respectively. Number of buses in the network is NB . Transfer conductance between buses i and j is G_{ij} and the susceptance between the same set of buses is B_{ij} .

b) Inequality constraints

The inequality constraints for EED problem are the operational limits of all the generators, prohibited operating zones (POZs) of thermal units and security constraints on system transmission lines and buses. Eqs. (5.17) - (5.20) represent the active power generation limits of thermal, wind, solar power (PV) generators and combined generation system, respectively. Eqs. (5.21) - (5.24) define the reactive power capabilities of the generators following the same order of thermal, wind, solar and solar-small hydro units.

$$\blacksquare \text{ Generator constraints: } P_{TGi}^{min} \leq P_{TGi} \leq P_{TGi}^{max} \quad \forall i \in N_{TG} \quad (5.17)$$

$$\text{Operational limits} \quad P_{ws}^{min} \leq P_{ws} \leq P_{ws}^{max} \quad (5.18)$$

$$P_{ss}^{min} \leq P_{ss} \leq P_{ss}^{max} \quad (5.19)$$

$$P_{ssh}^{min} \leq P_{ssh} \leq P_{ssh}^{max} \quad (5.20)$$

$$Q_{TGi}^{min} \leq Q_{TGi} \leq Q_{TGi}^{max} \quad \forall i \in N_{TG} \quad (5.21)$$

$$Q_{ws}^{min} \leq Q_{ws} \leq Q_{ws}^{max} \quad (5.22)$$

$$Q_{ss}^{min} \leq Q_{ss} \leq Q_{ss}^{max} \quad (5.23)$$

$$Q_{ssh}^{min} \leq Q_{ssh} \leq Q_{ssh}^{max} \quad (5.24)$$

The cost curve of thermal generator may be discontinuous as the whole operating range is sometimes unavailable due to vibration in shaft bearing, fault in the machine or its accessories such as pumps, boilers, etc. [95]. Therefore, in operational range, certain zones are introduced within which the thermal generator is not allowed to operate. These zones are known as prohibited operating zones (POZs) and can simply be represented as:

$$\blacksquare \text{ Generator constraints: } P_{TGi}^{minpoz,j} < \text{POZ}_{TGi}^j < P_{TGi}^{maxpoz,j} \quad (5.25)$$

POZs

where $P_{TGi}^{minpoz,j}$ and $P_{TGi}^{maxpoz,j}$ are the lower and upper limits (in MW) of the j -th POZ of the i -th thermal generator. Network security constraints are expressed as:

$$\blacksquare \text{ Security constraints: } V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{max} \quad \forall i \in NG \quad (5.26)$$

$$V_{Lp}^{min} \leq V_{Lp} \leq V_{Lp}^{max} \quad \forall p \in NL \quad (5.27)$$

$$S_{lq} \leq S_{lq}^{max} \quad \forall q \in nl \quad (5.28)$$

Eq. (5.26) defines the voltage limits imposed on the generator buses with NG being the number of generators (including renewables) or generator buses. Eq. (5.27) is for voltage constraint on load buses. Line capacity constraint is given in Eq. (5.28). NL and nl are the numbers of load buses and transmission lines, respectively, in the network. As mentioned before, most of the previous works did not consider network security constraints in EED study. However, as all these variables have certain defined bounds, and realistically, these constraints should be considered. Further, generator ramp up and ramp down rates are not considered in present study. Static model of ED or EED is not concerned with these rates as the study is performed for a specific interval with a definite network loading.

Among aforementioned various constraints, equality constraints of power balance are automatically satisfied with the convergence of power flow. Newton-Raphson iterative method is applied to perform power flow calculation using software tool MATPOWER

[135]. Inequality constraints on control variables viz. generator active power (except swing / slack bus generator) and generator bus voltages are self-limiting. The algorithm selects a feasible value within the defined range of a control variable for an iteration during the optimization process. As the scheduled power from a thermal generator with POZs is a decision variable, the algorithm is not allowed to select the value of the decision parameter within the ranges of POZs. Remaining inequality constraints of system state variables such as swing generator power, reactive power of all generators, line capacities and load bus voltages necessitate proper handling technique so that the defined limits are all adhered to.

The parameter of voltage deviation (VD) is calculated using Eq. (5.29). Voltage deviation is the indicator of voltage quality in the network and is formulated as the cumulative sum of voltage deviations of all load buses (from 1 p.u.) in the network.

$$VD = \left(\sum_{p=1}^{NL} |V_{Lp} - 1| \right) \quad (5.29)$$

5.3. Calculation of stochastic power of renewable sources

5.3.1 Probability distributions of renewable power sources

Fig. 5.2. Wind speed distribution (sample size 8000) for the windfarm at bus 5

Weibull probability density function (PDF) is predominantly used to represent wind speed distribution. The probability of wind speed v m/s following Weibull PDF is given by (same as in Eq. (3.48) in Chapter 3):

$$f_v(v) = \left(\frac{\beta}{\alpha}\right) \left(\frac{v}{\alpha}\right)^{(\beta-1)} e^{-(v/\alpha)^\beta} \text{ for } 0 < v < \infty \quad (5.30)$$

where α and β are the Weibull scale and shape parameters, respectively. Selected values of all PDF parameters are provided in Table 5.3. The parameter values are realistically chosen considering installed capacity of the power generating sources. Fig. 5.2 represents Weibull fitting and wind speed frequency distribution, obtained after running 8000 Monte-Carlo scenarios.

Table 5.3. PDF parameters for stochastic models of renewable sources

Wind power plant (bus 5)			PV plant (bus 11)		Combined PV + small-hydro (bus 13)			
No. of turbines	Total rated power, P_{wr}	Weibull PDF parameters	Rated power, P_{sr}	Lognormal PDF parameters	PV plant rated power, P_{sr}	Lognormal PDF parameters	Small-hydro rated power, P_{hr}	Gumbel PDF parameters
25	75 MW	$\alpha = 9$ $\beta = 2$	50 MW	$\mu = 5.2$ $\sigma = 0.6$	45 MW	$\mu = 5.0$ $\sigma = 0.6$	5 MW	$\lambda = 15$ $\gamma = 1.2$

Lognormal PDF correctly represents distribution of solar irradiance (G_s). The probability of solar irradiance (G_s) following lognormal PDF with mean μ and standard deviation σ is (same as in Eq. (3.51) in Chapter 3):

$$f_G(G_s) = \frac{1}{G_s \sigma \sqrt{2\pi}} \exp \left\{ -\frac{(\ln G_s - \mu)^2}{2\sigma^2} \right\} \text{ for } G_s > 0 \quad (5.31)$$

Lognormal fitting and frequency distribution of solar irradiance in Fig. 5.3 with chosen PDF parameters are obtained after running Monte Carlo simulation with a sample size of 8000.

Fig. 5.3. Solar irradiance distribution (sample size 8000) for the PV unit at bus 11

It is well established that river flow rate follows Gumbel distribution [165]-[166], an extreme value distribution. The probability of river flow rate Q_h following Gumbel distribution with location parameter λ and scale parameter γ is written as:

$$f_Q(Q_h) = \frac{1}{\gamma} \exp\left(\frac{Q_h - \lambda}{\gamma}\right) \exp\left[-\exp\left(\frac{Q_h - \lambda}{\gamma}\right)\right] \quad (5.32)$$

Fig. 5.4. Solar irradiance distribution (sample size 8000) for the PV unit at bus 13

Fig. 5.5. River flow rate distribution (sample size 8000) for the small-hydro unit at bus 13

At bus 13 of the adapted IEEE 30-bus system, a small-hydro together with a PV unit is connected, replacing the conventional generator. Fig. 5.4 is for the solar irradiance distribution and lognormal fitting available for the PV at bus 13, while Fig. 5.5 is for the river flow rate frequency distribution and Gumbel fitting. Both these diagrams are generated

after running 8000 Monte Carlo scenarios with selected values of PDF parameters provided in Table 5.3.

5.3.2 Power outputs from wind, photovoltaic and small-hydro units

The windfarm connected to bus 5 is assumed to have 25 turbines of 3 MW each, thereby, totaling the farm capacity to 75 MW. Output from a wind turbine varies according to the wind speed it encounters. The relationship between output power and wind speed (v) is expressed as [57]:

$$p_w(v) = \begin{cases} 0, & \text{for } v < v_{in} \text{ and } v > v_{out} \\ p_{wr} \left(\frac{v - v_{in}}{v_r - v_{in}} \right) & \text{for } v_{in} \leq v \leq v_r \\ p_{wr} & \text{for } v_r < v \leq v_{out} \end{cases} \quad (5.33)$$

where p_{wr} is the rated output power of a single wind turbine. v_{in} , v_r and v_{out} are the turbine cut-in, rated and cut-out wind speeds, respectively. The various speed values considered in our study are $v_{in} = 3$ m/s, $v_r = 16$ m/s and $v_{out} = 25$ m/s, in line with the data of Enercon E82-E4 turbine.

The solar irradiance (G_s) to energy conversion for the PV unit is given by [60]:

$$P_s(G_s) = \begin{cases} P_{sr} \left(\frac{G_s^2}{G_{std} R_c} \right) & \text{for } 0 < G_s < R_c \\ P_{sr} \left(\frac{G_s}{G_{std}} \right) & \text{for } G_s \geq R_c \end{cases} \quad (5.34)$$

where G_{std} is the solar irradiance in standard environment, set as 1000 W/m². R_c is a certain irradiance point, set as 120 W/m². These data are applicable to both the PV plant connected to bus 11 and bus 13. P_{sr} is the rated output power of the PV unit.

The power output from a small-hydro unit depends upon the water flow rate (Q_h) and effective pressure head (H_{hyd}). The power output from small-hydro unit can be mathematically represented as [164]:

$$P_H(Q_h) = \eta \rho g Q_h H_{hyd} \quad (5.35)$$

where η is the efficiency of turbine-generator assembly, ρ is the water density and g is the acceleration due to gravity. Numerical values considered for these parameters to calculate hydro power are, $\eta = 0.85$, $\rho = 1000$ kg/m³, $g = 9.81$ m/s² and $H_{hyd} = 25$ m.

5.3.3 Calculation of wind power probabilities

The output power from wind turbine is discrete at a couple of zones of wind speeds as observed from Eq. (5.33). The power output is zero when wind speed (v) is below cut-in speed (v_{in}) or above cut-out speed (v_{out}). Between rated wind speed (v_r) and cut-out speed (v_{out}), the turbine produces rated power output p_{wr} . Wind power probabilities for these discrete zones are computed by [57]:

$$f_w(p_w)\{p_w = 0\} = 1 - \exp\left[-\left(\frac{v_{in}}{\alpha}\right)^\beta\right] + \exp\left[-\left(\frac{v_{out}}{\alpha}\right)^\beta\right] \quad (5.36)$$

$$f_w(p_w)\{p_w = p_{wr}\} = \exp\left[-\left(\frac{v_r}{\alpha}\right)^\beta\right] - \exp\left[-\left(\frac{v_{out}}{\alpha}\right)^\beta\right] \quad (5.37)$$

The wind turbine power output is continuous between cut-in speed (v_{in}) and rated speed (v_r) of wind. The probability for the continuous region is calculated by [57]:

$$f_w(p_w) = \frac{\beta(v_r - v_{in})}{\alpha^\beta * p_{wr}} \left[v_{in} + \frac{p_w}{p_{wr}}(v_r - v_{in}) \right]^{\beta-1} \exp\left[-\left(\frac{v_{in} + \frac{p_w}{p_{wr}}(v_r - v_{in})}{\alpha}\right)^\beta\right] \quad (5.38)$$

5.3.4 Photovoltaic power over/under estimation cost calculation

Fig. 5.6 represents the histogram of available power from solar radiation for the site of PV unit connected to bus 11. It may not be possible to fully harness the available solar power as the PV power unit and its accessories have defined capacities. Moreover, the private owner of PV power plant may not qualify for the penalty payment beyond installed (or rated) capacity of the plant. Fig. 5.7 provides the histogram of real power that can be delivered by the PV power plant. The output power is capped at rated power of the unit. Scheduled power, an amount that is mutually agreed between the private operator and ISO, can be any point on horizontal axis of the diagram. The same is indicated with magenta dotted line. Now, the cost of overestimation in Eq. (5.8) can be computed by:

$$C_{Rs}(P_{ss} - P_{sav}) = K_{Rs}(P_{ss} - P_{sav}) = K_{Rs} \sum_{n=1}^{N_b^-} [P_{ss} - P_{sn-}] * f_{sn-} \quad (5.39)$$

where P_{sn-} is the available power which is less than the scheduled power P_{ss} , on left-half plane of P_{ss} in the histogram in Fig. 5.7. f_{sn-} is the relative frequency of occurrence of P_{sn-} . N_b^- is the number of discrete bins on left-half of P_{ss} or simply the number of pairs (P_{sn-}, f_{sn-}) generated for the PDF. It is observed that increasing number of segments (bins) beyond a

certain value does not notably impact the accuracy of results. Therefore, for practically acceptable results, a total (N_b) of 30 segments are considered for the problem under study.

Fig. 5.6. Available power from solar irradiance for the site of the PV unit at bus 11

Fig. 5.7. Distribution of available real power (MW) from the PV unit at bus 11

For underestimation of stochastic solar power, ISO is to bear certain penalty cost. The penalty cost given in Eq. (5.9) can be calculated as:

$$C_{Ps}(P_{sav} - P_{ss}) = K_{Ps}(P_{sav} - P_{ss}) = K_{Ps} \sum_{n=1}^{N_b^+} [P_{sn+} - P_{ss}] * f_{sn+} \quad (5.40)$$

where P_{sn+} is the available power which is more than the scheduled power P_{ss} , on right-half plane of P_{ss} in the histogram in Fig. 5.7. f_{sn+} is the relative frequency of occurrence of P_{sn+} .

N_b^+ is the number of discrete bins on right-half of P_{ss} or simply the number of pairs (P_{sn+}, f_{sn+}) generated for the PDF.

5.3.5 Combined photovoltaic and small-hydro power over/under estimation cost calculation

Available solar power for the site of solar generator and from the generator at bus 13 are represented by the histograms in Fig. 5.8. Rated power of selected hydro generator unit, connected to bus 13, is larger than the available hydro power calculated from stochastic river flow rate. Fig. 5.9 represents the subplots of available hydro-power for the site and from the hydro unit; both subplots are same. At bus 13, power outputs from both units are summed and the collective stochastic power output is shown in the histogram in Fig. 5.10. Simple arithmetic point by point addition of 8000 Monte-Carlo sample points of two sets of power distribution values (corresponding to the respective PDFs) is performed to come up with the histogram in Fig. 5.10. As mentioned earlier, small-hydro unit may not qualify for the reserve or penalty payment. However, as contribution from the unit is a small percentage of the aggregate power indicated in Fig. 5.10, the reserve and penalty cost are calculated including the hydro-unit for convenience.

Fig. 5.8. Available solar power (MW) for the site and from the PV unit at bus 13

Fig. 5.9. Available hydro power (MW) for the site and from the small-hydro unit at bus 13

Fig. 5.10. Available total real power (MW) from the combined PV and small-hydro system at bus 13

Like Eq. (5.39), the cost of overestimation for the combined system is:

$$C_{Rsh}(P_{ssh} - P_{shav}) = K_{Rsh}(P_{ssh} - P_{shav}) = K_{Rsh} \sum_{n=1}^{N_b^-} [P_{ssh} - P_{shn-}] * f_{shn-} \quad (5.41)$$

where P_{shn-} is the available power which is less than the scheduled power P_{ssh} , on left-half plane of P_{ssh} in the histogram in Fig. 5.10. f_{shn-} is the relative frequency of occurrence of P_{shn-} . N_b^- is the number of discrete bins on left-half of P_{ssh} or simply the number of pairs (P_{shn-}, f_{shn-}) generated for the PDF. Following Eq. (5.40), penalty cost for underestimation of the combined system is calculated as:

$$C_{Psh}(P_{shav} - P_{ssh}) = K_{Psh}(P_{shav} - P_{ssh}) = K_{Psh} \sum_{n=1}^{N_b^+} [P_{shn+} - P_{ssh}] * f_{shn+} \quad (5.42)$$

where P_{shn+} is the available power which is more than the scheduled power P_{ssh} , on right-half plane of P_{ssh} in the histogram in Fig. 5.10. f_{shn+} is the relative frequency of occurrence of P_{shn+} . N_b^+ is the number of discrete bins on right-half of P_{ssh} or simply the number of pairs (P_{shn+}, f_{shn+}) generated for the PDF.

Table 5.4. Direct, penalty and reserve cost coefficients for stochastic renewable energies

Direct cost coefficient (\$/MW)			Reserve cost coefficient (\$/MW)			Penalty cost coefficient (\$/MW)		
Wind (bus 5)	Solar (bus 11 & 13)	Small- hydro (bus 13)	Wind (bus 5)	Solar (bus 11)	Combined system (bus 13)	Wind (bus 5)	Solar (bus 11)	Combined system (bus 13)
g_w = 1.7	h_s = 1.6	m_h = 1.5	K_{Rw} = 3	K_{Rs} = 3	K_{Rsh} = 3	K_{Pw} = 1.4	K_{Ps} = 1.4	K_{Psh} = 1.4

Numerical values of direct, penalty and reserve cost coefficients for stochastic wind, solar and small-hydro power are provided in Table 5.4. The direct cost coefficients are decided in a way that the cost of wind energy is the highest followed by solar energy and finally, the least expensive hydroelectric power [159]. Reserve cost coefficient for maintaining the spinning reserve is higher than the respective direct cost coefficient. However, penalty cost for not using the available power is lower than the direct cost.

5.4. Simulation results, analyses and comparisons for MOEED study

In this section, simulation results applying both MOEA/D-SF and SMODE-SF algorithms on the study problem are summarized and analyzed. The algorithms are described in Chapter 2, sections 2.1.2 and 2.1.4. The user-defined input parameters for the algorithms are listed in Table 5.5.

Table 5.5. User-defined input data for MOEA/D-SF and SMODE-SF for MOEED study

MOEA/D-SF		SMODE-SF	
Parameter	Value	Parameter	Value
Population size, Np	200	Population size, Np	200
Number of weight vectors (equals Np)	200	Mutation factor, F	0.5
Neighborhood size, T	$0.15 * Np$	Crossover rate, CR	0.9
Probability to update the neighbor (or the whole population otherwise), δ_p	0.9	Max no. of generations, $maxgen$	200
Max number of positions replaced by better new solution in each subproblem at every generation, n_r	$0.01 * Np$		
Maximum number of function evaluation, $maxeval$	100000		
Crossover rate, CR	0.9		
Mutation factor, F	0.5		

5.4.1 The best Pareto front and the best compromise solution

The study case of MOEED is run 21 times applying each algorithm. The hypervolume (HV) indicator [147]-[148] is calculated for each Pareto front (PF) to evaluate its quality in terms of convergence and diversity. The method for calculation of hypervolume is described in Chapter 3, section 3.2, sub-section 3.2.2. The statistical details of HV indicator including maximum, minimum, mean and standard deviation values over 21 runs of each algorithm are presented in Table 5.6. The results are found to be quite consistent across all runs of an algorithm.

Table 5.6. Summary of hypervolume (HV) indicator values using two algorithms in MOEED study

Algorithm	Max	Min	Mean	Std dev
MOEA/D-SF	0.8352	0.8337	0.8346	0.0004
SMODE-SF	0.8707	0.8635	0.8684	0.0026

Well-known fuzzy decision-making technique is used to extract the best compromise solution from the set of non-dominated solutions of best Pareto front. The details of the technique are covered in Chapter 3, section 3.2, sub-section 3.2.2.

5.4.2 Comparison of Pareto fronts of the two algorithms

Fig. 5.11 is the comparison between the best and the worst Pareto fronts (PFs) given by the algorithm MOEA/D-SF. As mentioned before, the best PF is the PF with highest HV indicator value. Curves in Fig. 5.12 draw same comparison of best and worst PFs for algorithm SMODE-SF. It is obvious from these figures and the calculated HV indicator values that there is not much difference between the best and worst PFs obtained by an algorithm. The diversity and distribution of Pareto optimal solutions are found slightly better in the best PFs. The difference in convergence is negligible between the best and worst PFs of same algorithm. However, we are more interested in comparing results of the two algorithms. Hence, assessment of the best PFs attained by the two algorithms becomes pertinent. Fig. 5.13 shows comparison of the best Pareto fronts (PFs) obtained by MOEA/D-SF and SMODE-SF. As observed from the diagram, the diversity of SMODE-SF is better than MOEA/D-SF especially towards cost objective (the fact is also obvious from Fig. 5.11 and Fig. 5.12). In other words, SMODE-SF achieves lower minimum value of emission than what MOEA/D-SF attains, and this is true for all trial runs.

Fig. 5.11. Comparison of the best and worst Pareto fronts of MOEA/D-SF for MOEED study

Fig. 5.12. Comparison of the best and worst Pareto fronts of SMODE-SF for MOEED study

SMODE emphasized on diversified selection process where parents for evolution are chosen according to the summation of normalized objective values and diversity with respect to each other [11]. Further, two sets of populations are maintained throughout where first set of population members with lower normalized objective values in gridded objective space is given preference over the other for evolution. These additional measures augur well to maintain diversity for the real-world problem like EED. Qu *et. al.* [98] also highlighted several cases where superior diversity of SMODE was established over non-dominated sorting genetic algorithm-II (NSGA-II). In terms of convergence, MOEA/D is marginally

better than SMODE as PF of the former dominates some non-dominated solutions of the latter as observed in the diagram. In addition, distribution of solutions across PFs of MOEA/D-SF is more even as the algorithm works on the principle of uniform distribution of weight vectors [7]. Contrary to the best PF, the worst PF is the PF having the least HV indicator value. Fig. 5.14 compares the worst PFs of both the algorithms for the stated problem. As in the case of best PFs' comparison, diversity of Pareto optimal solutions is found better in SMODE-SF than in MOEA/D-SF. On the other hand, uniformity in distribution of solutions and convergence are superior in MOEA/D-SF.

Fig. 5.13. Comparison of the best Pareto fronts of two algorithms for MOEED study

Fig. 5.14. Comparison of the worst Pareto fronts of two algorithms for MOEED study

5.4.3 Simulation results of the two algorithms

Table 5.7 presents detailed simulation results alongwith settings of control variables using both the algorithms, MOEA/D-SF and SMODE-SF, for the best individual objectives and the best compromise solutions. An individual best objective (cost or emission) is picked up from the run (out of 21 runs) that gives the minimum value for that objective. The best compromise solution is extracted from the best Pareto front with the largest HV value across all runs of an algorithm. Control variables are the generator active power (except slack generator P_{TG1} connected to bus 1) and generator bus voltages. P_{ws} , P_{ss} and P_{ssh} are the scheduled power values from the wind, solar and combined solar-hydro units, respectively. Further, discontinuity in the generator cost curve is created by introducing POZs for thermal generator $TG2$ connected to bus 2. The two POZs are within ranges (30,40) MW and (55,65) MW. Active power of slack generator and reactive power of all generators are the state or dependent variables. In the optimization problem, these are treated as constraints which must be satisfied by the algorithm. The wind and solar generators are considered to be capable of absorbing reactive power (negative MVar) of about 0.4 p.u. and delivering reactive power (positive MVar) of about 0.5 p.u. of their rated capacity, in line with the justification provided in Chapter 3. Alongwith the values of objective functions, Table 5.7 also includes aggregate voltage drops of load buses (VD using Eq. (5.29)). The parameter $P_{ssh,h}$ (included in P_{ssh}) in the last row of the table signifies contribution from the small-hydro unit. The amount of power from this unit does not follow any pattern with regard to the optimization objectives because the values of power from the combined solar and small-hydro unit are obtained by simple pointwise summation of all Monte-Carlo simulation points generated independently for both the stochastic sources.

The best cost values achieved by both the algorithms among all trial runs are almost same and the settings of corresponding control variables are also comparable. MOEA/D-SF realizes marginally lower minimum cost value, while SMODE-SF attains lesser emission value. This is to do with the well-diverse PF obtained by SMODE-SF for the highly non-linear optimization problem. In comparison of minimum emission values, the emission amount in SMODE-SF is found to be lower than that in MOEA/D-SF. In the settings of control variables, 27 MW lesser loading is observed on thermal generators in the case of SMODE-SF. Transfer of this load to renewable sources reduces the emission (in the case of SMODE-SF), however, the generation cost increases due to escalation of reserve cost linked to the higher scheduled power from the renewable sources. The best compromise solutions of the two algorithms do not dominate each other on all objectives. MOEA/D-SF proposed

solution is lower on cost, while the solution suggested by SMODE-SF has a smaller emission value. So, it is upto the user to select the best compromise solution based on the importance exercised on an objective. The selected compromise solution can be any one of the two or a new solution out of many non-dominated points.

