KKU ENGINEERING JOURNAL 2016;43(S1):18-22 Research Article

KKU Engineering Journal

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Comparative performance of multiobjective evolutionary algorithms for solving multiobjective optimal reactive power dispatch problems

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Received April 2016
Accepted June 2016

Abstract

In this paper, comparative performance of multiobjective evolutionary algorithms (MOEAs) for solving multiobjective optimal reactive power dispatch (MOORPD) problems has been studied. The standard IEEE 30-bus and 57-bus power systems are posed to optimize active power loss and voltage deviation. Design variables include generator bus voltages, tap setting transformers, and shunt reactive power sources whereas design constraints are lower and upper bounds of the variables. A number of MOEAs are implemented to solve the test problems and their performances are compared statistically. It is shown that multiobjective gray wolf optimizer (MOGWO) is superior to other MOEAs based upon the hypervolume indicator. The results can be set as the baseline for performance testing of MOEAs for such optimization problems.

Keywords: Multiobjective optimal reactive power dispatch, Non-dominated solution, Multiobjective evolutionary algorithms, Pareto dominance

1. Introduction

In general, an electric power transmission system suffers from the problems of the voltage drop at line end, high active power loss as well as low stability from interference. To reduce such undesirable phenomena, the Multi Objective Optimal Reactive Power Dispatch (MOORPD) problem is usually assigned and solved so as to find the best possible solutions dealing with the problems. Generally, the aim of the MOORPD is to minimize the active power loss (P_{loss}) and voltage profile improvement (voltage deviation minimization: VD). The MOORPD is a process to control lower and upper limits of generator bus voltages, tap setting transformers, and shunt reactive power sources, while satisfying large number of equality and inequality constraints [1]. Several traditional techniques such as nonlinear programming (NLP) [2], quadratic programming (QP)[3], and an interior point method [4] have been used to solve single objective ORPD problems. The use of meta-heuristics such as genetic algorithm (GA) [5], differential evolution (DE) [6], particle swarm optimization (PSO) [7] etc., has also been reported. However, it has been found that there are needs to optimize several objective function at the same time as stated earlier. Thus, the use of multiobjective optimizers for MOORPD is of importance. In the literature, several MOEAs have been used to solve the MOORPD problems such as Non-dominated sorting genetic algorithm-II (NSGA-II) [8], multi objective particle swarm (MOPSO) [9], multi objective differential evolution (MODE)[10] etc. Nevertheless, since the last few decades, there have been a great many of MOEAs being developed and it is interesting to test them when solving MOORPD so that some top performers can be figured out.

In this paper, a variety of MOEAs have been employed to solve MOORPD problems. The design problems include the standard IEEE 30-bus and the IEEE 57-bus power system while design objectives are active power loss and voltage deviation. The power flow calculation is carried out by using Newton-Raphson Power Flow (NRPF). The optimum results obtained from the various optimizers are compared based on the hypervolume indicator and discussed.

2. Problem formulation

2.1 Objective functions

The design problem in this study has two objective functions including active power loss and voltage deviations, which can be detailed as:

2.1.1 Active power loss minimization

This aim is to minimize the system active power loss in transmission lines which can be expressed as.

$$P_{loss} = \sum_{k=1}^{nline} g_k \left[V_i^2 + V_j^2 - 2V_iV_j \cos(\delta_i - \delta_j) \right] \quad (1)$$

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doi: 10.14456/kkuenj.2016.59

where V_i, δ_i are voltage and phase angle of bus *i*; V_j, δ_j are voltage and phase angle of bus *j*, g_k is a conductance of transmission line *k*, *nline* is a number of transmission lines.

2.1.2 Voltage deviations minimization

This objective is to minimize the load bus voltage deviations between the normal value and those obtained from calculation. It can be expressed as:

$$VD = \sum_{k=1}^{nbus} \left| V_k - V_{dk} \right| \tag{2}$$

where V_k is voltage magnitude of bus *k*. V_{dk} is desired voltage magnitude of bus *k* ,usual 1.0 per unit . *nbus* is a number of load buses voltage.