Table 5.7. Simulation results of the optimization algorithms in MOEED study

Control & state variables	Min	Max	MOEA/D-SF – Best solutions			SMODE-SF – Best solutions		
			Cost	Emission	Comp	Cost	Emission	Comp
P_{TG1} (MW)	50	140	139.048	60.003	117.118	139.848	50.047	111.91
P_{TG2} (MW)	20	80	53.763	65	65	55	47.535	65
POZ (of $TG2$): [30,40]; [55,65]								
P_{TG3} (MW)	10	35	11.558	34.890	18.403	10	35	23.555
P_{ws} (MW)	0	75	52.616	74.290	55.447	53.391	74.282	54.058
P_{ss} (MW)	0	50	17.593	28.529	17.649	16.818	50	18.436
P_{ssh} (MW)	0	50	15.319	23.755	15.326	14.989	29.336	15.755
V_1 (p.u.)	0.95	1.10	1.0785	1.0545	1.076	1.0823	1.0738	1.0761
V_2 (p.u.)	0.95	1.10	1.0644	1.0465	1.0648	1.0672	1.0596	1.0662
V_5 (p.u.)	0.95	1.10	1.0436	1.0277	1.0444	1.0406	1.0393	1.0362
V_8 (p.u.)	0.95	1.10	1.0398	1.0232	1.0402	1.0345	1.0196	1.0362
V_{11} (p.u.)	0.95	1.10	1.0876	1.0619	1.0878	1.0743	1.0576	1.0778
V_{13} (p.u.)	0.95	1.10	1.0622	1.0457	1.0602	1.0668	1.0481	1.0432
Q_{TG1} (MVar)	-50	140	2.736	8.771	2.128	7.191	28.944	2.788
Q_{TG2} (MVar)	-20	60	21.153	19.405	21.410	27.547	21.749	34.504
Q_{TG3} (MVar)	-15	40	39.396	31.835	37.727	33.207	9.100	36.169
Q_{ws} (MVar)	-30	35	27.549	22.165	27.102	24.238	25.342	20.376
Q_{ss} (MVar)	-20	25	24.836	22.017	24.911	20.801	21.241	23.410
Q_{ssh} (MVar)	-20	25	21.071	21.514	20.328	24.052	20.950	15.620
Total cost (\$/h)			892.954	994.342	919.040	893.314	1020.490	927.049
Emission (t/h)			2.2772	0.1052	0.6221	2.3950	0.0959	0.4721
VD (p.u.)			0.4567	0.4542	0.4530	0.4369	0.468	0.4215
$P_{ssh,h}$ (MW)			3.50	3.135	3.50	3.163	3.183	3.296

5.4.4 Satisfying system constraints

A very important aspect of the constrained optimization problem is about complying with the limits of system constraints. Non-linear constraint, even in a single-objective non-convex problem, is a difficult proposition to deal with. For multi-objective problem such as the EED with stochastic renewable power, the situation is far more complex as the Pareto front (PF) involves numerous solutions which must be feasible. EED problem in many publications did not consider network security or generator reactive power constraint. Barring ref. [98], penalty function, straight disposal of infeasible solutions, etc. are some of the common methods used in literature. In this sub-section, we verify conformance to the limits of network constraints with the application of a constraint handling technique, superiority of feasible solutions (SF), for multi-objective evolutionary algorithms. The Pareto front (PF)

obtained from each trial run has 200 (population size) non-dominated solutions and all solutions proposed by both the algorithms are feasible. While it is not practical to validate all solutions here, we carefully select some solutions of certain trial runs and check the status of critical constraints. The critical constraints are reactive power of generators and voltages of load buses. The allowable range of load bus voltage is narrow, and generators are found to be operating near to the limits in many situations as observed from some of the solutions in Table 5.7. The worst aggregate voltage-drop (VD in Eq. (5.29)) among all trial runs with each algorithm is picked up and load bus voltage profile is studied for that VD . It is presumed that if all load buses satisfy the voltage bounds for the worst (maximum) VD value (and the corresponding solution), the voltage constraint will be satisfied for other solutions with smaller VD values. Again, for generator reactive power capability, the solutions listed in Table 5.7 show the compliance with the limits of the constraint. Additionally, we pick up the best PF of each algorithm and study the extreme solutions that effect minimum cost and minimum emission values.

Table 5.8. Settings of variables for the best individual objectives of the best PFs

Control & state variables	MOEA/D-SF – Best PF		SMODE-SF – Best PF	
	Best cost	Best emission	Best cost	Best emission
P_{TG1} (MW)	139.297	62.280	139.112	50.072
P_{TG2} (MW)	55	70.051	55	52.627
P_{TG3} (MW)	10.622	35	10	34.919
P_{ws} (MW)	52.380	68.682	53.714	71.168
P_{ss} (MW)	17.348	31.034	16.167	29.555
P_{ssh} (MW)	15.328	19.509	16.057	48.254
V_1 (p.u.)	1.0806	1.0690	1.0825	1.0732
V_2 (p.u.)	1.0659	1.0653	1.0646	1.0572
V_5 (p.u.)	1.0384	1.0473	1.0387	1.0076
V_8 (p.u.)	1.0376	1.0420	1.0316	1.0302
V_{11} (p.u.)	1.0866	1.0681	1.0696	1.0691
V_{13} (p.u.)	1.0615	1.0582	1.0633	1.0160
Q_{TG1} (MVar)	5.317	-0.89	13.849	32.209
Q_{TG2} (MVar)	26.047	27.845	21.72	29.609
Q_{TG3} (MVar)	37.51	34.543	32.692	36.783
Q_{ws} (MVar)	22.139	25.022	24.920	-5.19
Q_{ss} (MVar)	24.903	18.508	20.113	24.951
Q_{ssh} (MVar)	21.131	20.416	23.70	8.624
Total cost (\$/h)	893.003	989.276	893.503	1018.786
Emission (t/h)	2.3134	0.1091	2.2868	0.0961
VD (p.u.)	0.4464	0.4382	0.4304	0.5388
$P_{ssh,h}$ (MW)	3.50	3.20	3.131	3.254

Table 5.8 lists the settings of all variables for solutions that result in the best cost and emission in the best PFs of the two algorithms. Fig. 5.15 indicates the reactive power

schedule of all generators for solutions pertaining to the best individual objective values of the best PF using MOEA/D-SF. Fig. 5.16 describes the same schedule for solutions obtained with SMODE-SF. Looking at the diagrams and the reactive power limits provided in Table 5.7, it is obvious that many generators operate near to the limits of their reactive power capabilities. Therefore, caution must be exercised in satisfying this critical constraint on generator reactive power. A proper constraint handling technique such as SF helps to select the optimal settings of network control parameters so that the system can operate near to the limits without any violation. Another important observation specifically from the bar chart in Fig. 5.16 (i.e. reactive power schedule in Table 5.8 for SMODE-SF) and reactive power schedule in Table 5.7 (for SMODE-SF) is the high non-linearity of EED problem. The best emission value in Table 5.8 (i.e. 0.0961 t/h) of best PF obtained using SMODE-SF is almost equal to the best emission value listed in Table 5.7 (i.e. 0.0959 t/h) across all trial runs of the algorithm. However, the control parameter settings in both the cases are very much different. Precisely for that reason, the generator reactive power schedule in Fig. 5.16 (and Table 5.8) is totally different from the reactive power schedule in Table 5.7.

Fig. 5.15. Generator reactive power schedule for best objectives of the best PF using MOEA/D-SF

Fig. 5.16. Generator reactive power schedule for best objectives of the best PF using SMODE-SF

Fig. 5.17. Load bus voltage profiles for the worst VD values using the two algorithms

Each profile in Fig. 5.17 signifies load bus voltage profile for the worst VD value among the VD values resulting from all non-dominated solutions across all trial runs using one of the two algorithms. The worst VD reported by MOEA/D-SF is 0.5704 p.u. while that by SMODE-SF is 0.6201 p.u. The difference is due to higher diversity of SMODE-SF, helping the algorithm to attain a bigger extreme cost objective or a smaller extreme emission objective. An analysis of the voltage profiles reveals that the operating voltages of some buses are close to the limits (either upper or lower). This fact again reiterates the effectiveness and usefulness of a suitable constraint handling technique for the evolutionary algorithms. The combination of an evolutionary algorithm (EA) and a proper constraint

handling technique (such as SF) can systematically guide the search process of the EA towards global feasible optima.

5.5. Conclusion: MOEED study with stochastic wind-solar-small hydro power

This chapter proposes a method for finding Pareto optimal solutions of multi-objective economic-environmental power dispatch (MOEED) problem incorporating stochastic wind, solar and small-hydro power. In the context of current trends in energy sector and environmental regulation, such study becomes more relevant as it considers the clean and replenishable energy sources. Stochastic nature of the renewable sources considered in this work is modeled using appropriate probability density functions (PDFs). Discontinuity in generator cost function in the form of prohibited operating zones (POZs) is also included in the model of a selected thermal generator. Multi-objective evolutionary algorithms MOEA/D and SMODE are applied to solve the multimodal, non-linear and non-convex MOEED problem. System constraints including network security constraints are all duly satisfied with the aid of an appropriate constraint handling technique, superiority of feasible solutions (SF). A detailed analysis of the Pareto front with hypervolume (HV) indicator and a comparative study of the results obtained from several trials of the algorithms MOEA/D-SF and SMODE-SF are carried out. Results show that SMODE-SF outperforms MOEA/D-SF in terms of achieving diversity, though convergence of the latter is marginally better than the former. A list of conclusions for the chapter is as follows:

- Uncertain nature of renewable sources can be incorporated in the network with appropriate modelling using suitable probability density functions.
- Discontinuity in decision variables (such as POZs) can be easily incorporated in the optimization algorithm.
- Both MOEA/D and SMODE algorithms can be utilized in conjunction with the constraint handling method SF to optimize constrained optimization problems.
- Multi-objective optimization studies for MOEED with cost and emission objectives using the algorithms MOEA/D-SF and SMODE-SF show that MOEA/D-SF has better convergence, while SMODE-SF attains better diversity.

Chapter 6

6. Distribution network loss minimization

6.1. Introduction to distribution network loss minimization study

The distribution network of a power system incurs a significant amount of power loss, sometimes in the order of 10-13% of the generated output [167]. High distribution loss means inefficiency and poor voltage regulation of the network. To increase efficiency and enhance voltage regulation of the system, network is to be properly reconfigured. In addition, locally added distributed generators (DGs) in the forms of diesel generators, photovoltaics (PVs), wind turbines, etc., and shunt capacitors (SCs) can reduce losses, improve voltage profile and boost capacity of the system. However, reconfiguration of the network and/or allotment of the DG and/or SC cannot be random as that might result in poor performance and unintended operation of the network. Radial arrangements of the feeders in the network must be maintained after reconfiguration. The sizing and placement of DGs and SCs shall be optimized to minimize power loss in the radial distribution network (RDN) satisfying system constraints on power balance, line capacity and bus voltage. In summary, the problem is a mixed-integer non-linear problem where optimum locations (discrete integers) of the network switches and buses are to be determined together with optimal ratings (continuous variables) of the compensating devices. Our research presented in this chapter uses L-SHADE algorithm, a well-established optimization algorithm for the constrained, multimodal non-linear problems. L-SHADE improves the performance of SHADE algorithm with linear reduction of population size in successive generations. The algorithm performed best among non-hybrid algorithms for the optimization of real parameter single-objective functions in CEC 2014 competition [168]. Minimization of power loss in the distribution network is set as the objective and case studies are performed under various scenarios of only reconfiguration of network, only allocation of compensating components and a combination of both. Standard IEEE 33-bus and IEEE 69-bus radial distribution networks are studied under the purview of this chapter and simulation results are found to be among the best.

In rest of the chapter, section 6.2 covers the problem formulation for RDN loss minimization. Section 6.3 provides detail of the case studies performed in this work. The user-defined inputs for algorithm L-SHADE are provided in section 6.4. Simulation results and comparisons are included in section 6.5. The chapter ends with concluding remarks in section 6.6.

6.2. Mathematical formulation and calculation of power loss in the RDN

As both reconfiguration and component allocation play vital roles in RDN loss minimization, the approach to maintain radial nature of the network (after reconfiguration) is discussed in this sub-section, followed by calculation of power flow in the network.

6.2.1 Network reconfiguration

Fig. 6.1 and Fig. 6.2 show the base configurations for IEEE 33-bus and 69-bus systems, respectively, with dotted lines representing normally open tie switches. Nodes (buses) are numbered within the circles. As a first step to apply the algorithm for optimal reconfiguration, all sectionalizing and tie switches of the network are closed. This process creates certain loops in the network marked as Loop1 to Loop5 in the diagrams. Thereafter, any one switch (either tie or sectionalizing) in the loop is opened to maintain the radial nature of the network. The switch must be unique for each loop and opening of the switch must not isolate any node (bus) in the network. The algorithm performs several iterations to come up with the switch numbers, opening of which minimizes the power loss. It must be noted that this operation and allocation of compensating components are simultaneous. Outputs of the optimization algorithm are the identification numbers (labels) of tie switches, the bus numbers for allocating DGs and SCs and the ratings of DGs and SCs.

Fig. 6.1. Base configuration of IEEE 33-bus distribution network

Fig. 6.2. Base configuration of IEEE 69-bus distribution network

6.2.2 Power flow formulation

Fig. 6.3. Single line diagram of a radial feeder

A simple radial feeder configuration is represented by the single line diagram in Fig. 6.3. A set of recursive equations for computation of power flow is given by [169]:

$$P_{k+1} = P_k - P_{Lk+1} - R_{k,k+1} \cdot \frac{P_k^2 + Q_k^2}{V_k^2} \quad (6.1)$$

$$Q_{k+1} = Q_k - Q_{Lk+1} - X_{k,k+1} \cdot \frac{P_k^2 + Q_k^2}{V_k^2} \quad (6.2)$$

$$V_{k+1}^2 = V_k^2 - 2(R_{k,k+1} \cdot P_k + X_{k,k+1} \cdot Q_k) + (R_{k,k+1}^2 + X_{k,k+1}^2) \cdot \frac{P_k^2 + Q_k^2}{V_k^2} \quad (6.3)$$

where P_k and Q_k are the real and reactive power flowing out of bus k ; P_{Lk+1} and Q_{Lk+1} are the real load and reactive load, respectively, at bus $k + 1$. The line section between buses k

and $k + 1$ has a resistance of $R_{k,k+1}$ and a reactance of $X_{k,k+1}$. Magnitude of voltage of bus k is V_k . For convergence of power flow, the power balance Eqs. (6.1)-(6.2) must be satisfied. In addition, magnitudes of sending and receiving end bus voltages must satisfy Eq. (6.3). Newton-Raphson iterative method for calculation of power flow is adopted with the aid of software tool MATPOWER [135]. The power loss (P_{Loss}) in the line section connecting buses k and $k + 1$ is computed by:

$$P_{Loss}(k, k + 1) = R_{k,k+1} \cdot \frac{P_k^2 + Q_k^2}{V_k^2} \quad (6.4)$$

Total power loss (TP_{Loss}) in the network is summation of all the line losses as follows:

$$TP_{Loss} = \sum_{k=0}^{N-1} P_{Loss}(k, k + 1) \quad (6.5)$$

In this study, we consider that the DGs are supplying real power at unity power factor e.g. photo-voltaic systems, micro turbines, etc. Therefore, if a DG, delivering power output of P_{DG} , is added to a bus (say m -th bus), the real power demand in that bus changes from P_{Lm} to $(P_{Lm} - P_{DG})$. An additional shunt capacitor of rating Q_C at n -th bus is modeled as a constant impedance to ground at that bus. The algorithm checks all possible locations with all probable ratings of the DGs and SCs during the search process to find the optimum allocation.

During the process of network reconfiguration and component allocation, following network constraints must be satisfied:

$$V_{min} \leq V_k \leq V_{max} \quad (6.6)$$

$$I_{k,k+1} \leq I_{k,k+1(max)} \quad (6.7)$$

where Eq. (6.6) is for the allowable range of voltage magnitude of bus k between V_{min} and V_{max} . In this study, we consider $V_{min} = 0.90$ p.u. and $V_{max} = 1.05$ p.u. $I_{k,k+1}$ is the magnitude of current flowing in the line connecting buses k and $k + 1$, while $I_{k,k+1(max)}$ is the maximum permissible current through the same branch considering mainly the thermal capability of the line. It is mentioning worthwhile that for IEEE standard distribution networks, branch current limits are not explicitly stated. Cruz *et. al.* [170] made assumptions of 200A and 400A for 12.66kV IEEE-33 bus radial distribution network, while ref. [171] considered 400A, 250A and 150A. And also for IEEE-69 bus system, differences in presumed line capacities are observed in [117] and [171]. As the current carrying capacity of a branch transpires to be a user-defined parameter which might be dependent upon several

other factors (e.g. whether overhead transmission line or underground cable), it does not warrant mandatory checks for its limit violation. Moreover, at medium voltage level the network current is relatively low and further augmentation with local DGs mostly relieves the burden from a line. Therefore, if base configuration of a network can support the connected load, the network with added local DGs or/and SCs without change in load is unlikely to violate the line current limits. Therefore, the algorithm in this study does not check the condition of line current capacity constraint.

6.3. Case studies for RDN loss minimization

The case studies performed in this chapter for the two distribution networks are discussed in this section. Scenarios of only reconfiguration, only DG allocation, simultaneous reconfiguration and DG allocation, reconfiguration together with DG and SC allocation are considered in the case studies. It is worthwhile to note that the number of DGs and SCs, the aggregate power of the added DGs and the total VAR compensation by SCs – all affect the real power loss in the network. Increasing the quantities of DGs and SCs beyond certain numbers may not be technically and/or commercially feasible. Again, the DG penetration cannot be too high, else the network might turn into an active network. Too large collective rating of added DGs might increase required short circuit levels of the components connected to the system. Therefore, we judiciously limit the number and penetration of the DGs and SCs in line with some past reference papers for a meaningful and rational comparison of current results with previously reported results.

Table 6.1. Summary of case studies for RDN loss minimization

Network	Case no.	Case description	No. of DGs	Max DG penetration	No. of SCs	Max total SC compensation
33-bus	Case 1	Only reconfiguration	-	-	-	-
	Case 2	Only DG allocation	3	2.5 MW	-	-
	Case 3	Simultaneous reconfiguration and DG allocation	3	2.5 MW	-	-
	Case 4	DG and SC allocation	2	2.0 MW	2	2.3 MVar
	Case 5	Simultaneous reconfiguration, DG and SC allocation	3	2.0 MW	3	2.3 MVar
69-bus	Case 11	Only reconfiguration	-	-	-	-
	Case 12	Only DG allocation	3	2.5 MW	-	-
	Case 13	Simultaneous reconfiguration and DG allocation	3	2.5 MW	-	-
	Case 14	DG and SC allocation	2	2.25 MW	2	2.69 MVar
	Case 15	Simultaneous reconfiguration, DG and SC allocation	3	2.25 MW	3	2.69 MVar

Total load of 33-bus network is 3.72 MW and 2.30 MVar, while that of 69-bus network is 3.80 MW and 2.69 MVar. Line parameters and detailed data on load demands for the networks are provided in [172]. A summary of the case studies is presented in Table 6.1. For practicability of implementation, minimum rating of a DG is set to 200 kW, and that of a SC is set to 200 kVar. DG is considered operating at unity power factor and the network is fully loaded (100%). In a case study, the number and aggregate rating of the compensating components are not to exceed the values given in the table for the case. It may be noted that no literature performed case studies on simultaneous reconfiguration, DG and SC allocation, i.e. Case 5 and Case 15 in Table 6.1. The quantities and total ratings of the components are realistically chosen for these two cases.

6.4. Inputs for L-SHADE algorithm for cases of RDN loss minimization

L-SHADE algorithm is applied for minimization of RDN real power loss. The algorithm has been discussed in detail in Chapter 2, section 2.1.1.

Table 6.2. Inputs for L-SHADE algorithm in RDN loss minimization study

Parameter	Network and case no.		Value
	IEEE 33-bus	IEEE 69-bus	
Dimension of the optimization problem, d	Case 1	Case 11	5
	Case 2	Case 12	6
	Case 3	Case 13	11
	Case 4	Case 14	8
	Case 5	Case 15	17
Initial population size, Np_{ini}	Cases 1, 2 & 4	Cases 11, 12 & 14	100
	Cases 3 & 5	Cases 13 & 15	120
Maximum no. of fitness evaluations, $maxeval$	Cases 1, 2 & 4	Cases 11, 12 & 14	24000
	Case 3	Case 13	30000
	Case 5	Case 15	40000

Table 6.2 lists the dimensions of the optimization problem for various cases and also the applied parameters for L-SHADE algorithm. Case 1 and Case 11 are for only network reconfiguration for 33-bus and 69-bus systems, respectively. As mentioned before, 5 loops are recognized in each network. A unique sectionalizing switch is to be identified in each loop for opening. Therefore, a total of 5 decision variables are to be optimized in these cases. Case 2 and Case 12 are for allotment of suitably rated 3-DGs. The candidate bus for allocation of a DG can be any bus in the network. 3 variables represent 3 locations (buses) in the network while remaining 3 variables signify ratings of the 3-DGs. As Case 3 and Case

13 are for both reconfiguration and DG allocation, the number of decision variables in these cases is 11. Case 4 and Case 14 deal with optimal sizing and siting of 2-DGs and 2-SCs. Therefore, a total of 8 variables (4 locations + 4 ratings) are to be optimized in these cases. As Case 5 and Case 15 are for simultaneous reconfiguration, and allocations of the 3-DGs and 3-SCs, the number of variables in each case is 17 (5 switches + 6 locations + 6 ratings). Due to higher number of variables in cases 3, 13, 5 and 15, the selected initial population size is slightly larger than that in the remaining cases. Increasing the population size beyond 120 does not have notable impact on the outcome as more fitness evaluations are performed for these cases. It may be noted that the initial population size and maximum number of fitness evaluations are selected after a few trials of the algorithm.

6.5. Results and comparisons of RDN loss minimization cases

Simulation results with the application of L-SHADE algorithm are analyzed in this section. Each study case is run 5 times and the results are found to be consistent with little variations among optimum decision variables across different runs. Further analysis and discussion on network loss minimization are provided herein.

6.5.1 IEEE 33-bus system

[Table 6.3](#) summarizes the results of case studies for IEEE 33-bus system and the comparison of present study with similar past studies. The best loss values among comparable algorithms are highlighted in bold fonts. Optimal DG and SC ratings are included in the table and bus numbers to allocate the components are provided in the parentheses next to the ratings.

In **Case 1** of network reconfiguration for 33-bus system, algorithm L-SHADE achieves lowest loss value alongwith heuristic method of uniform voltage distribution based constructive reconfiguration algorithm (UVDA) [\[121\]](#). In study **Case 2** of DG siting and sizing for 33-bus system, algorithm L-SHADE attains real power loss value of **72.90 kW**, least amongst all. Another important aspect to note on this case study is the aggregate rating for the DGs. While L-SHADE limits the total rating to 2.5 MW, adaptive cuckoo search algorithm (ACSA) [\[120\]](#) selects more than 3.2 MW. The difference is significant as larger DG rating incurs higher cost of installation. Enhancement of DG capacity implies augmentation of ratings of all related accessories. Investment cost of a diesel generator-based 1 MW DG is found to be 50 times higher than the investment cost of a 1 MVar capacitor

bank [173]. Therefore, installed capacity of DG must be given due importance when the distribution network is reinforced with DG to minimize system losses. The aggregate DG ratings vs real power losses for case studies pertaining to IEEE 33-bus system using various algorithms are plotted in the bar chart in Fig. 6.4. Though fireworks algorithm (FWA) [119] selects lower ratings for the DGs, the loss is considerably high. As an example, in **Case 2** of DG allocation, FWA [119] proposes DG capacity which is 700 kW less than what L-SHADE suggests. However, the loss achieved by FWA [119] is about 22% higher than the loss obtained by L-SHADE algorithm. Output of UVDA [121] with a total DG rating of about 2.7 MW is better than that of ACSA [120]. On voltage regulation front, a higher rating for DG helps to maintain slightly better voltage level as observed from the results of ACSA [120]. However, voltage regulation is not the primary objective in this optimization.

In **Case 3** of simultaneous reconfiguration and DG allocation in 33-bus network, present study reports a loss value of **53.15 kW**, almost same as reported by ACSA [120]. However, total selected DG rating by ACSA [120] is about 3.3 MW, close to 90% loading of the network. L-SHADE algorithm optimally distributes 2.5 MW of DG power and suitably reconfigures the network such that the lowest loss can be achieved with minimum capacity of the DG. It may be noted that ref. [119] adopts sequential approach in placing and sizing the DGs. Network reconfiguration is followed by the identification of candidate buses for DG allocation and finally, the optimization of DG capacity is performed. However, as observed from the results of all methods, simultaneous siting and sizing of DGs are more effective in reducing system losses. L-SHADE algorithm outperforms intersect mutation differential evolution (IMDE) [117] in a notable manner in **Case 4** where correctly sized DGs and SCs, two of each, are to be allocated. With almost same ratings of the components (specifically DG) as in [117] but with little reshuffle in positioning, the system real power loss is brought down further by about 11.25%, from 32.08 kW to **28.47 kW**. Back-tracking search algorithm (BSA) [118] algorithm could lower real power loss to an extent, however selected DG size is much bigger. In **Case 5**, LSHADE algorithm attains minimum power loss of **15.63 kW** by network reconfiguration together with optimal addition of total 2 MW of DGs and 2.3 MVar of SCs.