2.3 Equality constraints

The equality constraints of the ORPD are real and reactive power balance at each node i.e. load flow equations given by *g(x)*,

$$\begin{aligned} &\left(P_{Gi} - P_{Di}\right) - \sum_{j=1}^{N_B} \left| Y_{ij} V_i V_j \right| \cos\left(\theta_{ij} + \delta_i - \delta_j\right) = 0 \\ &\text{for } \; i = 1,2,3,\ldots,N_B - 1 \end{aligned} \tag{3}$$

$$\begin{aligned} &\left(Q_{Gi} - Q_{Di}\right) + \sum_{j=1}^{N_B} \left| Y_{ij} V_i V_j \right| \sin\left(\theta_{ij} + \delta_i - \delta_j\right) = 0 \\ &\text{for } \; i = 1,2,3,\ldots,N_{PQ} \end{aligned} \tag{4}$$

where P_{Gi} is an active power generation at bus i, Q_{Gi} is a reactive power generation at bus i, P_{Di} is an active power demand at bus i, Q_{Di} is a reactive power demand at bus i; Y_{ij}, θ_{ij} are magnitude and angle of Y_{bus} between bus i and bus j, N_B is the number of bus, and N_{PQ} is the number of PQ bus, respectively. It should be noted that these constraints are dealt with during the process of activating the Newton-Raphson power flow.

2.4 Inequality constraints

MOORPD inequality constraints indicate the limitations of the equipment in the power system such as generation size, voltage bus control size, tap setting transformers and shunt reactive power sources. As a result, there are two types of inequality constraints the inequality constraints on security limits (dependent variables) and the inequality constraints on control (independent) variable limits. The formers are given by:

$$P_{Gslack}^{\min} \le Q_{Gslack} \le Q_{Gslack}^{\max} \tag{5}$$

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max} \quad i = 1,2,3,\ldots,N_{PQ} \tag{6}$$

$$V_{PQ}^{\min} \le V_{PQ} \le V_{PQ}^{\max} \quad i = 1,2,3,\ldots,N_G \tag{7}$$

While, the latters are are given by:

$$V_{Gi}^{\min} \le V_{Gi} \le V_{Gi}^{\max} \tag{8}$$

$$T_i^{\min} \le T_i \le T_i^{\max} \tag{9}$$

$$Q_{comp,i}^{\min} \le Q_{comp,i} \le Q_{comp,i}^{\max} \tag{10}$$

where $Q_{Gi}^{min}, Q_{Gi}^{max}$ are minimum and maximum of reactive power generation at bus *i*; $V_{Gi}^{min}, V_{Gi}^{max}$ are minimum and maximum of magnitude voltage at bus *i*; T_i^{min}, T_i^{max} are minimum and maximum of a tap setting transformer at bus *i*; $Q_{comp,i}^{min}, Q_{comp,i}^{max}$ are minimum and maximum of a shunt reactive power source at bus *i*, respectively.

3. Multi objective optimization

Multiobjective optimization is a design problem posed to find optimal design variables such that optimizing more than one objective functions. The optimal solutions are trade-off between the design objectives; as a result, there have been more than one optimum solution, traditionally called a set of Pareto optimal solutions or a Pareto front in cases that they are viewed in the objective function domain. A typical mathematical formulation of multi objective optimization can be written as:

$$\mathbf{f} = \{ f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_N(\mathbf{x}) \} \tag{11}$$

Subject to

$$\begin{aligned} &g_i(\mathbf{x}) \le 0 \\ &h_i(\mathbf{x}) = 0 \end{aligned} \tag{12}$$

where $f_N(\mathbf{x})$ is the number of objective functions; $\mathbf{x} = (x_1, x_2, \ldots, x_n)^T$ is a vector of the decision variables; $g_i\ (\mathbf{x}) \le 0$ and $h_i(\mathbf{x}) = 0$ are inequality and equality constraints respectively. The constraints define the feasible region and vector **x** in the feasible region is called a feasible solution.