Table 6.3. Simulation results and comparison of RDN case studies for IEEE 33-bus system

Case no.	Case description	Parameter	Various optimization algorithms				
			L-SHADE	FWA [119]	ACSA [120]	UVDA [121]	IMDE [117] BSA [118]
Case 1	Only reconfiguration	Open switches	7, 9, 14, 32, 37	7, 9, 14, 28, 32	7, 9, 14, 28, 32	7, 9, 14, 32, 37	
		Real power loss (kW)	139.55	139.98	139.98	139.55	
		Min. bus voltage, p.u. (bus no.)	0.9378 (32)	0.9413 (32)	0.9413 (32)	0.9378 (32)	
Case 2	Only DG allocation	Open switches	33, 34, 35, 36, 37	33, 34, 35, 36, 37	33, 34, 35, 36, 37	33, 34, 35, 36, 37	
		Real power loss (kW)	72.90	88.68	74.26	74.21	
		DG sizes in kW (bus no.)	733.9 (14), 733.5 (25), 1032.6 (30)	589.7 (14), 189.5 (18), 1014.6 (32)	779.8 (14), 1125.1 (24), 1349.6 (30)	875 (11), 931 (24), 925 (29)	
		Min. bus voltage, p.u. (bus no.)	0.9658 (33)	0.9680 (30)	0.9778 (33)	0.962 (33)	
Case 3	Simultaneous reconfiguration and DG allocation	Open switches	7, 9, 14, 27, 30	7, 11, 14, 28, 32	11, 28, 31, 33, 34	7, 10, 13, 27, 32	
		Real power loss (kW)	53.15	67.11	53.21	57.29	
		DG sizes in kW (bus no.)	523.7 (12), 779.6 (18), 1196.7 (25)	531.5 (18), 615.8 (29), 536.7 (32)	964.6 (7), 896.8 (18), 1438.1 (25)	649 (15), 486 (21), 1554 (29)	
		Min. bus voltage, p.u. (bus no.)	0.9688 (31)	0.9713 (14)	0.9806 (31)	0.976 (32)	
Case 4	DG and SC allocations	Open switches	33, 34, 35, 36, 37				33, 34, 35, 36, 37 33, 34, 35, 36, 37
		Real power loss (kW)	28.47				32.08 30.87
		DG sizes in kW (bus no.)	840 (12), 1140.1 (30)				1080 (10), 860 (13), 896.4 (31) 1310.5 (30)
		SC sizes in kVAr (bus no.)	455.5 (12), 1039.1 (30)				254.8 (16), 334.8 (14), 932.3 (30) 899.8 (30)
		Min. bus voltage, p.u. (bus no.)	0.9804 (25)				0.979 (25) -
Case 5	Simultaneous reconfiguration, DG and SC allocations	Open switches	7, 11, 12, 17, 26				
		Real power loss (kW)	15.63				
		DG sizes in kW (bus no.)	555.1 (15), 811.2 (25), 633.7 (32)				
		SC sizes in kVAr (bus no.)	701.1 (3), 402.1 (9), 1196.8 (30)				
		Min. bus voltage, p.u. (bus no.)	0.9891 (12)

Fig. 6.4. Selected total DG capacity vs real power loss with various optimization methods for case studies of IEEE 33-bus system

Fig. 6.5. Bus voltage profiles of IEEE 33-bus system for different case studies

Voltage profiles of network buses for the case studies of IEEE 33-bus system are represented in Fig. 6.5. All bus voltages are found to be within allowable limits [0.90 p.u.-1.05 p.u.]. Most uniform profile is justifiably obtained in **Case 5** where network reconfiguration is accompanied by allocation of 3-DGs and 3-SCs. Voltage level is also acceptably uniform, indeed better at some buses, in **Case 4** with selected distribution of 2-DGs and 2-SCs. In **Case 4**, though the voltage level at some buses is high, the same is drastically low at a few buses. Therefore, a more even distribution of compensating components ensures more uniform voltage profile, lower losses in the network. The worst voltage profile is expectedly obtained in **Case 1** of only network reconfiguration.

6.5.2 IEEE 69-bus system

Simulation results and comparison of case studies for IEEE 69-bus system are summarized in Table 6.4. In **Case 11** of network reconfiguration, L-SHADE achieves the lowest loss of **98.60 kW** along with some other algorithms listed in table. The minor variation in results for **Case 11** is possibly due to approximation of some network data. As observed from the results of the case, any one switch among 55, 56, 57 and 58 can be opened in the corresponding loop without notable change in network loss value. Study case of only DG allotment is **Case 12** where remarkably low loss value of **69.60 kW** is realized in present study. Fig. 6.6 shows the selected aggregate DG rating vs real power loss for case studies pertaining to IEEE 69-bus system using various algorithms. Like **Case 2** for 33-bus system, ACSA [120] selects the largest total capacity for the DGs in **Case 12**. In **Case 13** of simultaneous network reconfiguration and DG allocation, the minimum real power loss of **35.54 kW** is achieved by L-SHADE algorithm while total capacity of the added DGs is capped at 2.5 MW. When compared with UVDA [121], the loss is about 1.5 kW lower with about 200 kW less total proposed capacity for the DGs. Major improvement in network loss is observed in **Case 14** (allocation of 2-DGs and 2-SCs) when compared with similar available study using IMDE [117]. With almost similar ratings of the equipment but change in placement of those, L-SHADE brings the loss down to 7.28 kW, a reduction of almost 47%. **Case 15** of 69-bus system incurs minimum power loss of **4.82 kW** when simultaneous network reconfiguration and optimum allocations of total 2.25 MW of DGs and 2.69 MVar of SCs are executed.

Table 6.4. Simulation results and comparison of RDN case studies for IEEE 69-bus system

Case no.	Case description	Parameter	Various optimization algorithms				
			L-SHADE	FWA [119]	ACSA [120]	UVDA [121]	IMDE [117]
Case 11	Only reconfiguration	Open switches	14, 55, 61, 69, 70	14, 56, 61, 69, 70	14, 57, 61, 69, 70	14, 58, 61, 69, 70	
		Real power loss (kW)	98.60	98.59	98.59	98.58	
		Min. bus voltage, p.u. (bus no.)	0.9495 (61)	0.9495 (61)	0.9495 (61)	0.9495 (61)	
Case 12	Only DG allocation	Open switches	69, 70, 71, 72, 73	69, 70, 71, 72, 73	69, 70, 71, 72, 73	69, 70, 71, 72, 73	
		Real power loss (kW)	69.60	77.85	72.44	72.63	
		DG sizes in kW (bus no.)	423.1 (11), 380.4 (18), 1696.5 (61)	225.8 (27), 1198.6 (61), 408.5 (65)	602.2 (11), 380.4 (18), 2000 (61)	604 (11), 417 (17), 1410 (61)	
		Min. bus voltage, p.u. (bus no.)	0.9776 (65)	0.9740 (62)	0.9890 (65)	0.9688 (65)	
Case 13	Simultaneous reconfiguration and DG allocation	Open switches	14, 58, 61, 69, 70	13, 55, 63, 69, 70	14, 58, 61, 69, 70	14, 58, 63, 69, 70	
		Real power loss (kW)	35.54	39.25	37.02	37.11	
		DG sizes in kW (bus no.)	517.6 (11), 559.4 (27), 1423.0 (61)	1127.2 (61), 275.0 (62), 415.9 (65)	541.3 (11), 1724.0 (61), 553.6 (65)	538 (11), 673 (17), 1472 (61)	
		Min. bus voltage, p.u. (bus no.)	0.9811 (61)	0.9796 (61)	0.9869 (50)	0.9816 (63)	
Case 14	DG and SC allocations	Open switches	69, 70, 71, 72, 73				69, 70, 71, 72, 73
		Real power loss (kW)	7.28				13.83
		DG sizes in kW (bus no.)	492 (17), 1703.3 (61)				1738 (62), 479 (24)
		SC sizes in kVAr (bus no.)	354.3 (17), 1241.9 (61)				109 (63), 1192 (61)
		Min. bus voltage, p.u. (bus no.)	0.9936 (69)				0.9915 (68)
Case 15	Simultaneous reconfiguration, DG and SC allocations	Open switches	14, 17, 69, 72, 73				
		Real power loss (kW)	4.82				
		DG sizes in kW (bus no.)	394.3 (12), 200 (21), 1655.7 (61)				
		SC sizes in kVAr (bus no.)	521.1 (12), 947.8 (49), 1221.1 (61)				
		Min. bus voltage, p.u. (bus no.)	0.9956 (17)

Fig. 6.6. Selected total DG capacity vs real power loss with various optimization methods for case studies of IEEE 69-bus system

Fig. 6.7. Bus voltage profiles of IEEE 69-bus system for different case studies

Fig. 6.7 shows bus voltage profiles for various case studies performed for the IEEE 69-bus radial distribution network. All bus voltages are within allowable limits. The profile is rightly most uniform and even for **Case 15** when network reconfiguration is coupled with DG and

SC allocations. Further, the network is able to maintain the voltage nearer to 1 p.u. for cases where SCs are added (**Case 14** and **Case 15**). Shunt capacitors deliver reactive power (VAR) that supports the network voltage. However, boosting network capacity with many compensating equipment may drive the network to voltage overshoot. Therefore, careful judgement is necessary as adding large number of equipment may not be economically viable, technically feasible or may well turn out to be virtually ineffective.

Fig. 6.8. Convergence of L-SHADE algorithm for Case 5 and Case 15 of RDN loss minimization

The convergence curves of selected case studies for RDN loss minimization are portrayed in Fig. 6.8. **Case 5** and **Case 15** have the highest number of decision variables with most of those being discrete integers. The algorithm requires maximum number of fitness evaluations to converge to optimal solutions. The **Case 5** for smaller distribution network takes about 30,000 fitness evaluations to converge, while **Case 15** for larger network needs around 34,000 fitness evaluations to arrive at an optimal solution. Due to presence of discrete variables (switch nos. and bus nos.), the algorithm sometimes gets trapped at intermediate points.

6.6. Conclusion: loss minimization in RDN

This chapter presents a useful and effective application of L-SHADE algorithm for simultaneous optimization of discrete and continuous variables in a real-world problem of distribution network. The proposed algorithm is highly efficient and productive in finding optimal solutions for the single-objective optimization cases discussed in this chapter. With

a more appropriate selection of network switches for opening, with a little reshuffle in the placement of compensating devices, and with a more accurate distribution of the component capacity, L-SHADE algorithm achieves the lowest real power loss among equivalent algorithms in any case study. Further, network operation is found to be the most efficient when reconfiguration is accompanied by the component allocation. Lowering loss by any margin is technically and commercially beneficial. Energy signifies costs to the utility and consumer. Any savings in energy cost, when compounded over a period, turn out to be a substantial amount. Moreover, a reduction in real power loss means a lower level of heat generation as a direct consequence. Thus, the lifespan of system components is enhanced indirectly due to positive long-term effects of a lesser heat emission.

Chapter 7

7. Optimal siting of wind turbines in a windfarm

7.1. A single-objective approach to optimal siting of wind turbines in a windfarm

The placement of wind turbines in a windfarm is a complex task as several factors need to be taken into consideration. During recent years, researchers have applied various evolutionary algorithms to windfarm layout problem by converting it to a single-objective or at the most a 2-objective optimization problem. The prime factor governing placement of turbines is the wake effect attributed to the loss of kinetic energy by wind as it passes over the turbine blades. A downstream turbine inside the wake region generates less than its rated output. Optimization of wake loss helps extract more power out of the wind. The cost of turbine is tactically entwined with generated output to form a single objective of cost per unit of output power e.g. ‘cost/kW’. This section of the chapter proposes an application of L-SHADE algorithm in minimizing the objective cost/kW for a comparative study with the available results of other evolutionary algorithms in the literature. Case studies with (a) constant wind speed and variable wind direction and (b) variable wind speed and variable wind direction are performed. The simulation results are compared with studies performed using GA by Mosetti *et al.* [122] and Grady *et al.* [123] and using binary PSO by Pookpant *et al.* [127]. Though many past studies have used other optimization algorithms for the same problem, conscious efforts are made for prudent and valid comparisons with studies that have adopted same mathematical models and parameters influencing the objective function of ‘cost/kW’.

In the remainder of this section of the chapter, windfarm mathematical models are included in sub-section 7.1.1. Case studies and objective of optimization are discussed in sub-section 7.1.2. Sub-section 7.1.3 presents the simulation results and comparison with past studies. The chapter ends with conclusion and close out remarks in sub-section 7.1.4.

7.1.1 Windfarm mathematical modeling

As wind flows across a turbine, the wind speed decreases and the turbulence intensity increases, thus forming a wake behind the turbine. The wake not only continues to move in the downstream direction, but also expands laterally. Because of wake effect, turbines located downstream generate less power. Out of several wake models, the popular and

extensively used Jensen wake decay model [174]-[175] is adopted here for calculation of wind speed inside the wake region. In the equations here, for clarity, k -th turbine is considered under the influence of a single turbine at m -th location (Fig. 7.1a). It is worthwhile to note that the case studies performed in this chapter are with turbines of same size (turbine hub height and rotor diameter) and type in the windfarm.

Fig. 7.1. (a) Linear Wake Model: k -th turbine under the influence of a single m -th turbine (b) i -th turbine partially influenced by the wake of j -th turbine

Assuming that the momentum is conserved in the wake, the wind speed in the wake region is calculated by –

$$u_k = u_{0k} \left[1 - \frac{2a}{\left(1 + \alpha_m \frac{x_{mk}}{r_{m1}} \right)} \right] \quad (7.1)$$

$$a = \frac{1 - \sqrt{1 - C_T}}{2} \quad (7.2)$$

$$r_{m1} = r_m \sqrt{\frac{1 - a}{1 - 2a}} \quad (7.3)$$

$$\alpha_m = \frac{0.5}{\ln\left(\frac{h_m}{z_0}\right)} \quad (7.4)$$

where u_{0k} is the local wind speed at k -th turbine without considering the wake effect, x_{mk} is the distance between m -th & k -th turbine, r_m is the radius of m -th turbine rotor, r_{m1} is the downstream rotor radius of m -th turbine, h_m is the hub height of m -th turbine, α_m is the

entrainment constant pertaining to m -th turbine, a is the axial induction factor, C_T is the thrust coefficient of the wind turbine rotor, z_0 is the surface roughness of the windfarm.

The wake region is conical for linear wake model and radius of the wake region is represented by wake influence radius defined as:

$$r_{wm} = \alpha_m x_{mk} + r_{m1} \quad (7.5)$$

Local wind speed at k -th turbine is dependent upon the hub height of the turbine as velocity of wind changes with height from ground. Logarithmic law has been implemented here to calculate the local wind speed.

$$u_{0k} = u_{ref} \log\left(\frac{h_k}{z_0}\right) / \log\left(\frac{h_{ref}}{z_0}\right) \quad (7.6)$$

where h_{ref} is the reference height and u_{ref} is the wind speed at reference height. When both turbines (m -th and k -th turbine) are of same height, $u_{0k} = u_{0m}$.

When one area is inside multiple wake flows, the velocity deficit will be enhanced. If i -th turbine is under the influence of multiple wakes, considering superimposition of several wakes, the wind speed at the position of i -th turbine can be written as [130]:

$$u_i = u_{0i} \left[1 - \sqrt{\sum_{j=1}^{N_t} \frac{A_{ij}}{\pi r_i^2} \left(1 - \frac{u_{ij}}{u_{0j}} \right)^2} \right] \quad (7.7)$$

where u_{0i} & u_{0j} are the local wind speeds (free stream velocity) at i -th & j -th turbines, respectively, without considering the wake effect. u_{ij} is the wind velocity at i -th turbine under the influence of j -th turbine, N_t is the number of turbines affecting the i -th turbine with wake effects, r_i is the rotor radius of i -th turbine. A_{ij} is the overlapped rotor area of i -th turbine under wake influence radius (r_{wj}) of j -th turbine (Fig. 7.1b). Under full wake condition, which is the case for turbines of same height, $A_{ij} = \pi r_i^2$.

Mosetti *et al.* [122] proposed a simplified cost model where number of turbines in a windfarm is the only variable. Non-dimensional cost/year of a single turbine is assumed as 1 with a maximum 1/3 cost reduction for each additional turbine if many turbines are installed in the windfarm. The cost model with N turbines in a wind park is expressed as:

$$Cost = N \left(\frac{2}{3} + \frac{1}{3} e^{-0.00174N^2} \right) \quad (7.8)$$

7.1.2 Case studies and objective formulation

Three case studies were performed in [122]-[123] for a windfarm area of $2\text{km} \times 2\text{km}$ equally divided into 100 cells with center of any cell being able to accommodate a turbine. All turbines were of same type and size. The first case, Case 1 of the study, considered a situation where the wind blew at a constant speed from a fixed direction. Grady *et al.* [123] found the most optimal layout analytically considering only one column of 10 cells along wind direction in the optimization process and the optimal arrangement of that column was extended in same order to other nine columns. The results have further been validated by González *et al.* [131] and Pookpant *et al.* [127]. The optimal layout for Case 1 of constant wind speed ($u_0 = 12 \text{ m/s}$) from a fixed direction (north) is replicated here in Fig. 7.2 for ready reference.

Fig. 7.2. Optimal placement of wind turbines for Case 1

This work focuses on remaining two cases, the scenarios of which are described below:

- a) Case 2: constant wind speed and variable wind direction - This case considers a constant wind speed (u_0) of 12m/s blowing with equal probability from all directions. The wind direction is discretized into 36 segments of 10° each.
- b) Case 3: variable wind speed and variable wind direction - This case deals with a more complicated scenario where the wind speed and direction are variables. Three possible wind speeds of 8m/s , 12m/s and 17m/s are considered. Like in earlier case, the wind direction is discretized into 36 segments of 10° each. Wind from north direction is denoted with the angle of 0° and an incremental angle of 10° is considered clockwise.

Therefore, the angle of 90° implies wind from the east, while 270° is for wind from the west direction. Wind distribution diagram for the case is indicated in Fig. 7.3. The probability of occurrence of a particular wind speed from a specific direction is given in the wind distribution diagram with the sum of all probabilities being equal to 1.

Fig. 7.3. Wind probability distribution diagram for Case 3

Table 7.1. Wind turbine data and other relevant parameters

Sl. No.	Parameter	Value
1	Rotor diameter, $2r$	40 m
2	Thrust coefficient, C_T	0.88
3	Hub height, h	60 m
4	Rotor efficiency, C_P	0.4
5	Air density, ρ	1.2254 kg/m ³
6	Surface roughness of windfarm, z_0	0.3 m

Turbine and other relevant data are listed in Table 7.1 for the optimization problem. The values are taken from [122]-[123]. Power output of i -th turbine in kW is given by:

$$P_i = 0.5 * \rho * \pi * r_i^2 * u_i^3 * C_P / 1000 \quad (7.9)$$

Eq. (7.9) was re-written and used in [122] with little numerical approximation as in Eq. (7.10). In order to compare with previous results Eq. (7.10) is applied for various cases of power calculations in this section of the chapter.

$$P_i = 0.3u_i^3 \quad (7.10)$$

Total power output of the windfarm having N turbines,

$$P_{total} = \sum_{k=0}^{360} \sum_{i=1}^N f_k P_i(u_i) \quad (7.11)$$

where f_k is the wind probability for a wind speed from a specific direction and $\sum_{k=0}^{360} f_k = 1$. P_i is the actual power output from i -th turbine as a function of wind speed u_i . The objective function cost/kW is calculated as:

$$\text{cost/kW} = \frac{\text{Cost}}{P_{\text{total}}} \quad (7.12)$$

Windfarm aerodynamic efficiency η is found using formula:

$$\eta = \frac{\sum_{k=0}^{360} \sum_{i=1}^N f_k P_i(u_i)}{\sum_{k=0}^{360} \sum_{i=1}^N f_k P_{i,\max}(u_{i,\max})} \quad (7.13)$$

where $P_{i,\max}$ is the maximum power output from i -th turbine as a function of maximum possible wind speed $u_{i,\max}$ had there been no wake effect.

7.1.3 Simulation results and comparisons for single-objective optimization cases

The algorithm L-SHADE is described in Chapter 2, section 2.1.1. This part describes simulation results of application of the algorithm in windfarm layout optimization problem. The windfarm has 100 possible locations where the turbines can be placed. The problem is thus a 100-dimensional problem with each location representing a variable. The variable can take a discrete value of either 0 or 1. A value of '0' means the location is empty while '1' indicates the location has a turbine. During evolution through mutation and crossover the value of any element may become a fraction, in which case it is rounded off to the nearest integer value of either 0 or 1. A population size of $Np_{\text{ini}} = 300$ has been considered for the optimization problem during initialization. Maximum 30,000 (*maxeval*) number of fitness evaluations are performed for the objective function during each run of the algorithm.

For each case, the optimization algorithm is run for 10 times and the best value achieved for the objective function from multiple runs is selected. A computer with Intel Core i5 CPU@2.7GHz and 4GB RAM can perform one run of the algorithm on MATLAB platform in about 13.5 minutes for Case 2 and in about 15.5 minutes for Case 3. The moderate run time is attributed mainly to the discretization of wind directions into 36 segments rather than to high dimension of the problem. In each generation, the algorithm is to perform power computations for 36 different wind directions. [Table 7.2](#) compares the results of present study with equivalent past studies for both Case 2 and Case 3. In Case 2 where wind blows at constant speed from all directions with equal probability, the distance between two wind turbines is the main factor affecting wake loss and hence output from the farm. Grady *et al.* [\[123\]](#) could arrive at an optimal layout given in [Fig. 7.4 \(i\)](#). Pookpant *et al.* [\[127\]](#) applied binary particle swarm optimization (BPSO) algorithm with time varying acceleration

coefficients (TVAC) and quoted to have obtained better fitness function. However, discrepancy is observed in the literature as tabulated results mention of 40 turbines while the layout in the paper shows 35 turbines only. The 35 turbines, arranged as in Fig. 7.4 (ii), can generate an output of about 15796 kW with fitness function (cost/kW) of 0.0015648.

Table 7.2. Comparison of wind turbine optimal placement study Case 2 and Case 3

Optimization method	Case 2				Case 3			
	No. of turbines	Power (kW)	Windfarm Efficiency	Cost/kW	No. of turbines	Power (kW)	Windfarm Efficiency	Cost/kW
GA [122]	19	9245	93.86%	0.0017371	15	13460	94.62%	0.0009941
GA [123]	39	17220	85.17%	0.0015666	39	32038	86.62%	0.0008403
BPSO-TVAC [127]	35	15796	87.06%	0.0015648	46	36433	82.76%	0.0008523
L-SHADE	40	17920	86.42%	0.0015341	39	32351	86.68%	0.0008322

The optimum layout resulted by L-SHADE algorithm, as shown in Fig. 7.4 (iii), portrays similarity with the layout proposed by Grady *et al.* [123]. The objective cost/kW is slightly improved (approximately by 2%) by the L-SHADE optimization with one additional turbine, totaling to 40 numbers. Total power output is also increased with a more efficient turbine configuration. Layout proposed by Mosetti *et al.* [122] gives highest efficiency because of the lowest number of turbines in the same windfarm area. Nevertheless, efficiency is not a criterion for the optimization problem. If cost/kW is targeted to be the objective function, layout suggested by L-SHADE algorithm provides the lowest fitness value.

Table 7.2 includes results for study of Case 3 when wind speed and direction are variables. Fitness function achieved by Grady *et al.* [123] with layout in Fig. 7.5 (i) was much improved than what had been attained by Mosetti *et al.* [122]. Pookpunt *et al.* [127] in

Fig. 7.4. Optimal placement of wind turbines using various algorithms for Case 2
(constant wind speed and variable wind direction)

(i) Genetic Algorithm [123]

(ii) Binary PSO-TVAC [127]

(iii) L-SHADE

Fig. 7.5. Optimal placement of wind turbines using various algorithms for Case 3
(variable wind speed and variable wind direction)

applying optimization algorithm BPSO-TVAC described a power model where maximum output from a turbine is capped at its rated capacity of 630 kW beyond wind speed of 12.8m/s. Though the calculation does not seem to have factored in the saturation of power for Case 3 where peak wind speed reaches 17m/s. The statement can be corroborated with a simple observation that if output power from a turbine is restricted to 630kW, 46 turbines cannot produce a total output power of about 39359kW as claimed in [127]. Further, wind frequency distribution table in the paper shows values for 37 discretized segments from 0° upto 360°, instead of 350°. Due to aforementioned contentious observations, straight comparison of results in [127] with those in [122]-[123] seems questionable. Objective function, power and efficiency are recalculated with analogous power model and wind probabilities for the layout arrangement as suggested in [127] and reproduced here in Fig. 7.5 (ii). The comparable results thus obtained are included in Table 7.2 for Case 3.

Optimization with L-SHADE algorithm leads to the layout with same number of turbines as in [123] but with a reshuffled configuration as indicated in Fig. 7.5 (iii). Turbines are found congregated at outermost cells of the meshed area and all outer cells are occupied between angles 280° and 350° where high wind probabilities prevail. Unlike Case 2, wind turbines are positioned at adjacent cells along north-south and east-west directions. It may be because of low wind frequencies from straight north (0°), east (90°), south (180°) and west (270°) directions in Case 3. Wake loss due to such juxtaposition is far more compensated by sparse allocation of turbines along other directions. The resulting fitness function cost/kW for the layout arrangement is the lowest together with higher efficiency and greater output power than those recorded in [123]. The cost/kW obtained by L-SHADE is about 1% lower than that reported by GA [123]. A typical plot of convergence to optimum fitness value by the

proposed L-SHADE algorithm for Case 3 is given in Fig. 7.6. The algorithm is found to converge within 15000 fitness evaluations.

Fig. 7.6. Convergence of L-SHADE algorithm for Case 3 of windfarm layout optimization

7.1.4 Conclusion: a single-objective approach to optimal siting of wind turbines

This section of the chapter proposes a useful approach and an effective application of L-SHADE algorithm in the problem of discrete location optimization of wind turbines in a windfarm for various scenarios of wind speed and direction. The optimal configurations of wind turbines obtained using the algorithm are more efficient, thereby producing high power output. The differences among optimal objective function values of various evolutionary algorithms are subtle. Nonetheless, this study does improve the results and L-SHADE arguably performs better than any other optimization algorithm applied for the windfarm layout optimization problem.

7.2. A multi-objective approach to optimal siting of wind turbines in a windfarm

An efficient windfarm layout to harness maximum power out of the wind is highly desirable from technical and commercial perspectives. A bit of flexibility on layout gives leeway to the designer of windfarm in planning facilities for erection, installation and future maintenance. This section of the chapter proposes an approach where several options of optimized usable windfarm layouts can be obtained in a single run of decomposition based multi-objective evolutionary algorithm (MOEA/D). A set of Pareto optimal vectors is obtained with the objective of maximum output (power) at minimum wake loss or in other words, maximum output at maximum efficiency. Maximization of both output power and windfarm aerodynamic efficiency are set as two objectives for optimization. The formulation of the objectives thus helps to obtain several Pareto optimal solutions in a single run of the algorithm. As all solutions are theoretically usable, the designer can make an appropriate selection from a pool of closely matched optimized solutions considering factors like installed capacity, budget and site constraints. Our selection and proposal of Pareto optimal layouts are for installed capacity based on the statistical data of commercial wind turbine sites presented in [176]. Vestas V80-2.0MW model turbine data are utilized and the turbines are optimally placed in a rectangular shaped windfarm with specified number of cells. Detailed case studies with same and different available hub heights for the wind turbines are performed. The wind condition in this study considers a couple of realistic cases of variable wind speed and direction in line with the windroses for the month of April in Midland and Corpus Christi, Texas [177].

In organizing rest of this section of the chapter, we present the mathematical models and useful numerical data used for the windfarm in sub-section 7.2.1. Application of MOEA/D algorithm in turbine location optimization is explained in sub-section 7.2.2. Description and results of the case studies are included in sub-section 7.2.3. The chapter ends with conclusion and close out remarks in sub-section 7.2.4.

7.2.1 Mathematical models and numerical data

a) Linear wake model

Jensen wake model [174]-[175], as described in sub-section 7.1.1 of this chapter, is adopted here. The wind speed at i -th turbine under the influence of multiple wakes induced by N_t upstream turbines is given in Eq. (7.7) and the same is replicated here for convenience:

$$u_i = u_{0i} \left[1 - \sqrt{\sum_{j=1}^{N_t} \frac{A_{ij}}{\pi r_i^2} \left(1 - \frac{u_{ij}}{u_{0j}} \right)^2} \right] \quad (7.14)$$

b) Turbine power output model

Power output curve of Vestas V-80 model, which has a rotor diameter of 80m, is used here to calculate output power from the turbine. The curve is reproduced in Fig. 7.7 with fairly accurate liner approximation. Mathematically, the power output in kW as a function of wind speed u can be expressed as:

$$P(u) = \begin{cases} 0, & \text{for } u < u_c \text{ and } u > u_f \\ 60 * (u - u_c), & \text{for } u_c \leq u < u_c + \frac{25}{19} \\ 250 * (u - u_c - 1), & \text{for } u_c + \frac{25}{19} \leq u \leq 13 \\ 2000, & \text{for } 13 < u \leq u_f \end{cases} \quad (7.15)$$

where u_c and u_f are the turbine cut-in and cut-out wind speeds, respectively.

Fig. 7.7. Linear approximation of power output curve for Vestas V-80 turbine

c) Wind condition model

The wind condition of constant speed from a fixed direction is good for theoretical study purpose. However, this situation hardly exists in real world. Many previous research papers including the study in previous section of this chapter considered a constant wind speed of 12 m/s at hub height from either single or multiple directions. Standard [157] stipulates the design requirement of wind turbines and defines highest turbulent class IA for the turbine

which is certified to perform for maximum annual average wind speed of 10m/s at hub height. So, a constant wind speed of 12m/s at the hub height is a hypothetical case for which technical feasibility, economic viability and practical applicability seem yet to be determined. In this work, we choose a couple of wind probability distribution diagrams, in line with the windroses for the month of April of sites in Midland and Corpus Christi, Texas [177]. Midland is designated as site 1, and Corpus Christi is site 2. The selected locations are considered to be high potential sites for wind energy. Instead of discretizing the wind speeds in 1 m/s, an approximation with four dominant discrete wind speeds is made in the wind probability distribution diagrams in Fig. 7.8 and Fig. 7.9 for site 1 and site 2, respectively. North (N) direction is set as 0° and an increment of 22.5° is considered in clockwise direction to divide 360° in 16 segments. In each of these 16 directions, the probability of occurrence of each discrete wind speed is indicated in the bar chart. The summation of all the probabilities equals 1. As observed from the wind distribution diagrams, the wind is dominant from south direction for site 1 in Midland, while for site 2 in Corpus Christi, high intensity wind blows from south-east direction and negligible wind from west direction.

Fig. 7.8. Wind probability distribution diagram 1 for site 1 – Midland, Texas

Fig. 7.9. Wind probability distribution diagram 2 for site 2 – Corpus Christi, Texas

d) Objective model

Aerodynamic efficiency of the windfarm is calculated by,

$$\eta = \frac{\sum_{k=0}^{360} \sum_{i=1}^N f_k P_i(u_i)}{\sum_{k=0}^{360} \sum_{i=1}^N f_k P_{i,max}(u_{i,max})} \quad (7.16)$$

where N is the total number of turbines, $P_{i,max}$ is the maximum power output from i -th turbine as a function of wind speed $u_{i,max}$ had there been no wake effect, P_i is the actual power output from i -th turbine as a function of wind speed u_i considering wake effect from upstream turbine(s). The probability of occurrence of each wind speed from each direction is defined by factor f_k and $\sum_{k=0}^{360} f_k = 1$.

Total power output of the windfarm is given by,

$$P_{total} = \sum_{k=0}^{360} \sum_{i=1}^N f_k P_i(u_i) \quad (7.17)$$

In the multi-objective optimization, the two objective functions are: (i) maximize power output ' P_{total} ' and (ii) maximize efficiency ' η '. A careful observation on the objectives reveals that increasing number of turbines will increase power output from the windfarm. However, as more and more turbines are added to the designated cells, wake effect starts to increase, thus lowering the overall efficiency of the windfarm. Fewer turbines in the windfarm will result in the least or almost zero wake loss. So, the designer is required to choose an acceptable value of overall efficiency on desired installed capacity. When placement optimization is performed for a defined area, MOEA/D provides the set of Pareto

optimal solutions containing all possible layouts ranging from layouts that provide maximum possible power output at lowest (but maximum achievable) efficiency to layouts that provide minimum power output at highest efficiency of very close to 100%. To elaborate, any Pareto optimal point will contain information on a specific number of turbines with best possible layout arrangement that minimizes wake loss.

Several research papers including the study in previous section of this chapter have considered cost or cost per unit power output as the objective. Though the cost model as a function of only number of turbines, proposed by Mosetti *et al.* [122], is widely used in literature, the basis of such model is not proven with actual data. Chen *et al.* [133] applied JEDI model which had turbine rated power, number and type of turbines in a windfarm as variables. The JEDI model can be interpreted as a model based on the statistical analysis of a wide range of data including cost of land lease, job market, labor cost, etc. Chen *et al.* [178] proposed another cost model which considered cost of wind turbine hub as a percentage of total cost of the turbine. However, this cost model [178] accounted for only the installation cost of turbines. Cost of wind power is evaluated based on levelized cost of energy (LCOE) [179]. LCOE is calculated over a period of time of the wind farm incorporating initial installation, erection and commissioning cost, annual fixed charge rate (FCR), annual operation and maintenance cost, etc. and the energy produced by the farm. Due to limited availability of publicized commercial price of turbines, it is difficult to quantify cost of the hub of a wind turbine as a small (hub) height difference may have insignificant impact on LCOE. Nevertheless, intuitively it can be assumed that turbines with higher hub heights will cost more than those with lower hub heights. The algorithm in this study picks shorter hub heights for the turbines with equal probability for evaluation, although any simplified cost model is not set as a primary objective for optimization.

e) Windfarm selection and turbine data

A rectangular windfarm of 6000m $\times$ 2000m is considered for all case studies performed under the scope of this work with each cell size being 300m $\times$ 400m. The grid size is selected in this manner because commercial turbines are hardly placed near to each other [176] and Jensen wake decay model is applicable for far wake region in the downstream of a turbine, a distance beyond two to five times the rotor diameter of the turbine depending on ambient turbulence [180]. A turbine can be placed at the center of any cell. So, there are 100 possible locations where the turbines can be positioned. Such grid spacing will also ensure the minimum safe distance between any two turbines. The safe distance is defined as the

minimum distance, if followed while placing the turbines in a windfarm, it will ensure that accidental fall of one turbine does not cause damage to the others [130]. The turbine and other relevant data are listed in Table 7.3. Vestas V-80 wind turbine is one of the popular turbine models and the same is selected here for study purpose. Power output characteristic curve and various turbine speeds (i.e. cut-in, cut-out and rated speeds) do not vary much for different makes of 2-MW turbine. As an obvious fact, the output power of a windfarm changes with the change in turbine type, size and wind characteristic of the site. In general, a larger rotor diameter or a higher hub height of the turbine would produce a greater power output if available in the wind.

Table 7.3. Wind turbine (Vestas V-80) and other relevant data

Parameter	Value
Turbine model	Vestas V-80
Rated power, P_{rated}	2000 kW
Rotor diameter, D	80 m
Thrust coefficient, C_T	0.8
Hub (tower) height (IEC IA) [157]	60 m, 67 m or 78 m
Cut-in speed, u_c	4 m/s
Cut-out speed, u_f	25 m/s
Surface roughness of windfarm, z_0	0.3 m
Reference height, h_{ref}	60 m

7.2.2 Application of MOEA/D algorithm to optimal siting of wind turbines

The algorithm MOEA/D is discussed in detail in Chapter 2, section 2.1.2.1. However, as optimal placement of wind turbines in a windfarm is a discrete location optimization problem, sometimes even with turbines of different hub heights, some specific steps are implemented in the formulation of decision vectors. The multi-objective optimization problem (MOP) is defined as:

Minimize $F(x) = \{f_1(x), f_2(x)\}$, where, $f_1(x) = -'P_{total}'$ and $f_2(x) = -'\eta'$

Variable $x \in \Omega$, Ω being the decision vector (variable) space. If Np is the population size, there will be Np decision vectors $x^1, x^2, \dots, x^{Np}$ for the optimization problem. The windfarm has 100 possible locations where the turbines can be placed. Each decision vector x^m for $m = 1, 2, \dots, Np$ is formulated as a 100-dimensional vector with each of the element assuming a discrete integer value which represents the status of that location. For only one type of turbines in the windfarm, each element of m -th vector x^m adopts a discrete value of either 0 or 1 i.e. $x_k^m \in \{0, 1\}$ for $k = 1, 2, \dots, 100$. '0' means the location is empty while '1'

indicates the location has a turbine. For the case where 3 different variants of hub heights are present, $x_k^m \in \{0,1,2,3\}$ for $k = 1,2, \dots, 100$. Again, '0' means the location is empty while '1, 2 or 3' indicates the variant for the turbine at that location. For both the cases, random initialization of x is done with probability of selection of '0' set at 75%, while other integer value(s) is(are) equally likely to be initialized with remaining probability. This helps to obtain low power output solutions when the number of turbines is very few in the windfarm and possibly drop some impracticable solutions when the windfarm occupancy is close to 100%. During evolution through mutation and crossover, the value of any element in x may become a fraction, in which case it is rounded off to the nearest integer value. The algorithm is developed on MATLAB platform and simulations are run on a computer with Intel Core i5 CPU @2.7GHz and 4GB RAM. The selected parameters for MOEA/D algorithm in the problem are given in Table 7.4.

Table 7.4. Input data for MOEA/D algorithm for windfarm layout optimization

Parameter	Value
Population size, Np	600
Number of weight vectors, Np	600
Neighborhood size, T	$0.1*Np$
Probability to update the neighbor (else the whole population), δ_p	0.9
Max number of positions replaced by better new solution in each subproblem at every generation, n_r	$0.01*Np$
Maximum number of function evaluation, $maxeval$	300000
Crossover rate, CR	0.5
Mutation factor, F	0.5

7.2.3 Case studies for multi-objective optimization cases

A total of four case studies for two different wind conditions together with detailed analyses of results are included in this section for the rectangular windfarm. The first two cases consider same hub height for all the turbines, while in the remaining cases, we let the algorithm choose best suited hub heights to maximize power and efficiency. Turbine cost is not set as a primary objective of optimization. Hence, in latter cases, it is anticipated that the algorithm will tend to choose higher hub heights for the turbines as wind speed at a higher altitude is greater than that at a lower altitude. However, power output saturates at rated power of the turbine. So, it cannot be forthrightly concluded that increasing tower height is always beneficial to extract more power. The probability and direction of various wind speeds, setting of the turbines are the factors affecting power output from a windfarm. Painstaking efforts and time are required even for an algorithm to do the number crunching

and successfully find an optimal solution. MOEA/D algorithm effectively performs the task of optimization and in a single run, it proposes a set of closely optimized solutions so that the designer can make a choice what suits his planning best.

a) Case 11 and Case 12 (same hub height)

Case 11 and Case 12 consider same hub height of 60m for all turbines for wind conditions at site 1 and site 2, respectively. Four discrete wind speeds as per wind distribution diagrams in Fig. 7.8 and Fig. 7.9 are considered at the reference height of 60m. In summary, $u_{ref0} < 4\text{m/s}$, $u_{ref1} = 8.2\text{m/s}$, $u_{ref2} = 10.8\text{m/s}$ and $u_{ref3} = 14.4\text{m/s}$ at $h_{ref} = 60\text{m}$. A cursory glance at turbine power curve reveals that the turbine delivers its peak rated power at a wind speed of 13m/s. Wind speed beyond that does not increase power output and the turbine delivers same rated output till cut-out wind speed is reached. Wind velocity encountered by a wind turbine under the influence of wake is determined by Eq. (7.14). Power output and objective functions are calculated using Eqs. (7.15) - (7.17). After setting the parameters of MOEA/D, the optimization algorithm is run for 10 times for each study case to check consistency of results. The plots of Pareto fronts i.e. non-dominated solutions for objectives of the selected runs are shown in Fig. 7.10 and Fig. 7.11 for wind characteristics at site 1 and site 2, respectively. The problem being a discrete location optimization problem, all non-dominated solutions may not be unique and wind probabilities being random, the Pareto front curves may not always be smooth. Addition or removal of a turbine will change power output and efficiency to an extent depending upon the location to where it is added or from where it is removed. Nonetheless, the curve presents an obvious fact of decrease in efficiency with the increase in output power (i.e. increase in number of turbines). The curves for number of turbines versus the power output at achievable efficiency are plotted in Fig. 7.12 for Case 11 and in Fig. 7.13 for Case 12. In general, slightly higher efficiency is observed with same number of turbines for wind condition at site 2. This is because greater probabilities of higher wind speeds at site 2 help to generate more power out of the turbines. The algorithm provides optimal layouts for each discrete number of turbines over a wide range. For example, in Case 11, the Pareto front corresponds to optimal layouts with number of turbines ranging from 5 to 85 and for Case 12, it is between 4 and 85 turbines. Diversity of the solutions can slightly be adjusted and sometimes can be made larger with little alteration of probability of '0' during initialization of decision variables as described in sub-section 7.2.2. This is merely a piece of information to the readers as the diversity achieved in the cases here is good enough for practical applications where the occupancy of wind turbines in a windfarm hardly exceeds 50%.

Fig. 7.10. Plot of Pareto front for Case 11 (site 1) of windfarm layout optimization problem

Fig. 7.11. Plot of Pareto front for Case 12 (site 2) of windfarm layout optimization problem

NREL report [176] gives insight of land use requirement of wind power plants in United States based on statistical data. Average area requirement for the power plant is 34.5 ± 22.4 hectare per MW of installed capacity. The range being very wide, we choose two extreme values to make our selection of optimized layouts. Following the guidelines, we can have minimum 11 and maximum 50 turbines in the windfarm. From the pool of optimized solutions, we select layouts for 11 turbines for site 1 and site 2, presented in Fig. 7.14 and Fig. 7.15, respectively. Fig. 7.16 and Fig. 7.17 indicate the optimized layouts of 50 turbines for wind conditions at site 1 and site 2, respectively.

Fig. 7.12. Variation of output power and efficiency with no. of turbines (Case 11, site 1)

Fig. 7.13. Variation of output power and efficiency with no. of turbines (Case 12, site 2)

It is evident from the optimal layouts that turbines try to locate far from one another to minimize wake loss. The algorithm place 11 turbines sparsely at both sites (Fig. 7.14 and Fig. 7.15) to achieve very high efficiency of more than 99% as recorded in Table 7.5. The wind distribution diagram of site 1 reveals that the dominant wind directions are from between south east and south west. Therefore, in Fig. 7.16, a higher concentration of turbines is noticed towards south side. Furthermore, as wind probability is high from south-west direction, all cells at that side are occupied. The turbines at north side allocate themselves at outermost grid to minimize the effect of wake loss when predominant wind direction is from south, thus forming an efficient arrangement.

Fig. 7.14. Optimal layout with 11 turbines (Case 11, site 1)

Fig. 7.15. Optimal layout with 11 turbines (Case 12, site 2)

Fig. 7.16. Optimal layout with 50 turbines (Case 11, site 1)

Fig. 7.17. Optimal layout with 50 turbines (Case 12, site 2)

Wind intensity and probability of occurrence are the highest from south-east side at site 2. As observed from the optimized layout in Fig. 7.17, cells at south-east side are all occupied and along that direction, turbines are remotely placed to avoid high wake losses. In both Fig. 7.16 and Fig. 7.17, juxtaposition of turbines is observed along east-west direction. Wind probabilities at both the sites are relatively low from east and west directions. Therefore, wake loss for such adjacency along east-west direction is far more compensated with sparse allocation of wind turbines along other directions. Further, as wind probabilities from all directions have certain weights at site 1, the turbines are little more distributed (Fig. 7.16) than at site 2 (Fig. 7.17) where turbines are more concentrated. Similar to layouts with 11 and 50 turbines, one can choose any optimal layout containing an intermediate number of turbines. As mentioned beforehand, the selection is based on required installed capacity, budget, site constraints like land availability, other site auxiliary facilities and feasibility of integration of wind power into the grid. Some results of optimum layouts with different numbers of turbines alongwith corresponding power outputs and efficiencies are listed in Table 7.5. Power output may seem low compared to the installed capacity. Statistical data reveal that modern land-based windfarms operate at an annual capacity factor somewhere between 20% and 50% [181]. Capacity factor is the ratio of amount of energy delivered during a year to the amount of energy that would have been generated had the electricity generating sources run at their rated capacity throughout the year. Therefore, the calculated capacity factors for the case studies are conclusive and realistic.

Table 7.5. Data of selected optimal layouts for Case 11 and Case 12

Case 11, site 1				Case 12, site 2			
No. of turbines	Power Output (MW)	Efficiency	Capacity factor	No. of turbines	Power Output (MW)	Efficiency	Capacity factor
10	5.21	99.5%	26.1%	10	7.98	99.5%	39.9%
11	5.72	99.2%	26.0%	11	8.76	99.3%	39.8%
20	10.18	97.1%	25.5%	20	15.61	97.3%	39.0%
30	14.78	94.1%	24.6%	30	22.97	95.4%	38.3%
40	19.16	91.4%	23.9%	40	30.09	93.8%	37.6%
50	23.40	89.4%	23.4%	50	36.50	91.0%	36.5%
60	27.38	87.1%	22.8%	60	42.47	88.2%	35.4%

b) Case 13 and Case 14 (different hub heights)

In these case studies, different available hub heights (60m, 67m and 78m) of the wind turbines are included in the optimization process. Case 13 utilizes wind data from site 1 while Case 14 is performed with site 2 wind data. The algorithm selects required hub heights for the turbines based on optimization objectives of maximizing output power and efficiency. Wind speeds at the reference height are considered same as in Case 11 and Case 12 i.e. $u_{ref0} < 4\text{m/s}$, $u_{ref1} = 8.2\text{m/s}$, $u_{ref2} = 10.8\text{m/s}$ and $u_{ref3} = 14.4\text{m/s}$ at $h_{ref} = 60\text{m}$. The change in local wind speed for a difference in hub height follows logarithmic law in Eq. (7.6). Wind velocity in wake, power output and objectives are calculated using Eqs. (7.14) - (7.17). The plots of Pareto fronts i.e. non-dominated solutions for objectives of the selected runs are shown in Fig. 7.18 and Fig. 7.19 for the wind characteristics at site 1 and site 2, respectively. Little more unevenness in the Pareto fronts is noted here than in the case studies with same hub height. One probable explanation is the presence of more variants of wind turbines in the optimization process. The objective value changes in an irregular pattern if a single factor out of number of turbines, tower height of the turbine or location changes during function evaluation process. Nevertheless, appropriate trend of dipping efficiency is observed with increase in number of turbines i.e. increase in power output. Further, site 2 being more potent to produce wind power, the power output and efficiency are higher for site 2 than those for site 1 with same number of turbines.

Fig. 7.18. Plot of Pareto front for Case 13 (site 1) of windfarm layout optimization problem

Fig. 7.19. Plot of Pareto front for Case 14 (site 2) of windfarm layout optimization problem

Fig. 7.20. Variation of output power and efficiency with no. of turbines (Case 13, site 1)

Fig. 7.21. Variation of output power and efficiency with no. of turbines (Case 14, site 2)

The curves for number of turbines versus the power output at achievable efficiency are plotted in Fig. 7.20 for Case 13 and in Fig. 7.21 for Case 14. Plots in Fig. 7.22 and Fig. 7.23 enlighten on the distribution of selected hub heights for the Pareto solutions in both the cases. For better readability, bar charts of selected hub heights at some useful discrete solutions are provided in Fig. 7.24 and Fig. 7.25 for Case 13 and Case 14, respectively. As expected, turbines with highest hub heights are predominantly selected by the algorithm as the same can generate more power at most of the conditions of wind occurrences. When occupancy in the farm gets higher, the turbines may come close to each other in some of the optimized layouts. They may place themselves in adjacent cells resulting in pronounced

wake loss. In such cases, a small number of turbines with lower hub heights can be used as power output will not change to a great extent if those are replaced with higher hub heights. Indeed, resulting efficiency might marginally increase with a mix of lower and higher hub heights of turbines in the windfarm as the summary in Table 7.6 reveals. A probable cause linked to the increase in efficiency is the saturation of output power beyond a certain wind speed. To elaborate, increase in hub height means a higher available wind speed and wind power at the hub height. But actual power output from the turbine does not increase to the same extent due to either wake loss or saturation of turbine output. The statement is further clarified during the analysis of optimal layouts obtained with different numbers of turbines for the two wind conditions.