4. Numerical experiment

This investigation is conducted using MATLAB. For each test system, 10 independent runs for each optimizer were operated. A personal computer (PC) with Intel Core i7-4790K CPU 4.00 GHz 16.0 GB RAM was used. The IEEE 30-bus and the IEEE 57-bus power systems are employed as the test problems of MOORPD. More details of MOEA optimization settings are:

4.1 Parameter settings

The general parameters of various algorithms such as the population size (N_{pop}), the maximum number of iteration ($\max_{iter}$) and the allowable archive size (N_{Arc}) for each test system are pre-specified. For the IEEE 30-bus power system, $N_{pop} = 20$, $\max_{iter} = 100$, and $N_{Arc} = 500$. For the IEEE 57-bus power system, $N_{pop} = 30$, $\max_{iter} = 100$, and $N_{Arc} = 500$. The other parameters specifically used by a particular optimizer are given below:

4.1.1 Multiobjective Differential Evolution Population-based Increment Learning (MDEPBIL) setting [11] : initial learning rate (LR_0)=0.25, mutation probability (*Mut_prob*)=0.05, mutation shift (*Mut_shft*)=0.20, crossover probability (p_c)=0.7, Scaling factor for differentail evolution (DE) operator (F)=0.8,and probability of chosing element from offspring in crossover (C_R)=0.5.

4.1.2 Multiobjective Particle Swarm Optimisation (MOPSO) setting [12] : inertia weight (w)=0.5, intertia weight damping rate (wdamp)=0.99, personal learning coefficient (c_1)=1, global learning coefficient (c2)=2, number of grids per dimension (nGrid)=7, inflation rate (alpha)=0.1, leader selection pressure (beta)=2 deletion selection pressure (gamma)=2, and mutation rate (mu)=0.1.

4.1.3 Multiobjective Population-based Increment Learning (MOBPBIL) setting [13]: initial learning rate (LR_0)=0.5, mutation probability (*Mut_prob*)=0.05, and mutation shift (*Mut_shft*)=0.2.

4.1.4 Multiobjective Differential Evolution (MODEMO) setting [14]: crossover probability (p_c)=0.7, Scaling factor for differential evolution (DE) operator (F)=0.8, and probability of choosing element from offspring in crossover (C_R)=0.5.

4.1.5 Multiobjective Differential Evolution (MODEs) setting [14]: scaling factor for differential evolution (DE) operator (F)=0.5, and Crossover probability in DE algorithm (C_R)= 0.2.

4.1.6 Multiobjective Niched Pareto Genetic Algorithm II using Real Codes(MORNPGA) setting [15]: crossing-over probability (p_c) = 1.0, and mutation probability (p_m) = 0.5.

4.1.7 Multiobjective Non-Dominated Sorting Genetic Algorithm II using binary codes (MORNSGA) setting [15]:crossing-over probability (p_c) = 1.0, and mutation probability (p_m) = 0.1.

4.1.8 Multiobjective Grey Wolf Optimizer(MOGWO) setting [16]: grid inflation parameter (*alpha*)=0.1, number of grids per each dimension (*nGrid*)=10, leader selection pressure parameter (*beta*)=4, and extra (to be deleted) repository member selection pressure (*gamma*)=2.

4.1.9 Multiobjective Particle Swarm Optimisation (MORPSO) setting [12]: starting inertia weight (W_{st}) = 0.75, ending inertia weight (W_{en}) = 0.1, cognitive learning factor (C_1) = 0.75, and social learning factor (C_2) = 0.75.

4.1.10 Multiobjective Population-Base Incremental Learning muliple prob vectors + crossing-over version using binary codes (MORPESA) setting [17]: mutation probability(*Mut_prob*)=0.1.

4.2 Test systems

For test system include IEEE 30-bus and the IEEE 57-bus power systems.

4.2.1 IEEE 30 bus power system

The IEEE 30-bus power system comprises of 6 generators at bus 1, 2, 5, 8, 11 and 13 (See Figure 1). Bus 1 is set as the slack bus whereas the rest are generator bus voltages. 4 under load tap setting transformers are used, which are placed in line 6-9, 6-10, 4-12, and 28-27. The shunt reactive power sources are placed in bus 10, 24 and 29. There are 41 transmission lines, as shown in Figure 1. The system data and initial operating conditions can be found in [18]. The upper and lower limits of PVbus voltages, PQbus voltages, and tap setting transformer (p.u.) are shown in Table 2. The upper and lower limits of control variables are shown in Table 3.