Fig. 7.22. Plot of selected hub heights for all optimal solutions (Case 13, site 1)

Fig. 7.23. Plot of selected hub heights for all optimal solutions (Case 14, site 2)

Fig. 7.24. Selected hub heights at some discrete optimal solutions (Case 13, site 1)

Fig. 7.25. Selected hub heights at some discrete optimal solutions (Case 14, site 2)

Fig. 7.26. Optimal layout with 11 turbines (Case 13, site 1)

Fig. 7.27. Optimal layout with 11 turbines (Case 14, site 2)

Following same reasoning mentioned in Case 11 and Case 12, our selection of optimal layouts consists of 11 and 50 turbines for Case 13 and Case 14. Fig. 7.26 and Fig. 7.27 represent the optimum layouts with 11 turbines for the wind conditions at site 1 and site 2, respectively. Expectedly, the algorithm selects the tallest towers for all turbines and the turbines are dispersed to minimize wake loss. As listed in Table 7.6, Case 14 has a greater efficiency than Case 13 as the wind intensity and probability are higher at site 2 than at site 1. Optimized layouts for the two cases with 50 turbines are provided in Fig. 7.28 and Fig. 7.29. Similar to Case 11, turbines are a bit more distributed in Case 13 for site 1. Due to much higher probabilities of wind from certain directions at site 2, the turbines are more

concentrated in Case 14. It is worthwhile to note that only one variant of layout with 50 turbines is presented here. Table 7.6 records some more results of arrangements with 50 turbines. All 78m high turbines can generate maximum power output with insignificant reduction in efficiency for the reason stated earlier. The user has the flexibility to do some trade-off between the two objectives and select a solution that suits to his requirements. Not only that, as optimal layouts are available for each discrete number of turbines over a wide range (e.g. from 4 nos. to 99 nos. in Case 14), one can easily manipulate the plot plan during design stage in case a turbine is required to be added or to be removed.

The metaheuristics applied to wind turbine placement problem till date could find only one optimal layout with certain number of turbines either with optimization of a single objective or with a compromise solution of multiple objectives. The application of MOEA/D to windfarm layout optimization, proposed in this section of the chapter, can provide hundreds of usable solutions in a single run of the algorithm. Though it cannot be claimed forthrightly that no solution proposed by MOEA/D can be improved. Indeed, no metaheuristic can make such an authoritative statement. However, the solutions proposed by MOEA/D are among the best and notable improvement of these solutions is difficult by mere trial and error method.

Fig. 7.28. Optimal layout with 50 turbines (Case 13, site 1)

Fig. 7.29. Optimal layout with 50 turbines (Case 14, site 2)

Table 7.6. Data of selected optimal layouts for Case 13 and Case 14

Case no.	No. of turbines	Power (MW)	Efficiency	Capacity factor	Selected hub heights		
					60m	67m	78m
Case 13, site 1	11	6.17	97.50%	28.0%	0	0	11
	20	10.97	96.07%	27.4%	1	1	18
	20	11.05	96.05%	27.6%	0	0	20
	30	16.00	93.90%	26.7%	2	4	24
	30	16.16	93.66%	26.9%	0	0	30
	40	20.80	91.61%	26.0%	6	0	34
	40	20.98	91.40%	26.2%	1	0	39
	45	23.31	90.36%	25.9%	1	1	43
	45	23.36	90.28%	26.0%	0	0	45
	50	25.56	89.45%	25.6%	3	1	46
	50	25.65	89.44%	25.6%	1	1	48
	50	25.72	89.43%	25.7%	0	0	50
	60	30.13	87.40%	25.1%	0	1	59
	60	30.16	87.40%	25.1%	0	0	60
Case 14, site 2	11	9.60	98.93%	43.6%	0	0	11
	20	16.74	96.93%	41.8%	3	3	14
	20	16.90	96.89%	42.2%	2	1	17
	30	25.17	95.38%	41.9%	1	0	29
	30	25.22	95.28%	42.0%	0	0	30
	40	32.92	93.81%	41.1%	2	1	37
	40	33.07	93.70%	41.3%	0	0	40
	45	36.56	92.70%	40.6%	1	4	40
	45	36.78	92.62%	40.9%	0	0	45
	50	40.10	91.42%	40.1%	2	2	46
	50	40.14	91.41%	40.1%	2	1	47
	50	40.31	91.37%	40.3%	0	0	50
	60	46.87	88.75%	39.1%	1	1	58
	60	46.91	88.75%	39.1%	1	0	59

Table 7.6 lists some of the optimal layouts with specific numbers of turbines. In general, it is observed that use of multiple hub heights is not hugely beneficial. The change in output power and efficiency is marginal. So, for practical convenience in design, logistics, future operation and maintenance, a windfarm with turbines of same hub height is a preferred choice with the presumption that a few shorter towers do not significantly affect the levelized cost of energy (LCOE).

7.2.4 Conclusion: a multi-objective approach to optimal siting of wind turbines

This section of the chapter proposes an effective application and an efficient approach to the discrete location optimization problem employing a multi-objective evolutionary algorithm, different from simplified single-objective or weighted sum multi-objective optimization methods suggested by other researchers. The process of optimization outputs the most efficient layouts with any selected number of turbines within a specified range. The method can also be applied for selection of different hub heights in search of optimal layouts. A single run of the optimization algorithm yields several closely matched solutions providing more flexibility and choices for windfarm layouts. A review of case studies, specifically of Case 13 and Case 14, reveals that the algorithm proposes several options for the layouts with same number of turbines. It may be noted that only few alternatives with same number of turbines are tabulated in the result section. The algorithm indeed proposes more options for the layouts. Optimal placement of wind turbines is a complex task as several factors affect the overall performance and output from the windfarm. The objectives of the algorithm can be twisted or altered based on the importance exercised on several governing factors. Moreover, if actual cost data are available, the new objective of cost can also be integrated into the optimization algorithm. A bi-objective formulation with cost and output power would help to easily determine the rate of change in cost with the installed capacity or output power. A tri-objective formulation including output power, windfarm efficiency and cost is also probable. In a multi-objective optimization problem, the designer should always perform trade-off among the objectives involved in the optimization. No matter what or how many the objectives are, the approach to wind turbine location optimization can be followed the way proposed in this section of the chapter.

Chapter 8

8. Summary, conclusion and future work

8.1. Summary and conclusion

This thesis covers some of the optimization problems in power system and applications of evolutionary algorithms to solve those problems. The importance of computational intelligence is discussed in Chapter 1 (section 1.1). Selected single and multi-objective evolutionary algorithms and power system optimization problems are reviewed in detail. The integration approach of a few constraint handling (CH) techniques such as superiority of feasible solutions (SF), epsilon constraint (EC) and stochastic ranking (SR) with single-objective optimization algorithm SHADE is described in Chapter 2. The CH technique SF is also integrated with multi-objective evolutionary algorithms MOEA/D and SMODE.

In Chapter 3 (section 3.1), the application of the 3-CH techniques to optimal power flow problem with various (single) objectives is presented. Comparative analyses among 3-CH techniques are also performed. The importance of a proper CH technique instead of the conventional penalty function method on a constrained problem, such as OPF, is established in the chapter. All critical constraints of the OPF problem are duly satisfied by the algorithms SHADE-SF, SHADE-EC and SHADE-SR. Further, the performances of both SF and EC methods are comparable, while the SR method lags behind the two on the problem of OPF.

Chapter 3 (section 3.2) contains solutions to multi-objective OPF (MOOPF) problem using algorithm MOEA/D-SF. The effectiveness of a CH technique for MOOPF problem is also exhibited with a comparative study between MOEA/D-SF and MOEA/D with a penalty factor. A formulation of OPF incorporating stochastic wind and solar power is included in Chapter 3 (section 3.3). With the adoption of appropriate probability density functions (PDFs), the variation in optimal generation cost is studied with the change in several control factors such as scheduled power from the renewable sources and the PDF parameters. The optimization is performed using SHADE-SF algorithm.

In Chapter 4, optimal reactive power dispatch (ORPD) problem is formulated considering uncertainties in load demand, wind and solar power. First section of the chapter is devoted to the comparison of results of SHADE-EC algorithm with the results of past studies available in the literature. Like the problem of OPF, importance in satisfying system constraints is exercised. The latter part of the chapter proposes the problem formulation and

solution approach to ORPD incorporating stochastic models of load demand, wind and solar power. Various scenarios of the demand, wind speed and solar irradiance are created. A scenario reduction technique is implemented. Finally, the algorithm minimizes real power loss and voltage deviation, independently, for various scenarios in the network.

Chapter 5 presents economic-environmental dispatch (EED) problem formulation and solution integrating thermal, wind, solar and small-hydro power sources. Like section 3.3 (in Chapter 3), suitable PDFs are adopted to calculate costs of uncertain and intermittent sources including small-hydro (run-of-river) power. Unlike past studies, the EED problem considers power system security constraints in the study. The optimization of cost and emission is performed using MOEA/D-SF and SMODE-SF algorithms. The results and Pareto fronts of the two algorithms are analyzed and compared.

Loss minimization of radial distribution network (RDN) is studied in Chapter 6. Appropriate network configuration, the addition of distributed generators (DGs) and shunt capacitors (SCs) can reduce the network real power loss for its economic and efficient operation. L-SHADE algorithm is successful in lowering the losses from the previously reported results using other algorithms under many scenarios of the network reinforcement with DGs or/and SCs. The algorithm can effectively handle a mixed-integer non-linear optimization problem such as RDN loss minimization.

The discrete location optimization problem of wind turbines in a windfarm is provided in Chapter 7. The first section (section 7.1) evaluates the effectiveness of L-SHADE algorithm in optimizing a high dimensional problem of only discrete variables. The case studies performed in this section consider the same data for turbines and conditions of wind as in some past studies. L-SHADE algorithm achieves arguably the best formations of wind turbines in the windfarm under different scenarios. The second section (section 7.2) suggests a multi-objective approach to optimal placement of wind turbines in a windfarm. The two objectives of maximizing energy output and aerodynamic efficiency help to attain multiple usable solutions i.e. multiple optimal arrangements of the wind turbines in a single run of the MOEA/D algorithm.

The research works presented in the thesis cover only some of the optimization problems in power system. The scope of optimization in power system is diverse and vast. We intend to perform many more tasks related to the optimization in power electronics and power systems in the future. A brief overview of future probable works is provided herein.

8.2. Future work

The major drawback in applying evolutionary algorithms in power system optimization is the huge execution time, especially the time taken to optimize an objective for a large electrical network. For example, 300,000 fitness evaluations in an OPF case study of IEEE 118-bus system take about 1 hour for a complete run using a computer with Intel Core i5 CPU @2.7GHz, 4GB RAM. Some algorithms can execute fast to converge to an acceptable solution, which may not be the best solution. These algorithms can be exploited more in the network with hundreds or even thousands of buses. Further, SHADE and L-SHADE algorithms are good in exploitation phase of the search process and they are found to be the consistent performers in optimizing non-convex, multi-modal real-world problems. However, the performance of these algorithms can be improved during early exploration phase. In future, this aspect of the algorithms shall further be studied. In this thesis, integration of only SF technique with MOEA/D is suggested. Other CH techniques like epsilon constraint (EC), self-adaptive penalty (SP) and stochastic ranking (SR) can also be integrated with the MOEAs to assess their performance on multi-objective optimization problems. Multi-objective OPF shall also be studied using improved variants of MOEA/D, vector evaluated genetic algorithm (VEGA), reference vector guided evolutionary algorithm (RVEA), NSGA-III, etc. For evaluation of Pareto fronts (PF) of two or more algorithms, metrics such as attainment surface (AS), inverse generational distance (IGD), etc. shall be employed. Further, advanced decision-making approaches like pseudo-weight method, marginal rate of return, Lp metric, etc. for finding compromise solutions shall be utilized.

In Chapter 3, OPF with stochastic wind and solar power are presented. In future, we propose integration of storage devices in the form of batteries or pumped hydro in the OPF study of network with large number of buses. Accurate models of doubly fed induction generators for wind turbines, FACTS devices can also be incorporated for a detailed study.

ORPD study with uncertain load demand, wind and solar power is performed in Chapter 4. The study can further be extended with inclusion of storage devices. Accurate models of PV inverters and wind generators can also be incorporated to take into account the actual reactive power capabilities of these devices. Multi-objective optimization and inclusion of voltage stability as the objective also remain a work for the future.

The EED formulation and solution incorporating wind-solar-small hydro power are included in Chapter 5. The proposed formulation on EED can further be studied using other well-known algorithms like multi-objective particle swarm optimization (MOPSO), multi-objective genetic algorithm (MOGA), non-dominated sorting genetic algorithm III (NSGA-III), etc. together with appropriate constraint handling techniques. Also, dynamic economic-environmental dispatch (DEED) problem with consideration of generator ramping rate and variation in load demands over a time-period incorporating stochastic nature of all the renewable sources and all network constraints remains a topic for future study.

In Chapter 6, network reconfiguration is executed by pre-identification of loops in the distribution network. Manual identification of loops in a large interconnected network becomes very difficult. Graph theory, minimal cut sets, etc. are some of the alternate methods that can be applied prior to identification of appropriate tie switches in the network. This approach will facilitate loss minimization of a large radial distribution network (RDN) with simultaneous reconfiguration, DG and SC allocation. A multi-objective case of RDN with the objectives of loss minimization and reliability enhancement will also be studied in the future. The cost of all installed equipment can be considered as an objective or a constraint in the problem to enhance usefulness and practicability of the proposed solutions.

In optimizing the location of wind turbines, a regular shaped windfarm is considered in Chapter 7. In future, optimal siting of turbines in an irregular shaped plot on a complex terrain shall be studied applying evolutionary algorithms. The optimal layout incorporating transmission system planning is also a work for the future.

The proposed algorithms in this thesis or any improved version of the algorithms will also be applied to the existing or new formulations of the following problems:

- Optimal power flow incorporating FACTS devices
- Unit commitment
- Optimal placement of phasor measuring units (PMUs)
- Optimal tuning of power system stabilizers

List of Publications

Journal Articles:

- 1) **Partha P. Biswas**, P. N. Suganthan, and Gehan AJ Amaratunga. "Optimal power flow solutions incorporating stochastic wind and solar power." *Energy Conversion and Management* 148 (2017): 1194-1207.
- 2) **Partha P. Biswas**, P. N. Suganthan, R. Mallipeddi, and Gehan AJ Amaratunga. "Optimal power flow solutions using differential evolution algorithm integrated with effective constraint handling techniques." *Engineering Applications of Artificial Intelligence* 68 (2018): 81-100.
- 3) **Partha P. Biswas**, P. N. Suganthan, B. Y. Qu, and Gehan AJ Amaratunga. "Multiobjective economic-environmental power dispatch with stochastic wind-solar-small hydro power." *Energy* 150 (2018): 1039-1057.
- 4) **Partha P. Biswas**, R. Mallipeddi, P. N. Suganthan, and Gehan AJ Amaratunga. "A multiobjective approach for optimal placement and sizing of distributed generators and capacitors in distribution network." *Applied Soft Computing* 60 (2017): 268-280
- 5) **Partha P. Biswas**, P. N. Suganthan, and Gehan AJ Amaratunga. "Decomposition based multi-objective evolutionary algorithm for windfarm layout optimization." *Renewable Energy* 115 (2018): 326-337.
- 6) **Partha P. Biswas**, P. N. Suganthan, and Gehan AJ Amaratunga. "Minimizing Harmonic Distortion in Power System with Optimal Design of Hybrid Active Power Filter using Differential Evolution." *Applied Soft Computing* 61 (2017): 486-496.
- 7) **Partha P. Biswas**, P. N. Suganthan, G. Wu, and Gehan AJ Amaratunga. "Parameter estimation of solar cells using datasheet information with the application of an adaptive differential evolution algorithm." *Renewable energy* 132 (2019): 425-438.
- 8) **Partha P. Biswas**, P. N. Suganthan, R. Mallipeddi, and Gehan AJ Amaratunga. "Optimal reactive power dispatch with uncertainties in load demand and renewable energy sources adopting scenario-based approach." *Applied Soft Computing* 75 (2019): 616-632.

Book Chapter:

- 1) **Partha P. Biswas**, and P. N. Suganthan. "Multi-objective evolutionary optimization." *Wiley Encyclopedia of Electrical and Electronics Engineering* (2018), DOI: 10.1002/047134608X.W8380.

Conference Papers:

- 1) **Partha P. Biswas**, P. N. Suganthan, and Gehan AJ Amaratunga. "Optimal placement of wind turbines in a windfarm using L-SHADE algorithm." In *Evolutionary Computation (CEC), 2017 IEEE Congress on*, pp. 83-88. IEEE 2017.
- 2) **Partha P. Biswas**, Noor H. Awad, P. N. Suganthan, Mostafa Z. Ali, and Gehan AJ Amaratunga. "Minimizing THD of multilevel inverters with optimal values of DC voltages and switching angles using LSHADE-EpSin algorithm." In *Evolutionary Computation (CEC), 2017 IEEE Congress on*, pp. 77-82. IEEE 2017.
- 3) **Partha P. Biswas**, P. N. Suganthan, and Gehan AJ Amaratunga. "Optimization of Wind Turbine Rotor Diameters and Hub Heights in a Windfarm Using Differential Evolution Algorithm." *Proceedings of Sixth International Conference on Soft Computing for Problem Solving*. Springer, Singapore, 2017.
- 4) **Partha P. Biswas**, R. Mallipeddi, P.N. Suganthan, and Gehan AJ Amaratunga. "Optimal reconfiguration and distributed generator allocation in distribution network using an advanced adaptive differential evolution." *Computational Intelligence (SSCI), 2017 IEEE Symposium Series on*. pp. 1-7. IEEE 2017.
- 5) **Partha P. Biswas**, P. N. Suganthan, and Gehan AJ Amaratunga. "Distribution network reconfiguration together with distributed generator and shunt capacitor allocation for loss minimization." In *Evolutionary Computation (CEC), 2018 IEEE Congress on*, pp. 1-7. IEEE 2018.
- 6) **Partha P. Biswas**, P. N. Suganthan, and Gehan AJ Amaratunga. "Optimal power flow solutions using population reduction technique of success history based adaptive differential evolution algorithm." *IEEE International Conference on Systems, Man and Cybernetics*, IEEE 2018 (accepted).

Unpublished / Under review manuscripts:

- 1) **Partha P. Biswas**, P. N. Suganthan, R. Mallipeddi, and Gehan AJ Amaratunga. "Multi-objective optimal power flow solutions with an effective constraint handling technique of evolutionary algorithms." *Soft Computing*, submitted.
- 2) **Partha P. Biswas**, P. N. Suganthan, R. Mallipeddi, and Gehan AJ Amaratunga. "Optimal power flow study of a wind integrated electrical network with optimum placement and sizing of FACTS devices." *Revision in progress*.

Appendix

Table A.1. Load data for IEEE 30-bus system

Bus No.	Load (100%)		Bus No.	Load (100%)	
	MW	MVAr		MW	MVAr
1	0	0	16	3.5	1.8
2	21.7	12.7	17	9	5.8
3	2.4	1.2	18	3.2	0.9
4	7.6	1.6	19	9.5	3.4
5	94.2	19	20	2.2	0.7
6	0	0	21	17.5	11.2
7	22.8	10.9	22	0	0
8	30	30	23	3.2	1.6
9	0	0	24	8.7	6.7
10	5.8	2	25	0	0
11	0	0	26	3.5	2.3
12	11.2	7.5	27	0	0
13	0	0	28	0	0
14	6.2	1.6	29	2.4	0.9
15	8.2	2.5	30	10.6	1.9
Total load: 283.4 MW, 126.2 MVAr					

Table A.2. Load data for IEEE 57-bus system

Bus No.	Load (100%)		Bus No.	Load (100%)	
	MW	MVAr		MW	MVAr
1	55	17	30	3.6	1.8
2	3	88	31	5.8	2.9
3	41	21	32	1.6	0.8
4	0	0	33	3.8	1.9
5	13	4	34	0	0
6	75	2	35	6	3
7	0	0	36	0	0
8	150	22	37	0	0
9	121	26	38	14	7
10	5	2	39	0	0
11	0	0	40	0	0
12	377	24	41	6.3	3
13	18	2.3	42	7.1	4.4
14	10.5	5.3	43	2	1
15	22	5	44	12	1.8
16	43	3	45	0	0
17	42	8	46	0	0
18	27.2	9.8	47	29.7	11.6
19	3.3	0.6	48	0	0
20	2.3	1	49	18	8.5
21	0	0	50	21	10.5
22	0	0	51	18	5.3
23	6.3	2.1	52	4.9	2.2
24	0	0	53	20	10
25	6.3	3.2	54	4.1	1.4
26	0	0	55	6.8	3.4
27	9.3	0.5	56	7.6	2.2
28	4.6	2.3	57	6.7	2
29	17	2.6			
Total load: 1250.8 MW, 336.4 MVAr					

Table A.3. Branch data for IEEE 30-bus system

Branch no.	Bus No.		R (p.u.)	X (p.u.)	B (total) (p.u.)	Rating (MVA)	Branch no.	Bus No.		R (p.u.)	X (p.u.)	B (total) (p.u.)	Rating (MVA)
	From	To						From	To				
1	1	2	0.0192	0.0575	0.0264	130	22	15	18	0.1070	0.2185	0	16
2	1	3	0.0452	0.1852	0.0204	130	23	18	19	0.0639	0.1292	0	16
3	2	4	0.0570	0.1737	0.0184	65	24	19	20	0.0340	0.0680	0	32
4	3	4	0.0132	0.0379	0.0042	130	25	10	20	0.0936	0.2090	0	32
5	2	5	0.0472	0.1983	0.0209	130	26	10	17	0.0324	0.0845	0	32
6	2	6	0.0581	0.1763	0.0187	65	27	10	21	0.0348	0.0749	0	32
7	4	6	0.0119	0.0414	0.0045	90	28	10	22	0.0727	0.1499	0	32
8	5	7	0.0460	0.1160	0.0102	70	29	21	22	0.0116	0.0236	0	32
9	6	7	0.0267	0.0820	0.0085	130	30	15	23	0.1000	0.2020	0	16
10	6	8	0.0120	0.0420	0.0045	32	31	22	24	0.1150	0.1790	0	16
11	6	9	0	0.2080	0	65	32	23	24	0.1320	0.2700	0	16
12	6	10	0	0.5560	0	32	33	24	25	0.1885	0.3292	0	16
13	9	11	0	0.2080	0	65	34	25	26	0.2544	0.3800	0	16
14	9	10	0	0.1100	0	65	35	25	27	0.1093	0.2087	0	16
15	4	12	0	0.2560	0	65	36	28	27	0	0.3960	0	65
16	12	13	0	0.1400	0	65	37	27	29	0.2198	0.4153	0	16
17	12	14	0.1231	0.2559	0	32	38	27	30	0.3202	0.6027	0	16
18	12	15	0.0662	0.1304	0	32	39	29	30	0.2399	0.4533	0	16
19	12	16	0.0945	0.1987	0	32	40	8	28	0.0636	0.2000	0.0214	32
20	14	15	0.2210	0.1997	0	16	41	6	28	0.0169	0.0599	0.0065	32
21	16	17	0.0824	0.1932	0	16							

Table A.4. Branch data for IEEE 57-bus system

Branch no.	Bus No.		R (p.u.)	X (p.u.)	B (total) (p.u.)	Rating (MVA)	Branch no.	Bus No.		R (p.u.)	X (p.u.)	B (total) (p.u.)	Rating (MVA)
	From	To						From	To				
1	1	2	0.0083	0.0280	0.1290	400	41	7	29	0	0.0648	0	100
2	2	3	0.0298	0.0850	0.0818	200	42	25	30	0.1350	0.2020	0	50
3	3	4	0.0112	0.0366	0.0380	200	43	30	31	0.3260	0.4970	0	50
4	4	5	0.0625	0.1320	0.0258	200	44	31	32	0.5070	0.7550	0	50
5	4	6	0.0430	0.1480	0.0348	200	45	32	33	0.0392	0.0360	0	50
6	6	7	0.0200	0.1020	0.0276	200	46	34	32	0	0.9530	0	50
7	6	8	0.0339	0.1730	0.0470	200	47	34	35	0.0520	0.0780	0.0032	50
8	8	9	0.0099	0.0505	0.0548	400	48	35	36	0.0430	0.0537	0.0016	200
9	9	10	0.0369	0.1679	0.0440	200	49	36	37	0.0290	0.0366	0	200
10	9	11	0.0258	0.0848	0.0218	200	50	37	38	0.0651	0.1009	0.0020	200
11	9	12	0.0648	0.2950	0.0772	200	51	37	39	0.0239	0.0379	0	50
12	9	13	0.0481	0.1580	0.0406	200	52	36	40	0.0300	0.0466	0	50
13	13	14	0.0132	0.0434	0.0110	200	53	22	38	0.0192	0.0295	0	200
14	13	15	0.0269	0.0869	0.0230	200	54	11	41	0	0.7490	0	50
15	1	15	0.0178	0.0910	0.0988	400	55	41	42	0.2070	0.3520	0	50
16	1	16	0.0454	0.2060	0.0546	200	56	41	43	0	0.4120	0	200
17	1	17	0.0238	0.1080	0.0286	200	57	38	44	0.0289	0.0585	0.0020	200
18	3	15	0.0162	0.0530	0.0544	200	58	15	45	0	0.1042	0	100
19	4	18	0	0.5550	0	50	59	14	46	0	0.0735	0	100
20	4	18	0	0.4300	0	50	60	46	47	0.0230	0.0680	0.0032	200
21	5	6	0.0302	0.0641	0.0124	50	61	47	48	0.0182	0.0233	0	200
22	7	8	0.0139	0.0712	0.0194	200	62	48	49	0.0834	0.1290	0.0048	50
23	10	12	0.0277	0.1262	0.0328	200	63	49	50	0.0801	0.1280	0	200
24	11	13	0.0223	0.0732	0.0188	200	64	50	51	0.1386	0.2200	0	200
25	12	13	0.0178	0.0580	0.0604	200	65	10	51	0	0.0712	0	100
26	12	16	0.0180	0.0813	0.0216	200	66	13	49	0	0.1910	0	100
27	12	17	0.0397	0.1790	0.0476	200	67	29	52	0.1442	0.1870	0	200
28	14	15	0.0171	0.0547	0.0148	200	68	52	53	0.0762	0.0984	0	200
29	18	19	0.4610	0.6850	0	50	69	53	54	0.1878	0.2320	0	200
30	19	20	0.2830	0.4340	0	50	70	54	55	0.1732	0.2265	0	200
31	21	20	0	0.7767	0	50	71	11	43	0	0.1530	0	50
32	21	22	0.0736	0.1170	0	200	72	44	45	0.0624	0.1242	0.0040	200
33	22	23	0.0099	0.0152	0	50	73	40	56	0	1.1950	0	50