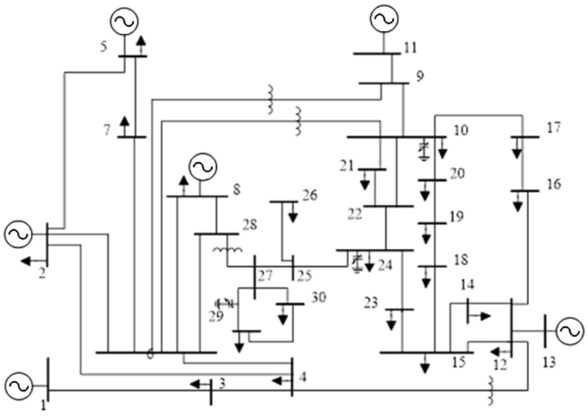

Figure 1 Single diagram of the IEEE 30-bus power system

4.2.2 IEEE 57 bus power system

The IEEE 57-bus power system comprises of 7 generators at bus 1, 2, 3, 6, 8, 9, and 12. The slack bus is Bus 1 whereas the rest are generator bus voltages. 17 under load tap setting transformers are used, which are placed in line 4-18, 4-18, 21-20, 24-25, 24-25, 24-26, 7-29, 34-32, 11-41, 15-45, 14-46, 10-51, 13-49, 11-43, 40-56, 39-57, and 9-55. The shunt reactive power sources are placed in bus 18, 25 and 53. 80 transmission lines are used. The system data and initial operating conditions can be found in [19].The upper and lower limits of PVbus voltages, PQbus voltages, and tap setting transformer (p.u.) are shown in Table 2. The upper and lower limits of control variables are shown in Table 3.

The details of the MOORPD test problems are given in Table 1. The upper and lower limits of PVbus voltages, PQbus voltages, and tap setting transformer (p.u.) are given in Table 2, while the upper and lower limits of control variables are shown in Table 3.

5. Results and discussion

After solving the IEEE 30-bus and IEEE 57-bus power system for 10 optimization runs of 10 algorithms, the comparative results are shown in Table 4 and Table5, respectively. From the tables, the best optimizer is decided based on the mean value of the hypervolume indicator. Boldface numbers are used to indicate the best algorithm which is MOGWO for both cases. For the measure of search consistency, the most consistent method is still MOGWO. The best Pareto fronts of the IEEE 30-bus and IEEE 57-bus power systems obtained from the various MOEAs are shown in Figure 2 and Figure 3, respectively. In the Figure 2, the reference point is the active power loss of 16.2639 MW and the voltage deviation of 0.1311 p.u., while the maximum and minimum of the active power loss and the voltage deviations are 16.271057 MW, 15.963755 MW, 0.131111 p.u. and 0.088702 p.u., respectively. In the Figure 3, the reference point is the active power loss of 26.0324 MW and the voltage deviation of 2.2511 p.u., while the maximum and minimum of the active power loss and the voltage deviations are 26.6715168 MW, 22.2612421 MW, 2.2511058 p.u. and 0.5062548 p.u., respectively. From both figures, it is seem that MOGWO algorithm obtained the best Pareto-front.

Table 1 The description of the test IEEE power system

Description	IEEE 30-bus	IEEE 57-bus
No. of buses	30	57
No. of generator	6	80
No. of transformer	4	15
No. of shunt reactive	3	3
No. of branches	41	80
No. of control variable	13	25
No. of discrete variable	6	20
No. of equality constraints	60	114
No. of inequality constraints	125	245

Table 2 The upper and lower limits of PVbus voltages, PQbus voltages, and tap setting transformer (p.u.)

$V_G^{\min}$	$V_G^{\max}$	$V_{PQ}^{\min}$	$V_{PQ}^{\max}$	$T_i^{\min}$	$T_i^{\max}$
0.9	1.1	0.9	1.1	0.9	1.1

Table 3 The upper and lower limits of shunt reactive power source (p.u.)