Branch no.	Bus No.		R (p.u.)	X (p.u.)	B (total) (p.u.)	Rating (MVA)	Branch no.	Bus No.		R (p.u.)	X (p.u.)	B (total) (p.u.)	Rating (MVA)
	From	To						From	To				
34	23	24	0.1660	0.2560	0.0084	50	74	56	41	0.5530	0.5490	0	50
35	24	25	0	1.1820	0	50	75	56	42	0.2125	0.3540	0	50
36	24	25	0	1.2300	0	50	76	39	57	0	1.3550	0	50
37	24	26	0	0.0473	0	50	77	57	56	0.1740	0.2600	0	50
38	26	27	0.1650	0.2540	0	200	78	38	49	0.1150	0.1770	0.0030	200
39	27	28	0.0618	0.0954	0	200	79	38	48	0.0312	0.0482	0	200
40	28	29	0.0418	0.0587	0	200	80	9	55	0	0.1205	0	200

Table A.5. Simulation results of SHADE-EC for OPF Case 10 (min. cost) of IEEE 118-bus system

Control variables	Range (MW)	Values (MW)	Control variables	Range (MW)	Values (MW)	Control variables	Values (p.u.)	Control variables	Values (p.u.)	Control variables	Values
P _{G1}	30-100	30	P _{G65}	147.3-491	289.7861	V _{G1}	1.0331	V _{G65}	1.0633	Q _{C5} (MVar)	4.2091
P _{G4}	30-100	30.0011	P _{G66}	147.6-492	288.1496	V _{G4}	1.0589	V _{G66}	1.0746	Q _{C34} (MVar)	4.3768
P _{G6}	30-100	30.0003	P _{G70}	30-100	30.0013	V _{G6}	1.0524	V _{G69}	1.0734	Q _{C37} (MVar)	0
P _{G8}	30-100	30.0001	P _{G72}	30-100	30	V _{G8}	1.0390	V _{G70}	1.0574	Q _{C44} (MVar)	3.6675
P _{G10}	165-550	316.5847	P _{G73}	30-100	30.0029	V _{G10}	1.0499	V _{G72}	1.0624	Q _{C45} (MVar)	18.8984
P _{G12}	55.5-185	67.3386	P _{G74}	30-100	30.0024	V _{G12}	1.0475	V _{G73}	1.0607	Q _{C46} (MVar)	12.4539
P _{G15}	30-100	30.0001	P _{G76}	30-100	30	V _{G15}	1.0471	V _{G74}	1.0472	Q _{C48} (MVar)	7.0676
P _{G18}	30-100	30	P _{G77}	30-100	30.0001	V _{G18}	1.0495	V _{G76}	1.0277	Q _{C74} (MVar)	24.8939
P _{G19}	30-100	30	P _{G80}	173.1-577	348.7927	V _{G19}	1.0470	V _{G77}	1.0522	Q _{C79} (MVar)	24.9781
P _{G24}	30-100	30.0009	P _{G85}	30-100	30.0034	V _{G24}	1.0583	V _{G80}	1.0604	Q _{C82} (MVar)	24.9993
P _{G25}	96-320	151.8905	P _{G87}	31.2-104	31.2	V _{G25}	1.0723	V _{G85}	1.0602	Q _{C83} (MVar)	12.0905
P _{G26}	124.2-414	219.9547	P _{G89}	212.1-707	384.4521	V _{G26}	1.0793	V _{G87}	1.0757	Q _{C105} (MVar)	3.9170
P _{G27}	30-100	30.0022	P _{G90}	30-100	30	V _{G27}	1.0508	V _{G89}	1.0722	Q _{C107} (MVar)	24.802
P _{G31}	32.1-107	32.1	P _{G91}	30-100	30	V _{G31}	1.0467	V _{G90}	1.0579	Q _{C110} (MVar)	0
P _{G32}	30-100	30.0008	P _{G92}	30-100	30.0056	V _{G32}	1.0491	V _{G91}	1.0643	T ₈ (p.u.)	0.9767
P _{G34}	30-100	30.0008	P _{G99}	30-100	30.0001	V _{G34}	1.0554	V _{G92}	1.0631	T ₃₂ (p.u.)	1.0599
P _{G36}	30-100	30	P _{G100}	105.6-352	177.085	V _{G36}	1.0526	V _{G99}	1.0629	T ₃₆ (p.u.)	0.9834
P _{G40}	30-100	30.0003	P _{G103}	42-140	42.0002	V _{G40}	1.0380	V _{G100}	1.0658	T ₅₁ (p.u.)	0.9783
P _{G42}	30-100	30.0039	P _{G104}	30-100	30	V _{G42}	1.0397	V _{G103}	1.0639	T ₉₃ (p.u.)	0.9816
P _{G46}	35.7-119	35.7002	P _{G105}	30-100	30	V _{G46}	1.0556	V _{G104}	1.0591	T ₉₅ (p.u.)	0.9989
P _{G49}	91.2-304	161.4983	P _{G107}	30-100	30.0001	V _{G49}	1.0641	V _{G105}	1.0569	T ₁₀₂ (p.u.)	0.9709
P _{G54}	44.4-148	44.4081	P _{G110}	30-100	30	V _{G54}	1.0466	V _{G107}	1.0505	T ₁₀₇ (p.u.)	0.9434
P _{G55}	30-100	30	P _{G111}	40.8-136	40.8001	V _{G55}	1.0468	V _{G110}	1.0603	T ₁₂₇ (p.u.)	0.9840
P _{G56}	30-100	30.0001	P _{G112}	30-100	30	V _{G56}	1.0463	V _{G111}	1.0698	Fuel cost (\$/h)	134930.8
P _{G59}	76.5-255	124.9755	P _{G113}	30-100	30	V _{G59}	1.0628	V _{G112}	1.0520	Loss (MW)	57.7743
P _{G61}	78-260	123.0032	P _{G116}	30-100	30.0004	V _{G61}	1.0615	V _{G113}	1.0565	VD (p.u.)	3.0986
P _{G62}	30-100	30				V _{G62}	1.0553	V _{G116}	1.0612	P _{G69} (MW) [0 – 805.2]	370.0274

Table A.6. Simulation results of SHADE-EC for OPF Case 11 (min. loss) of IEEE 118-bus system

Control variables	Range (MW)	Values (MW)	Control variables	Range (MW)	Values (MW)	Control variables	Values (p.u.)	Control variables	Values (p.u.)	Control variables	Values
P _{G1}	30-100	69.2562	P _{G65}	147.3-491	147.3053	V _{G1}	1.0449	V _{G65}	1.0481	Q _{C5} (MVar)	24.0221
P _{G4}	30-100	30.0006	P _{G66}	147.6-492	147.6041	V _{G4}	1.0592	V _{G66}	1.0553	Q _{C34} (MVar)	0.0026
P _{G6}	30-100	30.0858	P _{G70}	30-100	30.0003	V _{G6}	1.0553	V _{G69}	1.0551	Q _{C37} (MVar)	0.0439
P _{G8}	30-100	30.0016	P _{G72}	30-100	30.0033	V _{G8}	1.0383	V _{G70}	1.0552	Q _{C44} (MVar)	3.7410
P _{G10}	165-550	165.0016	P _{G73}	30-100	30.0005	V _{G10}	1.0444	V _{G72}	1.0616	Q _{C45} (MVar)	17.7293
P _{G12}	55.5-185	134.4268	P _{G74}	30-100	95.3726	V _{G12}	1.0547	V _{G73}	1.0601	Q _{C46} (MVar)	0.8487
P _{G15}	30-100	85.2075	P _{G76}	30-100	100	V _{G15}	1.0516	V _{G74}	1.0528	Q _{C48} (MVar)	7.1739
P _{G18}	30-100	30.0472	P _{G77}	30-100	99.9966	V _{G18}	1.0509	V _{G76}	1.0431	Q _{C74} (MVar)	24.9023
P _{G19}	30-100	60.5065	P _{G80}	173.1-577	286.5985	V _{G19}	1.0512	V _{G77}	1.0541	Q _{C79} (MVar)	24.9896
P _{G24}	30-100	30	P _{G85}	30-100	30.2455	V _{G24}	1.0585	V _{G80}	1.0599	Q _{C82} (MVar)	24.9651
P _{G25}	96-320	96.0013	P _{G87}	31.2-104	31.2014	V _{G25}	1.0663	V _{G85}	1.0606	Q _{C83} (MVar)	10.4608
P _{G26}	124.2-414	124.2005	P _{G89}	212.1-707	212.1023	V _{G26}	1.0591	V _{G87}	1.0751	Q _{C105} (MVar)	24.4707
P _{G27}	30-100	48.7736	P _{G90}	30-100	99.8452	V _{G27}	1.0523	V _{G89}	1.0705	Q _{C107} (MVar)	24.9052
P _{G31}	32.1-107	60.0812	P _{G91}	30-100	30.0005	V _{G31}	1.0515	V _{G90}	1.0636	Q _{C110} (MVar)	11.0418
P _{G32}	30-100	39.8483	P _{G92}	30-100	30.0298	V _{G32}	1.0516	V _{G91}	1.0668	T ₈ (p.u.)	0.9822
P _{G34}	30-100	71.5462	P _{G99}	30-100	40.2522	V _{G34}	1.0549	V _{G92}	1.0618	T ₃₂ (p.u.)	1.0445
P _{G36}	30-100	51.2414	P _{G100}	105.6-352	105.6627	V _{G36}	1.0523	V _{G99}	1.0606	T ₃₆ (p.u.)	0.9849
P _{G40}	30-100	99.9998	P _{G103}	42-140	42.0049	V _{G40}	1.0512	V _{G100}	1.0615	T ₅₁ (p.u.)	0.9803
P _{G42}	30-100	99.9826	P _{G104}	30-100	32.9397	V _{G42}	1.0512	V _{G103}	1.0628	T ₉₃ (p.u.)	0.9926
P _{G46}	35.7-119	81.2760	P _{G105}	30-100	52.9692	V _{G46}	1.0536	V _{G104}	1.0598	T ₉₅ (p.u.)	0.9893
P _{G49}	91.2-304	141.7159	P _{G107}	30-100	57.3334	V _{G49}	1.0523	V _{G105}	1.0596	T ₁₀₂ (p.u.)	0.9688
P _{G54}	44.4-148	147.8762	P _{G110}	30-100	30.0024	V _{G54}	1.0491	V _{G107}	1.0596	T ₁₀₇ (p.u.)	0.9636
P _{G55}	30-100	72.7346	P _{G111}	40.8-136	40.8001	V _{G55}	1.0492	V _{G110}	1.0636	T ₁₂₇ (p.u.)	0.9729
P _{G56}	30-100	99.8454	P _{G112}	30-100	51.6713	V _{G56}	1.0486	V _{G111}	1.0725	Fuel cost (\$/h)	155382.1
P _{G59}	76.5-255	251.7872	P _{G113}	30-100	30.0034	V _{G59}	1.0488	V _{G112}	1.0604	Loss (MW)	16.1763
P _{G61}	78-260	78.0009	P _{G116}	30-100	77.2546	V _{G61}	1.0507	V _{G113}	1.0565	VD (p.u.)	3.0974
P _{G62}	30-100	64.4183				V _{G62}	1.0497	V _{G116}	1.0457	P _{G69} (MW) [0 – 805.2]	3.1134

Table A.7. Simulation results of OPF Case AC1: handling discrete variables

Parameters	Range	SHADE-SF	SHADE-EC	SHADE-SR
P_{G2} (MW)	20 – 80	48.7155	48.7171	48.6483
P_{G5} (MW)	15 – 50	21.3797	21.3768	21.3967
P_{G8} (MW)	10 – 35	21.2484	21.2492	21.5202
P_{G11} (MW)	10 – 30	11.9450	11.9504	11.9261
P_{G13} (MW)	12 – 40	12	12	12.0082
V_1 (p.u.)	0.95 – 1.10	1.0858	1.0858	1.0833
V_2 (p.u.)	0.95 – 1.10	1.0663	1.0663	1.0643
V_5 (p.u.)	0.95 – 1.10	1.0350	1.0349	1.0328
V_8 (p.u.)	0.95 – 1.10	1.0395	1.0395	1.0376
V_{11} (p.u.)	0.95 – 1.10	1.0902	1.0903	1.0745
V_{13} (p.u.)	0.95 – 1.10	1.0407	1.0390	1.0486
Q_{c10} (MVar)	0.0 – 5.0	4.4	5	4.6
Q_{c12} (MVar)	0.0 – 5.0	1.2	2.6	4.4
Q_{c15} (MVar)	0.0 – 5.0	4.6	4	4.6
Q_{c17} (MVar)	0.0 – 5.0	4.8	5	4.8
Q_{c20} (MVar)	0.0 – 5.0	4.8	3.6	3.8
Q_{c21} (MVar)	0.0 – 5.0	5	5	5
Q_{c23} (MVar)	0.0 – 5.0	2.8	3.6	2.8
Q_{c24} (MVar)	0.0 – 5.0	5	5	5
Q_{c29} (MVar)	0.0 – 5.0	2.8	2.8	2.8
T_{11} (p.u.)	0.90 – 1.10	1.06	1.06	1.06
T_{12} (p.u.)	0.90 – 1.10	0.94	0.94	0.92
T_{15} (p.u.)	0.90 – 1.10	0.96	0.96	0.98
T_{36} (p.u.)	0.90 – 1.10	0.98	0.98	0.98
Fuel cost (\$/h)		800.5207	800.5192	800.5254
Emission (t/h)		0.3663	0.3663	0.3656
Loss (MW)		9.0332	9.0324	9.0134
VD (p.u.)		0.8986	0.8970	0.8695
L-index (max)		0.1388	0.1388	0.1392
P_{G1} (MW)	50 – 200	177.1446	177.1389	176.9139

Table A.8. IEEE 57-bus system generator emission coefficients for MOOPF study

Sl. no.	Generator	Bus	φ	ψ	ω	τ	ζ
1	G1	1	4	-5	6	0.00002	0.5
2	G2	2	3	-6	5	0.00005	1.5
3	G3	3	4	-5	4	0.00001	1.0
4	G6	6	3.5	-3	3.5	0.00002	0.5
5	G8	8	5	-5	4.5	0.00004	2.0
6	G9	9	4.5	-4	5	0.00001	2.0
7	G12	12	6	-5	5	0.00001	1.5

Table A.9. Simulation results for MOOPF Case 7

Control variables	Min	Max	Best Cost	Best Emission	Best Comp	Control & state variables	Min	Max	Best Cost	Best Emission	Best Comp
P _{G2} (MW)	30	100	95.3483	99.9828	99.9606	T ₄₆ (p.u.)	0.90	1.10	0.9651	0.9888	0.9549
P _{G3} (MW)	40	140	44.7669	139.996	69.0612	T ₅₄ (p.u.)	0.90	1.10	0.9031	0.9624	0.9032
P _{G6} (MW)	30	100	72.1588	99.9779	99.9702	T ₅₈ (p.u.)	0.90	1.10	0.9685	0.9742	0.9671
P _{G8} (MW)	100	550	455.795	298.820	366.0649	T ₅₉ (p.u.)	0.90	1.10	0.9470	0.9492	0.9555
P _{G9} (MW)	30	100	95.9665	99.9071	99.9467	T ₆₅ (p.u.)	0.90	1.10	0.9742	0.9660	0.9642
P _{G12} (MW)	100	410	358.704	303.417	354.1615	T ₆₆ (p.u.)	0.90	1.10	0.9359	0.9212	0.9211
V ₁ (p.u.)	0.95	1.10	1.0517	1.0604	1.0513	T ₇₁ (p.u.)	0.90	1.10	0.9581	0.9514	0.9615
V ₂ (p.u.)	0.95	1.10	1.0480	1.0584	1.0490	T ₇₃ (p.u.)	0.90	1.10	0.9927	1.0034	0.9955
V ₃ (p.u.)	0.95	1.10	1.0379	1.0497	1.0436	T ₇₆ (p.u.)	0.90	1.10	0.9636	1.0193	0.9595
V ₆ (p.u.)	0.95	1.10	1.0583	1.0447	1.0537	T ₈₀ (p.u.)	0.90	1.10	0.9827	0.9883	0.9741
V ₈ (p.u.)	0.95	1.10	1.0682	1.0470	1.0619	Fuel cost (\$/h)			41683.39	45387.44	42160.09
V ₉ (p.u.)	0.95	1.10	1.0348	1.0256	1.0340	Emission (t/h)			1.8670	1.0814	1.3183
V ₁₂ (p.u.)	0.95	1.10	1.0302	1.0313	1.0313	Loss (MW)			15.1614	15.7015	13.0947
Q _{C18} (MVar)	0	20	11.037	10.404	5.599	VD (p.u.)			1.3767	1.3601	1.4509
Q _{C25} (MVar)	0	20	16.958	15.442	14.192	P _{G1} (MW)	0	576	143.222	224.4	174.73
Q _{C53} (MVar)	0	20	14.071	13.717	13.277	Q _{G1} (MVar)	-140	200	60.644	53.054	46.227
T ₁₉ (p.u.)	0.90	1.10	0.9466	0.9435	0.9144	Q _{G2} (MVar)	-17	50	46.248	49.535	44.557
T ₂₀ (p.u.)	0.90	1.10	1.0302	1.0510	1.0478	Q _{G3} (MVar)	-10	60	15.520	20.117	32.987
T ₃₁ (p.u.)	0.90	1.10	1.0187	1.0070	1.0190	Q _{G6} (MVar)	-8	25	10.239	-0.135	1.135
T ₃₅ (p.u.)	0.90	1.10	0.9858	0.9867	0.9577	Q _{G8} (MVar)	-140	200	58.972	49.052	57.169
T ₃₆ (p.u.)	0.90	1.10	1.0919	1.0737	1.0774	Q _{G9} (MVar)	-3	9	0.678	3.346	7.419
T ₃₇ (p.u.)	0.90	1.10	1.0129	1.0536	1.0211	Q _{G12} (MVar)	-150	155	43.343	63.974	48.29
T ₄₁ (p.u.)	0.90	1.10	0.9973	0.9881	0.9941	Worst VD (p.u.)			1.6239		

Table A.10. Simulation results for MOOPF Case 8

Control variables	Best Cost	Best VD	Best Comp	Control & state variables	Best Cost	Best VD	Best Comp
P _{G2} (MW)	95.8612	99.6496	91.7938	T ₄₆ (p.u.)	0.9634	0.919	0.9212
P _{G3} (MW)	47.4191	52.3635	46.2879	T ₅₄ (p.u.)	0.9177	0.9	0.9
P _{G6} (MW)	65.2476	31.5877	45.0780	T ₅₈ (p.u.)	0.9573	0.9278	0.9288
P _{G8} (MW)	459.788	360.897	455.2776	T ₅₉ (p.u.)	0.9750	0.9791	0.9749
P _{G9} (MW)	97.1859	97.7108	99.2258	T ₆₅ (p.u.)	0.9744	1.0098	1.0176
P _{G12} (MW)	357.993	390.932	379.1813	T ₆₆ (p.u.)	0.9743	0.9	0.9
V ₁ (p.u.)	1.0382	1.0118	1.0175	T ₇₁ (p.u.)	0.9513	0.958	0.9593
V ₂ (p.u.)	1.0312	1.0117	1.0117	T ₇₃ (p.u.)	0.9803	1.0108	1.0063
V ₃ (p.u.)	1.0210	1.0114	1.0119	T ₇₆ (p.u.)	1.0069	0.9	0.9005
V ₆ (p.u.)	1.0383	1.0031	1.0035	T ₈₀ (p.u.)	1.0458	0.9916	0.9929
V ₈ (p.u.)	1.0623	1.0169	1.0170	Fuel cost (\$/h)	41717.47	42856.84	41822.11
V ₉ (p.u.)	1.0310	1.0076	1.0073	Emission (t/h)	1.9089	1.5205	1.9346
V ₁₂ (p.u.)	1.0284	1.0374	1.0377	Loss (MW)	15.9825	15.8536	16.8489
Q _{C18} (MVar)	9.481	0.238	0.132	VD (p.u.)	0.9251	0.5983	0.6079
Q _{C25} (MVar)	14.526	15.258	15.109	P _{G1} (MW)	143.287	233.512	150.805
Q _{C53} (MVar)	17.458	19.988	19.999	Q _{G1} (MVar)	62.752	-15.793	27.137
T ₁₉ (p.u.)	0.9013	0.9232	0.9176	Q _{G2} (MVar)	35.096	47.225	28.703
T ₂₀ (p.u.)	1.0905	1.0301	1.0301	Q _{G3} (MVar)	11.992	59.583	58.988
T ₃₁ (p.u.)	1.0046	0.9735	0.9746	Q _{G6} (MVar)	-3.243	-1.858	-7.834
T ₃₅ (p.u.)	1.0709	0.976	0.9654	Q _{G8} (MVar)	74.59	22.493	11.292
T ₃₆ (p.u.)	0.9463	1.097	1.0983	Q _{G9} (MVar)	3.652	8.324	8.575
T ₃₇ (p.u.)	1.0307	1.005	1.0071	Q _{G12} (MVar)	61.921	136.458	135.141
T ₄₁ (p.u.)	1.0086	0.9862	0.9856	Worst VD (p.u.)	0.9451		

Table A.11. Simulation results for MOOPF Case 9

Control variables	Best Cost	Best VD	Best Loss	Best Comp	Control & state variables	Best Cost	Best VD	Best Loss	Best Comp
P _{G2} (MW)	61.5305	49.5075	32.3104	77.4213	T ₄₆ (p.u.)	0.9477	0.9178	0.9547	0.9266
P _{G3} (MW)	46.5765	85.7386	136.015	57.0780	T ₅₄ (p.u.)	0.917	0.9011	0.9126	0.9002
P _{G6} (MW)	82.1513	33.0047	99.0798	95.1908	T ₅₈ (p.u.)	0.9525	0.9325	0.9769	0.9606
P _{G8} (MW)	462.709	327.786	311.673	371.4309	T ₅₉ (p.u.)	0.9483	0.9719	0.9653	0.9576
P _{G9} (MW)	99.8951	98.1196	98.5556	99.7451	T ₆₅ (p.u.)	0.9942	0.9914	0.9846	0.9884
P _{G12} (MW)	375.427	407.860	409.712	409.7179	T ₆₆ (p.u.)	0.9143	0.9006	0.9435	0.9076
V ₁ (p.u.)	1.0238	1.0239	1.0606	1.0239	T ₇₁ (p.u.)	0.9728	0.9495	0.9788	0.9741
V ₂ (p.u.)	1.0223	1.0137	1.0560	1.0198	T ₇₃ (p.u.)	0.9931	0.9976	1.0584	1.0011
V ₃ (p.u.)	1.0252	1.0145	1.0587	1.0123	T ₇₆ (p.u.)	0.9175	0.9007	1.0037	0.9058
V ₆ (p.u.)	1.0471	1.0023	1.0598	1.0251	T ₈₀ (p.u.)	1.029	0.9842	1.0064	1.0026
V ₈ (p.u.)	1.0656	1.0163	1.0700	1.0409	Fuel cost (\$/h)	41734.96	43977.26	44566.09	42059.16
V ₉ (p.u.)	1.0273	1.0006	1.0436	1.0147	Emission (t/h)	1.9919	1.5347	1.3409	1.4862
V ₁₂ (p.u.)	1.0188	1.0161	1.0423	1.0163	Loss (MW)	15.6905	13.8047	10.2706	12.2996
Q _{C18} (MVar)	10.129	0.083	11.688	2.767	VD (p.u.)	0.8559	0.6048	1.3064	0.6729
Q _{C25} (MVar)	10.476	18.268	10.117	16.097	P _{G1} (MW)	138.201	262.588	173.725	152.516
Q _{C53} (MVar)	10.167	20	11.747	19.795	Q _{G1} (MVar)	27.056	47.083	45.459	44.996
T ₁₉ (p.u.)	0.9669	1.0499	1.0022	0.9778	Q _{G2} (MVar)	49.995	24.248	46.293	47.693
T ₂₀ (p.u.)	1.0255	0.9248	1.0321	0.9851	Q _{G3} (MVar)	40.171	58.187	29.529	24.651
T ₃₁ (p.u.)	1.0109	0.9761	1.038	0.9735	Q _{G6} (MVar)	1.476	-4.669	-7.789	-6.937
T ₃₅ (p.u.)	0.9428	1.0338	0.9024	1.0442	Q _{G8} (MVar)	82.843	39.091	67.117	58.669
T ₃₆ (p.u.)	0.9846	1.0762	1.0668	0.994	Q _{G9} (MVar)	0.033	7.248	7.472	8.248
T ₃₇ (p.u.)	1.0192	1.0018	1.0241	1.0089	Q _{G12} (MVar)	53.335	74.232	34.159	58.175
T ₄₁ (p.u.)	1.0166	0.9909	1.0129	1.0075	Worst VD (p.u.)	1.4268			

Table A.12. Simulation results for MOOPF Case 10

Control variables	Best Cost	Best Emission	Best VD	Best Loss	Best Comp	Control & state variables	Best Cost	Best Emission	Best VD	Best Loss	Best Comp
P _{G2} (MW)	81.0365	99.7276	87.0897	31.8792	80.3420	T ₄₆ (p.u.)	0.9244	0.9179	0.9205	0.9432	0.9162
P _{G3} (MW)	42.5500	139.9611	136.046	136.420	84.7525	T ₅₄ (p.u.)	0.9173	0.9098	0.9055	0.9230	0.9005
P _{G6} (MW)	74.7836	99.7812	62.513	97.8027	99.0462	T ₅₈ (p.u.)	0.9545	0.9662	0.9298	0.9782	0.9393
P _{G8} (MW)	472.757	286.450	302.014	302.506	333.9391	T ₅₉ (p.u.)	0.9604	0.9480	0.9937	0.9618	0.9526
P _{G9} (MW)	90.1759	99.9973	97.2198	99.6245	98.2269	T ₆₅ (p.u.)	1.0057	1.0105	1.0006	0.9877	0.9837
P _{G12} (MW)	367.764	299.780	346.173	410.0	402.7431	T ₆₆ (p.u.)	0.9051	0.9071	0.9003	0.9528	0.9018
V ₁ (p.u.)	1.0382	1.0508	1.0174	1.0503	1.0207	T ₇₁ (p.u.)	0.953	0.9803	0.9457	0.9604	0.9617
V ₂ (p.u.)	1.0305	1.0406	1.0095	1.0442	1.0180	T ₇₃ (p.u.)	1.0793	0.9736	1.024	0.9749	0.9979
V ₃ (p.u.)	1.0252	1.0264	1.0097	1.0443	1.0157	T ₇₆ (p.u.)	0.9799	0.9047	0.9053	0.9683	0.9084
V ₆ (p.u.)	1.0548	1.0153	1.0016	1.0468	1.0267	T ₈₀ (p.u.)	1.0018	1.0057	0.9937	0.9642	0.9978
V ₈ (p.u.)	1.0606	1.0144	1.0153	1.0479	1.0295	Fuel cost (\$/h)	41727.36	45863.14	45368.12	44721.53	42648.69
V ₉ (p.u.)	1.0265	1.0050	1.0066	1.025	1.0060	Emission (t/h)	2.0928	1.0851	1.2173	1.3335	1.3437
V ₁₂ (p.u.)	1.0268	1.0295	1.0394	1.0343	1.0089	Loss (MW)	16.3533	17.8868	16.9705	10.4094	11.8862
Q _{C18} (MVar)	7.626	9.073	2.990	16.727	1.240	VD (p.u.)	1.0558	0.7543	0.6172	1.1961	0.6713
Q _{C25} (MVar)	17.948	13.980	17.290	13.628	12.280	P _{G1} (MW)	138.087	242.99	236.715	182.978	163.636
Q _{C53} (MVar)	14.79	18.621	19.893	11.034	18.179	Q _{G1} (MVar)	66.12	86.96	22.333	50.398	41.905
T ₁₉ (p.u.)	0.9611	1.0477	0.9228	1.0727	1.0007	Q _{G2} (MVar)	30.694	26.071	22.808	44.632	45.814
T ₂₀ (p.u.)	1.0142	1.0222	1.0281	0.9886	0.9605	Q _{G3} (MVar)	14.158	11.696	26.368	18.154	37.049
T ₃₁ (p.u.)	0.9802	0.9807	0.9687	1.0075	0.9790	Q _{G6} (MVar)	22.478	-2.948	-6.869	3.889	9.646
T ₃₅ (p.u.)	1.0688	1.0651	0.9946	0.9753	0.9680	Q _{G8} (MVar)	52.666	18.986	29.831	49.339	44.698
T ₃₆ (p.u.)	1.0635	1.0028	1.0970	1.0081	1.0619	Q _{G9} (MVar)	-0.461	4.567	6.984	-1.758	8.655
T ₃₇ (p.u.)	1.0170	1.0081	1.0103	1.0038	1.0131	Q _{G12} (MVar)	61.443	108.199	152.968	50.908	54.255
T ₄₁ (p.u.)	1.0090	0.9853	0.9849	0.9761	0.9947	Worst VD (p.u.)	1.4246

Fig. A.1. Stacked column representation of optimal transformer taps for all scenarios in ORPD Case 21

Fig. A.2. Stacked column representation of optimal transformer taps for all scenarios in ORPD Case 22

Fig. A.3. Stacked column representation of optimum VAR compensator settings for all scenarios in ORPD Case 21

Fig. A.4. Stacked column representation of optimum VAR compensator settings for all scenarios in ORPD Case 22

Bibliography

- [1] Storn, Rainer, and Kenneth Price. "Differential evolution—a simple and efficient heuristic for global optimization over continuous spaces." *Journal of global optimization* 11.4 (1997): 341-359.
- [2] Qin, A. Kai, Vicky Ling Huang, and Ponnuthurai N. Suganthan. "Differential evolution algorithm with strategy adaptation for global numerical optimization." *IEEE transactions on Evolutionary Computation* 13, no. 2 (2009): 398-417.
- [3] Mallipeddi, Rammohan, Ponnuthurai N. Suganthan, Quan-Ke Pan, and Mehmet Fatih Tasgetiren. "Differential evolution algorithm with ensemble of parameters and mutation strategies." *Applied soft computing* 11, no. 2 (2011): 1679-1696.
- [4] Tanabe, Ryoji, and Alex Fukunaga. "Success-history based parameter adaptation for differential evolution." In *Evolutionary Computation (CEC), 2013 IEEE Congress on*, pp. 71-78. IEEE, 2013.
- [5] Tanabe, Ryoji, and Alex S. Fukunaga. "Improving the search performance of SHADE using linear population size reduction." In *Evolutionary Computation (CEC), 2014 IEEE Congress on*, pp. 1658-1665. IEEE, 2014.
- [6] Das, Swagatam, Sankha Subhra Mullick, and Ponnuthurai N. Suganthan. "Recent advances in differential evolution—an updated survey." *Swarm and Evolutionary Computation* 27 (2016): 1-30.
- [7] Zhang, Qingfu, and Hui Li. "MOEA/D: A multiobjective evolutionary algorithm based on decomposition." *IEEE Transactions on evolutionary computation* 11, no. 6 (2007): 712-731.
- [8] Zhang, Qingfu, Wudong Liu, and Hui Li. "The performance of a new version of MOEA/D on CEC09 unconstrained MOP test instances." In *Evolutionary Computation, 2009. CEC'09. IEEE Congress on*, pp. 203-208. IEEE, 2009.
- [9] Miettinen, Kaisa. *Nonlinear multiobjective optimization*. Vol. 12. Springer Science & Business Media, 2012.
- [10] Zhao, Shi-Zheng, Ponnuthurai Nagaratnam Suganthan, and Qingfu Zhang. "Decomposition-based multiobjective evolutionary algorithm with an ensemble of neighborhood sizes." *IEEE Transactions on Evolutionary Computation* 16.3 (2012): 442-446.
- [11] Qu, Bo-Yang, and Ponnuthurai N. Suganthan. "Multi-objective evolutionary algorithms based on the summation of normalized objectives and diversified selection." *Information sciences* 180, no. 17 (2010): 3170-3181.
- [12] Qu, Bo-Yang, and Ponnuthurai Nagaratnam Suganthan. "Multi-objective differential evolution based on the summation of normalized objectives and improved selection method." In *Differential Evolution (SDE), 2011 IEEE Symposium on*, pp. 1-8. IEEE, 2011.
- [13] Mallipeddi, Rammohan, and Ponnuthurai N. Suganthan. "Ensemble of constraint handling techniques." *IEEE Transactions on Evolutionary Computation* 14, no. 4 (2010): 561-579.
- [14] Deb, Kalyanmoy. "An efficient constraint handling method for genetic algorithms." *Computer methods in applied mechanics and engineering* 186, no. 2-4 (2000): 311-338.
- [15] Takahama, Tetsuyuki, and Setsuko Sakai. "Constrained optimization by the ϵ constrained differential evolution with an archive and gradient-based mutation." In *Evolutionary Computation (CEC), 2010 IEEE Congress on*, pp. 1-9. IEEE, 2010.
- [16] Runarsson, Thomas P., and Xin Yao. "Stochastic ranking for constrained evolutionary optimization." *IEEE Transactions on evolutionary computation* 4, no. 3 (2000): 284-294.
- [17] Momoh, James A., Rambabu Adapa, and M. E. El-Hawary. "A review of selected optimal power flow literature to 1993. I. Nonlinear and quadratic programming approaches." *IEEE transactions on power systems* 14, no. 1 (1999): 96-104.
- [18] Momoh, James A., M. E. El-Hawary, and Ramababu Adapa. "A review of selected optimal power flow literature to 1993. II. Newton, linear programming and interior point methods." *IEEE Transactions on Power Systems* 14, no. 1 (1999): 105-111.
- [19] Wong, Kit Po, An Li, and M. Y. Law. "Development of constrained-genetic-algorithm load-flow method." *IEE proceedings-Generation, Transmission and Distribution* 144, no. 2 (1997): 91-99.
- [20] Yuryevich, Jason, and Kit Po Wong. "Evolutionary programming based optimal power flow algorithm." *IEEE transactions on Power Systems* 14, no. 4 (1999): 1245-1250.
- [21] Abaci, Kadir, and Volkan Yamacli. "Differential search algorithm for solving multi-objective optimal power flow problem." *International Journal of Electrical Power & Energy Systems* 79 (2016): 1-10.
- [22] Daryani, Narges, Mehrdad Tarafdar Hagh, and Saeed Teimourzadeh. "Adaptive group search optimization algorithm for multi-objective optimal power flow problem." *Applied Soft Computing* 38 (2016): 1012-1024.
- [23] Chaib, A. E., H. R. E. H. Boucekara, R. Mehasni, and M. A. Abido. "Optimal power flow with emission and non-smooth cost functions using backtracking search optimization algorithm." *International Journal of Electrical Power & Energy Systems* 81 (2016): 64-77.
- [24] Boucekara, H. R. E. H., A. E. Chaib, Mohammad Ali Abido, and Ragab A. El-Sehiemy. "Optimal power flow using an Improved Colliding Bodies Optimization algorithm." *Applied Soft Computing* 42 (2016): 119-131.
- [25] Mohamed, Al-Attar Ali, Yahia S. Mohamed, Ahmed AM El-Gaafary, and Ashraf M. Hemeida. "Optimal power flow using moth swarm algorithm." *Electric Power Systems Research* 142 (2017): 190-206.
- [26] Ayan, Kürsat, Ulaş Kılıç, and Burhan Baraklı. "Chaotic artificial bee colony algorithm based solution of security and transient stability constrained optimal power flow." *International Journal of Electrical Power & Energy Systems* 64 (2015): 136-147.

- [27] Kumar, A. Ramesh, and L. Premalatha. "Optimal power flow for a deregulated power system using adaptive real coded biogeography-based optimization." *International Journal of Electrical Power & Energy Systems* 73 (2015): 393-399.
- [28] Mahdad, Belkacem, and Kamel Srairi. "Security constrained optimal power flow solution using new adaptive partitioning flower pollination algorithm." *Applied Soft Computing* 46 (2016): 501-522.
- [29] Pandiarajan, K., and C. K. Babulal. "Fuzzy harmony search algorithm based optimal power flow for power system security enhancement." *International Journal of Electrical Power & Energy Systems* 78 (2016): 72-79.
- [30] Ghasemi, Mojtaba, Sahand Ghavidel, Mohsen Gitizadeh, and Ebrahim Akbari. "An improved teaching-learning-based optimization algorithm using Lévy mutation strategy for non-smooth optimal power flow." *International Journal of Electrical Power & Energy Systems* 65 (2015): 375-384.
- [31] Roy, Provas Kumar, and Chandan Paul. "Optimal power flow using krill herd algorithm." *International Transactions on Electrical Energy Systems* 25, no. 8 (2015): 1397-1419.
- [32] Pulluri, Harish, Ram Naresh, and Veena Sharma. "Application of stud krill herd algorithm for solution of optimal power flow problems." *International Transactions on Electrical Energy Systems* 27, no. 6 (2017).
- [33] Pulluri, Harish, Ram Naresh, and Veena Sharma. "A solution network based on stud krill herd algorithm for optimal power flow problems." *Soft Computing* 22, no. 1 (2018): 159-176.
- [34] Bouchekara, H. R. E. H., A. E. Chaib, and M. A. Abido. "Multiobjective optimal power flow using a fuzzy based grenade explosion method." *Energy Systems* 7, no. 4 (2016): 699-721.
- [35] Reddy, Salkuti Surender, and Ch Srinivasa Rathnam. "Optimal power flow using glowworm swarm optimization." *International Journal of Electrical Power & Energy Systems* 80 (2016): 128-139.
- [36] Ghasemi, Mojtaba, Sahand Ghavidel, Shima Rahmani, Alireza Roosta, and Hasan Falah. "A novel hybrid algorithm of imperialist competitive algorithm and teaching learning algorithm for optimal power flow problem with non-smooth cost functions." *Engineering Applications of Artificial Intelligence* 29 (2014): 54-69.
- [37] Zhang, Jingrui, Qinghui Tang, Po Li, Daxiang Deng, and Yalin Chen. "A modified MOEA/D approach to the solution of multi-objective optimal power flow problem." *Applied Soft Computing* 47 (2016): 494-514.
- [38] Reddy, S. Surender. "Solution of multi-objective optimal power flow using efficient meta-heuristic algorithm." *Electrical Engineering* (2017): 1-13.
- [39] Pulluri, Harish, Ram Naresh, and Veena Sharma. "An enhanced self-adaptive differential evolution based solution methodology for multiobjective optimal power flow." *Applied Soft Computing* 54 (2017): 229-245.
- [40] Niknam, Taher, Mohammad rasoul Narimani, Masoud Jabbari, and Ahmad Reza Malekpour. "A modified shuffle frog leaping algorithm for multi-objective optimal power flow." *Energy* 36, no. 11 (2011): 6420-6432.
- [41] Shabanpour-Haghighi, Amin, Ali Reza Seifi, and Taher Niknam. "A modified teaching-learning based optimization for multi-objective optimal power flow problem." *Energy Conversion and Management* 77 (2014): 597-607.
- [42] Ghasemi, Mojtaba, Sahand Ghavidel, Mohammad Mehdi Ghanbarian, and Mohsen Gitizadeh. "Multi-objective optimal electric power planning in the power system using Gaussian bare-bones imperialist competitive algorithm." *Information Sciences* 294 (2015): 286-304.
- [43] Yuan, Xiaohui, Binqiao Zhang, Pengtao Wang, Ji Liang, Yanbin Yuan, Yuehua Huang, and Xiaohui Lei. "Multi-objective optimal power flow based on improved strength Pareto evolutionary algorithm." *Energy* 122 (2017): 70-82.
- [44] Bhowmik, Arup Ratan, and Ajoy Kumar Chakraborty. "Solution of optimal power flow using non dominated sorting multi objective opposition based gravitational search algorithm." *International Journal of Electrical Power & Energy Systems* 64 (2015): 1237-1250.
- [45] Shaheen, Abdullah M., Sobhy M. Farrag, and Ragab A. El-Sehiemy. "MOPF solution methodology." *IET Generation, Transmission & Distribution* 11, no. 2 (2017): 570-581.
- [46] Ghasemi, Mojtaba, Sahand Ghavidel, Mohammad Mehdi Ghanbarian, Hamid Reza Massrur, and Masihallah Gharibzadeh. "Application of imperialist competitive algorithm with its modified techniques for multi-objective optimal power flow problem: a comparative study." *Information Sciences* 281 (2014): 225-247.
- [47] Ghasemi, Mojtaba, Sahand Ghavidel, Mohammad Mehdi Ghanbarian, Masihallah Gharibzadeh, and Ali Azizi Vahed. "Multi-objective optimal power flow considering the cost, emission, voltage deviation and power losses using multi-objective modified imperialist competitive algorithm." *Energy* 78 (2014): 276-289.
- [48] Bilel, Najlawi, Nejlaoui Mohamed, Affi Zouhaier, and Romdhane Lotfi. "An improved imperialist competitive algorithm for multi-objective optimization." *Engineering Optimization* 48, no. 11 (2016): 1823-1844.
- [49] Barocio, Emilio, Jose Regalado, Erick Cuevas, Felipe Uribe, Pavel Zúñiga, and Pedro J. Ramirez Torres. "Modified bio-inspired optimisation algorithm with a centroid decision making approach for solving a multi-objective optimal power flow problem." *IET Generation, Transmission & Distribution* 11, no. 4 (2017): 1012-1022.
- [50] Roy, Ranjit, and H. T. Jadhav. "Optimal power flow solution of power system incorporating stochastic wind power using Gbest guided artificial bee colony algorithm." *International Journal of Electrical Power & Energy Systems* 64 (2015): 562-578.
- [51] Panda, Ambarish, and M. Tripathy. "Optimal power flow solution of wind integrated power system using modified bacteria foraging algorithm." *International Journal of Electrical Power & Energy Systems* 54 (2014): 306-314.
- [52] Panda, Ambarish, and M. Tripathy. "Security constrained optimal power flow solution of wind-thermal generation system using modified bacteria foraging algorithm." *Energy* 93 (2015): 816-827.

- [53] Shi, Libao, Chen Wang, Liangzhong Yao, Yixin Ni, and Masoud Bazargan. "Optimal power flow solution incorporating wind power." *IEEE Systems Journal* 6, no. 2 (2012): 233-241.
- [54] Jabr, R. A., and B. C. Pal. "Intermittent wind generation in optimal power flow dispatching." *IET Generation, Transmission & Distribution* 3, no. 1 (2009): 66-74.
- [55] Mishra, S., Yateendra Mishra, and S. Vignesh. "Security constrained economic dispatch considering wind energy conversion systems." *Power and Energy Society General Meeting, 2011 IEEE*. IEEE, 2011.
- [56] Zhou, Wei, Yu Peng, and Hui Sun. "Optimal wind-thermal coordination dispatch based on risk reserve constraints." *International Transactions on Electrical Energy Systems* 21, no. 1 (2011): 740-756.
- [57] Dubey, Hari Mohan, Manjaree Pandit, and B. K. Panigrahi. "Hybrid flower pollination algorithm with time-varying fuzzy selection mechanism for wind integrated multi-objective dynamic economic dispatch." *Renewable Energy* 83 (2015): 188-202.
- [58] Tazvinga, Henerica, Bing Zhu, and Xiaohua Xia. "Optimal power flow management for distributed energy resources with batteries." *Energy Conversion and Management* 102 (2015): 104-110.
- [59] Kusakana, Kanzumba. "Optimal scheduling for distributed hybrid system with pumped hydro storage." *Energy Conversion and Management* 111 (2016): 253-260.
- [60] Reddy, S. Surender, P. R. Bijwe, and Abhijit R. Abhyankar. "Real-time economic dispatch considering renewable power generation variability and uncertainty over scheduling period." *IEEE Systems Journal* 9.4 (2015): 1440-1451.
- [61] Kusakana, Kanzumba. "Optimal scheduled power flow for distributed photovoltaic/wind/diesel generators with battery storage system." *IET Renewable Power Generation* 9, no. 8 (2015): 916-924.
- [62] Reddy, S. Surender. "Optimal scheduling of thermal-wind-solar power system with storage." *Renewable Energy* 101 (2017): 1357-1368.
- [63] Grudin, N. "Reactive power optimization using successive quadratic programming method." *IEEE Transactions on Power Systems* 13, no. 4 (1998): 1219-1225.
- [64] Ramos, J.L. Martinez, A. Gomez Exposito, and V. H. Quintana. "Transmission power loss reduction by interior-point methods: implementation issues and practical experience." *IEEE Proceedings-Generation, Transmission and Distribution* 152, no. 1 (2005): 90-98.
- [65] El Ela, A.A. Abou, M. A. Abido, and S. R. Spea. "Differential evolution algorithm for optimal reactive power dispatch." *Electric Power Systems Research* 81, no. 2 (2011): 458-464.
- [66] Basu, M. "Quasi-oppositional differential evolution for optimal reactive power dispatch." *International Journal of Electrical Power & Energy Systems* 78 (2016): 29-40.
- [67] Mandal, Barun, and Provas Kumar Roy. "Optimal reactive power dispatch using quasi-oppositional teaching learning based optimization." *International Journal of Electrical Power & Energy Systems* 53 (2013): 123-134.
- [68] Mei, Rebecca Ng Shin, Mohd Herwan Sulaiman, Zuriani Mustaffa, and Hamdan Daniyal. "Optimal reactive power dispatch solution by loss minimization using moth-flame optimization technique." *Applied Soft Computing* 59 (2017): 210-222.
- [69] Rajan, Abhishek, and Tanmoy Malakar. "Exchange market algorithm based optimum reactive power dispatch." *Applied Soft Computing* 43 (2016): 320-336.
- [70] Chen, Gonggui, Lilan Liu, Zhizhong Zhang, and Shanwai Huang. "Optimal reactive power dispatch by improved GSA-based algorithm with the novel strategies to handle constraints." *Applied Soft Computing* 50 (2017): 58-70.
- [71] Shaw, Binod, V. Mukherjee, and S. P. Ghoshal. "Solution of reactive power dispatch of power systems by an opposition-based gravitational search algorithm." *International Journal of Electrical Power & Energy Systems* 55 (2014): 29-40.
- [72] Mehdi, Mehdi, Behnam Mohammadi-Ivatloo, Reza Dadashzadeh-Bonab, and Kazem Zare. "Solution of optimal reactive power dispatch of power systems using hybrid particle swarm optimization and imperialist competitive algorithms." *International Journal of Electrical Power & Energy Systems* 83 (2016): 104-116.
- [73] Rajan, Abhishek, and T. Malakar. "Optimal reactive power dispatch using hybrid Nelder-Mead simplex based firefly algorithm." *International Journal of Electrical Power & Energy Systems* 66 (2015): 9-24.
- [74] Ghasemi, Mojtaba, Sahand Ghavidel, Mohammad Mehdi Ghanbarian, and Amir Habibi. "A new hybrid algorithm for optimal reactive power dispatch problem with discrete and continuous control variables." *Applied soft computing* 22 (2014): 126-140.
- [75] Naderi, Ehsan, Hossein Narimani, Mehdi Fathi, and Mohammad Rasoul Narimani. "A novel fuzzy adaptive configuration of particle swarm optimization to solve large-scale optimal reactive power dispatch." *Applied Soft Computing* 53 (2017): 441-456.
- [76] Heidari, Ali Asghar, Rahim Ali Abbaspour, and Ahmad Rezaee Jordehi. "Gaussian bare-bones water cycle algorithm for optimal reactive power dispatch in electrical power systems." *Applied Soft Computing* 57 (2017): 657-671.
- [77] Nuaekaew, Kasem, Pramin Artrit, Nantiwat Pholdee, and Sujin Bureerat. "Optimal reactive power dispatch problem using a two-archive multi-objective grey wolf optimizer." *Expert Systems with Applications* 87 (2017): 79-89.
- [78] Chen, Gonggui, Lilan Liu, Yanyan Guo, and Shanwai Huang. "Multi-objective enhanced PSO algorithm for optimizing power losses and voltage deviation in power systems." *COMPEL: The International Journal for Computation and Mathematics in Electrical and Electronic Engineering* 35, no. 1 (2016): 350-372.
- [79] Shargh, S., B. Mohammadi-ivatloo, H. Seyedi, and M. Abapour. "Probabilistic multi-objective optimal power flow considering correlated wind power and load uncertainties." *Renewable Energy* 94 (2016): 10-21.

- [80] Mohseni-Bonab, Seyed Masoud, Abbas Rabiee, Behnam Mohammadi-Ivatloo, Saeid Jalilzadeh, and Sayyad Nojavan. "A two-point estimate method for uncertainty modeling in multi-objective optimal reactive power dispatch problem." *International Journal of Electrical Power & Energy Systems* 75 (2016): 194-204.
- [81] Liang, Ruey-Hsun, Jia-Ching Wang, Yie-Tone Chen, and Wan-Tsun Tseng. "An enhanced firefly algorithm to multi-objective optimal active/reactive power dispatch with uncertainties consideration." *International Journal of Electrical Power & Energy Systems* 64 (2015): 1088-1097.
- [82] Mohseni-Bonab, Seyed Masoud, Abbas Rabiee, and Behnam Mohammadi-Ivatloo. "Voltage stability constrained multi-objective optimal reactive power dispatch under load and wind power uncertainties: A stochastic approach." *Renewable Energy* 85 (2016): 598-609.
- [83] Mohseni-Bonab, Seyed Masoud, and Abbas Rabiee. "Optimal reactive power dispatch: a review, and a new stochastic voltage stability constrained multi-objective model at the presence of uncertain wind power generation." *IET Generation, Transmission & Distribution* 11, no. 4 (2017): 815-829.
- [84] Mohseni-Bonab, Seyed Masoud, Abbas Rabiee, and Behnam Mohammadi-Ivatloo. "Multi-objective Optimal Reactive Power Dispatch Considering Uncertainties in the Wind Integrated Power Systems." In *Reactive Power Control in AC Power Systems*, pp. 475-513. Springer, Cham, 2017.
- [85] Adarsh, B. R., T. Raghunathan, T. Jayabarathi, and Xin-She Yang. "Economic dispatch using chaotic bat algorithm." *Energy* 96 (2016): 666-675.
- [86] Jayabarathi, T., T. Raghunathan, B. R. Adarsh, and Ponnuthurai Nagarathnam Suganthan. "Economic dispatch using hybrid grey wolf optimizer." *Energy* 111 (2016): 630-641.
- [87] Meng, Anbo, Jinbei Li, and Hao Yin. "An efficient crisscross optimization solution to large-scale non-convex economic load dispatch with multiple fuel types and valve-point effects." *Energy* 113 (2016): 1147-1161.
- [88] Modiri-Delshad, Mostafa, S. Hr Aghay Kaboli, Ehsan Taslimi-Renani, and Nasrudin Abd Rahim. "Backtracking search algorithm for solving economic dispatch problems with valve-point effects and multiple fuel options." *Energy* 116 (2016): 637-649.
- [89] Secui, Dinu Calin. "A new modified artificial bee colony algorithm for the economic dispatch problem." *Energy Conversion and Management* 89 (2015): 43-62.
- [90] Gjorgiev, Blaže, and Marko Čepin. "A multi-objective optimization based solution for the combined economic-environmental power dispatch problem." *Engineering Applications of Artificial Intelligence* 26, no. 1 (2013): 417-429.
- [91] Zhang, Yong, Dun-Wei Gong, and Zhonghai Ding. "A bare-bones multi-objective particle swarm optimization algorithm for environmental/economic dispatch." *Information sciences* 192 (2012): 213-227.
- [92] Rao, B. Srinivasa, and K. Vaisakh. "Multi-objective adaptive Clonal selection algorithm for solving environmental/economic dispatch and OPF problems with load uncertainty." *International Journal of Electrical Power & Energy Systems* 53 (2013): 390-408.
- [93] Mondal, Soumitra, Aniruddha Bhattacharya, and Sunita Halder nee Dey. "Multi-objective economic emission load dispatch solution using gravitational search algorithm and considering wind power penetration." *International Journal of Electrical Power & Energy Systems* 44, no. 1 (2013): 282-292.
- [94] Yao, Fang, Zhao Yang Dong, Ke Meng, Zhao Xu, Herbert Ho-Ching Lu, and Kit Po Wong. "Quantum-inspired particle swarm optimization for power system operations considering wind power uncertainty and carbon tax in Australia." *IEEE Transactions on Industrial Informatics* 8, no. 4 (2012): 880-888.
- [95] Jadhav, H. T., and Ranjit Roy. "Gbest guided artificial bee colony algorithm for environmental/economic dispatch considering wind power." *Expert Systems with Applications* 40, no. 16 (2013): 6385-6399.
- [96] Abul'Wafa, Ahmed R. "Optimization of economic/emission load dispatch for hybrid generating systems using controlled Elitist NSGA-II." *Electric Power Systems Research* 105 (2013): 142-151.
- [97] Ghasemi, Ali, Milad Gheydi, Mohammad Javad Golkar, and Mohammad Eslami. "Modeling of Wind/Environment/Economic Dispatch in power system and solving via an online learning meta-heuristic method." *Applied Soft Computing* 43 (2016): 454-468.
- [98] Qu, B. Y., J. J. Liang, Y. S. Zhu, Z. Y. Wang, and Ponnuthurai N. Suganthan. "Economic emission dispatch problems with stochastic wind power using summation based multi-objective evolutionary algorithm." *Information Sciences* 351 (2016): 48-66.
- [99] Zhu, Yongsheng, Jie Wang, and Boyang Qu. "Multi-objective economic emission dispatch considering wind power using evolutionary algorithm based on decomposition." *International Journal of Electrical Power & Energy Systems* 63 (2014): 434-445.
- [100] Azizpanah-Abarghoee, Rasoul, Taher Niknam, Alireza Roosta, Ahmad Reza Malekpour, and Mohsen Zare. "Probabilistic multiobjective wind-thermal economic emission dispatch based on point estimated method." *Energy* 37, no. 1 (2012): 322-335.
- [101] Khan, Naveed Ahmed, Ahmed Bilal Awan, Anzar Mahmood, Sohail Razzaq, Adnan Zafar, and Guftaar Ahmed Sardar Sidhu. "Combined emission economic dispatch of power system including solar photo voltaic generation." *Energy Conversion and management* 92 (2015): 82-91.
- [102] Gopalan, Sachit A., Victor Sreeram, and Herbert HC Lu. "A review of coordination strategies and protection schemes for microgrids." *Renewable and Sustainable Energy Reviews* 32 (2014): 222-228.
- [103] Jordehi, Ahmad Rezaee. "Allocation of distributed generation units in electric power systems: A review." *Renewable and Sustainable Energy Reviews* 56 (2016): 893-905.
- [104] Nojavan, Sayyad, Mehdi Jalali, and Kazem Zare. "Optimal allocation of capacitors in radial/mesh distribution systems using mixed integer nonlinear programming approach." *Electric Power Systems Research* 107 (2014): 119-124.
- [105] Sultana, Sneha, and Provas Kumar Roy. "Optimal capacitor placement in radial distribution systems using teaching learning based optimization." *International Journal of Electrical Power & Energy Systems* 54 (2014): 387-398.

-
- [106] Nguyen, Thuan Thanh, Thang Trung Nguyen, Anh Viet Truong, Quyen Thi Nguyen, and Tuan Anh Phung. "Multi-objective electric distribution network reconfiguration solution using runner-root algorithm." *Applied Soft Computing* 52 (2017): 93-108.
 - [107] Nguyen, Thuan Thanh, and Anh Viet Truong. "Distribution network reconfiguration for power loss minimization and voltage profile improvement using cuckoo search algorithm." *International Journal of Electrical Power & Energy Systems* 68 (2015): 233-242.
 - [108] Naveen, S., K. Sathish Kumar, and K. Rajalakshmi. "Distribution system reconfiguration for loss minimization using modified bacterial foraging optimization algorithm." *International Journal of Electrical Power & Energy Systems* 69 (2015): 90-97.
 - [109] Flaih, F. M., Xiangning, L., Dawoud, S. M., & Mohammed, M. A. (2016, October). Distribution system reconfiguration for power loss minimization and voltage profile improvement using Modified particle swarm optimization. In *Power and Energy Engineering Conference (APPEEC), 2016 IEEE PES Asia-Pacific* (pp. 120-124). IEEE.
 - [110] Viral, Rajkumar, and D. K. Khatod. "An analytical approach for sizing and siting of DGs in balanced radial distribution networks for loss minimization." *International Journal of Electrical Power & Energy Systems* 67 (2015): 191-201.
 - [111] Ayodele, T. R., A. S. O. Ogunjuyigbe, and O. O. Akinola. "Optimal Location, Sizing, and Appropriate Technology Selection of Distributed Generators for Minimizing Power Loss Using Genetic Algorithm." *Journal of Renewable Energy* 2015 (2015).
 - [112] Kansal, Satish, Vishal Kumar, and Barjeev Tyagi. "Optimal placement of different type of DG sources in distribution networks." *International Journal of Electrical Power & Energy Systems* 53 (2013): 752-760.
 - [113] Kefayat, M., A. Lashkar Ara, and SA Nabavi Niaki. "A hybrid of ant colony optimization and artificial bee colony algorithm for probabilistic optimal placement and sizing of distributed energy resources." *Energy Conversion and Management* 92 (2015): 149-161.
 - [114] Naik, S. Gopiya, D. K. Khatod, and M. P. Sharma. "Optimal allocation of combined DG and capacitor for real power loss minimization in distribution networks." *International Journal of Electrical Power & Energy Systems* 53 (2013): 967-973.
 - [115] Aman, M. M., G. B. Jasmon, K. H. Solangi, A. H. A. Bakar, and H. Mokhlis. "Optimum simultaneous DG and capacitor placement on the basis of minimization of power losses." *International Journal of Computer and Electrical Engineering* 5, no. 5 (2013): 516.
 - [116] Muthukumar, K., and S. Jayalalitha. "Optimal placement and sizing of distributed generators and shunt capacitors for power loss minimization in radial distribution networks using hybrid heuristic search optimization technique." *International Journal of Electrical Power & Energy Systems* 78 (2016): 299-319.
 - [117] Khodabakhshian, Amin, and Mohammad Hadi Andishgar. "Simultaneous placement and sizing of DGs and shunt capacitors in distribution systems by using IMDE algorithm." *International Journal of Electrical Power & Energy Systems* 82 (2016): 599-607.
 - [118] Fadel, Waleed, Ulas Kilic, and Sezai Taskin. "Placement of Dg, Cb, and Tcsc in radial distribution system for power loss minimization using back-tracking search algorithm." *Electrical Engineering* (2016): 1-12.
 - [119] Imran, A. Mohamed, M. Kowsalya, and D. P. Kothari. "A novel integration technique for optimal network reconfiguration and distributed generation placement in power distribution networks." *International Journal of Electrical Power & Energy Systems* 63 (2014): 461-472.
 - [120] Nguyen, Thuan Thanh, Anh Viet Truong, and Tuan Anh Phung. "A novel method based on adaptive cuckoo search for optimal network reconfiguration and distributed generation allocation in distribution network." *International Journal of Electrical Power & Energy Systems* 78 (2016): 801-815.
 - [121] Bayat, A., A. Bagheri, and R. Noroozian. "Optimal siting and sizing of distributed generation accompanied by reconfiguration of distribution networks for maximum loss reduction by using a new UVDA-based heuristic method." *International Journal of Electrical Power & Energy Systems* 77 (2016): 360-371.
 - [122] Mosetti, G., Carlo Poloni, and B. Diviacco. "Optimization of wind turbine positioning in large windfarms by means of a genetic algorithm." *Journal of Wind Engineering and Industrial Aerodynamics* 51.1 (1994): 105-116.
 - [123] Grady, S. A., M. Y. Hussaini, and Makola M. Abdullah. "Placement of wind turbines using genetic algorithms." *Renewable energy* 30.2 (2005): 259-270.
 - [124] Mittal, Anshul. Optimization of the layout of large wind farms using a genetic algorithm. Diss. Case Western Reserve University, 2010.
 - [125] Emami, Alireza, and Pirooz Noghreh. "New approach on optimization in placement of wind turbines within wind farm by genetic algorithms." *Renewable Energy* 35.7 (2010): 1559-1564.
 - [126] Marmidis, Grigorios, Stavros Lazarou, and Eleftheria Pyrgioti. "Optimal placement of wind turbines in a wind park using Monte Carlo simulation." *Renewable energy* 33.7 (2008): 1455-1460.
 - [127] Pookpant, Sittichoke, and Weerakorn Ongsakul. "Optimal placement of wind turbines within wind farm using binary particle swarm optimization with time-varying acceleration coefficients." *Renewable Energy* 55 (2013): 266-276.
 - [128] Eroğlu, Yunus, and Serap Ulusam Seçkiner. "Design of wind farm layout using ant colony algorithm." *Renewable Energy* 44 (2012): 53-62.
 - [129] Chen, K., M. X. Song, Z. Y. He, and X. Zhang. "Wind turbine positioning optimization of wind farm using greedy algorithm." *Journal of Renewable and Sustainable Energy* 5, no. 2 (2013): 023128.
 - [130] Chen, K., M. X. Song, X. Zhang, and S. F. Wang. "Wind turbine layout optimization with multiple hub height wind turbines using greedy algorithm." *Renewable Energy* 96 (2016): 676-686.
 - [131] González, Javier Serrano, Angel G. Gonzalez Rodriguez, José Castro Mora, Jesús Riquelme Santos, and Manuel Burgos Payan. "Optimization of wind farm turbines layout using an evolutive algorithm." *Renewable energy* 35, no. 8 (2010): 1671-1681.
-

-
- [132] DuPont, Bryony, Jonathan Cagan, and Patrick Moriarty. "An advanced modeling system for optimization of wind farm layout and wind turbine sizing using a multi-level extended pattern search algorithm." *Energy* 106 (2016): 802-814.
 - [133] Chen, Ying, Hua Li, Bang He, Pengcheng Wang, and Kai Jin. "Multi-objective genetic algorithm based innovative wind farm layout optimization method." *Energy Conversion and Management* 105 (2015): 1318-1327.
 - [134] Feng, Ju, Wen Zhong Shen, and Chang Xu. "Multi-objective random search algorithm for simultaneously optimizing wind farm layout and number of turbines." *Journal of Physics: Conference Series*. Vol. 753. No. 3. IOP Publishing, 2016.
 - [135] R.D. Zimmerman, C.E. Murillo-Sánchez, R.J. Thomas, Matpower (Available at:) <http://www.pserc.cornell.edu/matpower>
 - [136] Alsac, O., and B. Stott. "Optimal load flow with steady-state security." *IEEE transactions on power apparatus and systems* 3 (1974): 745-751.
 - [137] Bhattacharya, A., and P. K. Chattopadhyay. "Application of biogeography-based optimisation to solve different optimal power flow problems." *IET generation, transmission & distribution* 5, no. 1 (2011): 70-80.
 - [138] Kessel, P., and H. Glavitsch. "Estimating the voltage stability of a power system." *IEEE Transactions on power delivery* 1, no. 3 (1986): 346-354.
 - [139] Derrac, Joaquín, Salvador García, Daniel Molina, and Francisco Herrera. "A practical tutorial on the use of nonparametric statistical tests as a methodology for comparing evolutionary and swarm intelligence algorithms." *Swarm and Evolutionary Computation* 1, no. 1 (2011): 3-18.
 - [140] Coello, Carlos A. Coello. "Theoretical and numerical constraint-handling techniques used with evolutionary algorithms: a survey of the state of the art." *Computer methods in applied mechanics and engineering* 191, no. 11-12 (2002): 1245-1287.
 - [141] Shaheen, Abdullah M., Ragab A. El-Sehiemy, and Sobhy M. Farrag. "Solving multi-objective optimal power flow problem via forced initialised differential evolution algorithm." *IET Generation, Transmission & Distribution* 10, no. 7 (2016): 1634-1647.
 - [142] Ishibuchi, Hisao, and Tadahiko Murata. "Multi-objective genetic local search algorithm." In *Evolutionary Computation, 1996., Proceedings of IEEE International Conference on*, pp. 119-124. IEEE, 1996.
 - [143] Deb, Kalyanmoy, Amrit Pratap, Sameer Agarwal, and T. A. M. T. Meyarivan. "A fast and elitist multiobjective genetic algorithm: NSGA-II." *IEEE transactions on evolutionary computation* 6, no. 2 (2002): 182-197.
 - [144] Yao, Weifeng, Junhua Zhao, Fushuan Wen, Zhaoyang Dong, Yusheng Xue, Yan Xu, and Ke Meng. "A multi-objective collaborative planning strategy for integrated power distribution and electric vehicle charging systems." *IEEE Transactions on Power Systems* 29, no. 4 (2014): 1811-1821.
 - [145] Zhu, Yongsheng, Jie Wang, and Boyang Qu. "Multi-objective economic emission dispatch considering wind power using evolutionary algorithm based on decomposition." *International Journal of Electrical Power & Energy Systems* 63 (2014): 434-445.
 - [146] Trivedi, Anupam, Dipti Srinivasan, Kunal Pal, Chiranjib Saha, and Thomas Reindl. "Enhanced multiobjective evolutionary algorithm based on decomposition for solving the unit commitment problem." *IEEE Transactions on Industrial Informatics* 11, no. 6 (2015): 1346-1357.
 - [147] While, Lyndon, Philip Hingston, Luigi Barone, and Simon Huband. "A faster algorithm for calculating hypervolume." *IEEE transactions on evolutionary computation* 10, no. 1 (2006): 29-38.
 - [148] Bringmann, Karl, and Tobias Friedrich. "Approximation quality of the hypervolume indicator." *Artificial Intelligence* 195 (2013): 265-290.
 - [149] Srinivas, Nidamarthi, and Kalyanmoy Deb. "Multiobjective optimization using nondominated sorting in genetic algorithms." *Evolutionary computation* 2, no. 3 (1994): 221-248.
 - [150] Chen, Chun-Lung, Tsung-Ying Lee, and Rong-Mow Jan. "Optimal wind-thermal coordination dispatch in isolated power systems with large integration of wind capacity." *Energy conversion and management* 47, no. 18-19 (2006): 3456-3472.
 - [151] Chang, Tian Pau. "Investigation on frequency distribution of global radiation using different probability density functions." *International Journal of Applied Science and Engineering* 8, no. 2 (2010): 99-107.
 - [152] Ackermann T. Wind power in power system Chapter 43. John Wiley & Sons; 2012
 - [153] Engelhardt, Stephan, Istvan Erlich, Christian Feltes, Jörg Kretschmann, and Fekadu Shewarega. "Reactive power capability of wind turbines based on doubly fed induction generators." *IEEE Transactions on Energy Conversion* 26, no. 1 (2011): 364-372.
 - [154] Eftekharnajad, Sara, Vijay Vittal, Gerald Thomas Heydt, Brian Keel, and Jeffrey Loehr. "Impact of increased penetration of photovoltaic generation on power systems." *IEEE transactions on power systems* 28, no. 2 (2013): 893-901.
 - [155] Albarracín, Ricardo, and M. Alonso. "Photovoltaic reactive power limits." In *Environment and Electrical Engineering (EEEIC), 2013 12th International Conference on*, pp. 13-18. IEEE, 2013.
 - [156] Cabrera-Tobar, A., E. Bullich-Massagué, M. Aragües-Penalba, and O. Gomis-Bellmunt. "Reactive power capability analysis of a photovoltaic generator for large scale power plants." (2016): 53-6.
 - [157] International Electrotechnical Commission. "IEC 61400-1: Wind turbines part 1: Design requirements." *International Electrotechnical Commission* (2005).
 - [158] Morales, Juan M., Antonio J. Conejo, Kai Liu, and Jin Zhong. "Pricing electricity in pools with wind producers." *IEEE Transactions on Power Systems* 27, no. 3 (2012): 1366-1376.
 - [159] Black, Veatch. "Cost and performance data for power generation technologies." *Prepared for the National Renewable Energy Laboratory* (2012).
-

-
- [160] Mallipeddi, Rammohan, S. Jeyadevi, Ponnuthurai N. Suganthan, and S. Baskar. "Efficient constraint handling for optimal reactive power dispatch problems." *Swarm and Evolutionary Computation* 5 (2012): 28-36.
 - [161] Bjelogrić, Milan, Milan S. Calović, Petar Ristanović, and Borivoje S. Babić. "Application of Newton's optimal power flow in voltage/reactive power control." *IEEE Transactions on Power Systems* 5, no. 4 (1990): 1447-1454.
 - [162] Growe-Kuska, Nicole, Holger Heitsch, and Werner Romisch. "Scenario reduction and scenario tree construction for power management problems." In *Power tech conference proceedings, 2003 IEEE Bologna*, vol. 3, pp. 7-pp. IEEE, 2003.
 - [163] Paish, Oliver. "Small hydro power: technology and current status." *Renewable and sustainable energy reviews* 6, no. 6 (2002): 537-556.
 - [164] Wijesinghe, Anuradha, and Loi Lei Lai. "Small hydro power plant analysis and development." In *Electric Utility Deregulation and Restructuring and Power Technologies (DRPT), 2011 4th International Conference on*, pp. 25-30. IEEE, 2011.
 - [165] Mujere, Never. "Flood frequency analysis using the Gumbel distribution." *International Journal on Computer Science and Engineering* 3, no. 7 (2011): 2774-2778.
 - [166] Cabus, Pieter. "River flow prediction through rainfall-runoff modelling with a probability-distributed model (PDM) in Flanders, Belgium." *Agricultural Water Management* 95, no. 7 (2008): 859-868.
 - [167] Ng, H. N., M. M. A. Salama, and A. Y. Chikhani. "Classification of capacitor allocation techniques." *IEEE Transactions on power delivery* 15, no. 1 (2000): 387-392.
 - [168] Liang, J. J., B. Y. Qu, and P. N. Suganthan. "Problem definitions and evaluation criteria for the CEC 2014 special session and competition on single objective real-parameter numerical optimization." *Computational Intelligence Laboratory, Zhengzhou University, Zhengzhou China and Technical Report, Nanyang Technological University, Singapore* (2013).
 - [169] Chiou, Ji-Pyng, Chung-Fu Chang, and Ching-Tzong Su. "Variable scaling hybrid differential evolution for solving network reconfiguration of distribution systems." *IEEE Transactions on Power Systems* 20, no. 2 (2005): 668-674.
 - [170] Cruz, M. R. M., D. Z. Fitiwi, S. F. Santos, and J. P. S. Catalão. "Influence of distributed storage systems and network switching/reinforcement on RES-based DG integration level." In *European Energy Market (EEM), 2016 13th International Conference on the*, pp. 1-5. IEEE, 2016.
 - [171] Kanwar, Neeraj, Nikhil Gupta, K. R. Niazi, and Anil Swarnkar. "Improved meta-heuristic techniques for simultaneous capacitor and DG allocation in radial distribution networks." *International Journal of Electrical Power & Energy Systems* 73 (2015): 653-664.
 - [172] Aman, M. M., G. B. Jasmon, A. H. A. Bakar, and H. Mokhlis. "Optimum network reconfiguration based on maximization of system loadability using continuation power flow theorem." *International journal of electrical power & energy systems* 54 (2014): 123-133.
 - [173] Rahmani-andebili, Mehdi. "Simultaneous placement of DG and capacitor in distribution network." *Electric Power Systems Research* 131 (2016): 1-10.
 - [174] Jensen, Niels Otto. "A note on wind generator interaction." (1983).
 - [175] Katic, I., J. Højstrup, and Niels Otto Jensen. "A simple model for cluster efficiency." In *European wind energy association conference and exhibition*, pp. 407-410. 1986.
 - [176] Denholm, Paul, Maureen Hand, Maddalena Jackson, and Sean Ong. *Land use requirements of modern wind power plants in the United States*. No. NREL/TP-6A2-45834. National Renewable Energy Lab.(NREL), Golden, CO (United States), 2009.
 - [177] <https://www.tceq.texas.gov/airquality/monops/windroses.html>
 - [178] Chen, Ying, Hua Li, Kai Jin, and Qing Song. "Wind farm layout optimization using genetic algorithm with different hub height wind turbines." *Energy Conversion and Management* 70 (2013): 56-65.
 - [179] Moné, Christopher, Tyler Stehly, Ben Maples, and Edward Settle. "Cost of wind energy review." *National Renewable Energy Laboratory (NREL): Golden, CO, USA* (2015).
 - [180] Tong, Weiyang, Souma Chowdhury, Jie Zhang, and Achille Messac. "Impact of different wake models on the estimation of wind farm power generation." In *12th AIAA Aviation Technology, Integration, and Operations (ATIO) Conference and 14th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference*, p. 5430. 2012.
 - [181] European Wind Energy Association. *The economics of wind energy*. EWEA, 2009.
-