IEEE30bus			IEEE57bus		
Bus	$Q_{comp}^{\min}$	$Q_{comp}^{\max}$	Bus	$Q_{comp}^{\min}$	$Q_{comp}^{\max}$
10	0	0.22	18	0	10
24	0	0.15	25	0	5.9
29	0	0.15	53	0	6.3

Table 4 Statistical comparison of result of the IEEE 30-bus power system with hypervolume

Algorithm	Best	Worst	Mean	Std.Dev.
MDEPBIL	0.0075164	0.0017472	0.0054576	0.002156
MOPSO	0.0100649	0.0058136	0.0079852	0.001398
MOBPBIL	0.0096932	0.0047553	0.0080790	0.001568
MODEMO	0.0092376	0.0016282	0.0067288	0.00234
MODEs	0.0113431	0.0064588	0.0082888	0.00124
MORNPGA	0.0074546	0.0044814	0.0061029	0.000945
MORNSGA	0.0083362	0.0030884	0.0063505	0.001680
MOGWO	0.0096330	0.0072013	**0.0087575**	0.000655
MORPSO	0.0089406	0.0065423	0.0078388	0.000733
MORPESA1	0.0113197	0.0056585	0.0083801	0.00151

Table 5 Statistical comparison of result of the IEEE 57-bus power system with hypervolume

Algorithm	Best	Worst	Mean	Std.Dev.
MDEPBIL	5.627706	3.682647	4.539523	0.719524
MOPSO	2.543698	0.120526	1.593809	0.982869
MOBPBIL	6.071489	3.288047	4.120897	1.051255
MODEMO	5.554075	0.399714	2.903512	2.268346
MODEs	4.222762	3.833545	4.004724	0.145350
MORNPGA	4.787113	2.094060	3.190180	0.972534
MORNSGA	5.286547	3.743513	4.437886	0.565457
MOGWO	7.072235	3.411733	**4.832789**	0.961155
MOPSO	2.543698	0.120526	1.593809	0.982869
MORPESA1	4.728260	3.089275	3.621505	0.682074

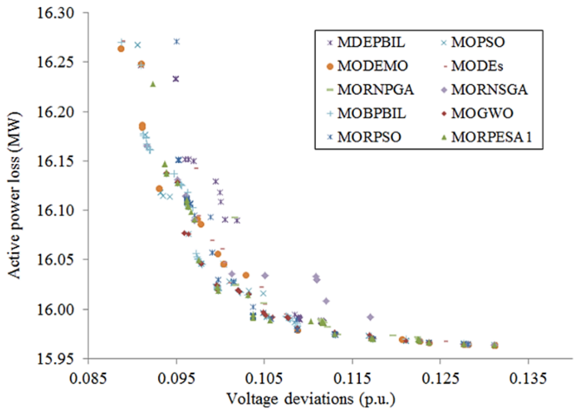

Figure 2 The best obtained Pareto-fronts for IEEE 30-bus power system

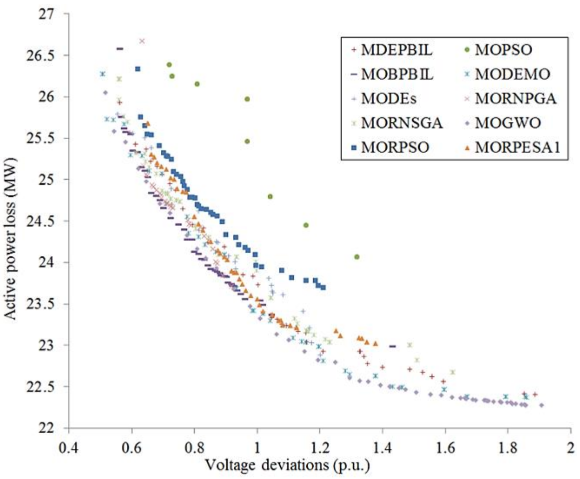

Figure 3 The best obtained Pareto-fronts for IEEE 57-bus power system

6. Conclusions

In this paper, a comparative performance of MOEAS for multi objective optimal reactive power dispatch has been investigated. The MOORPD problem has two objective functions that are active power loss and voltage deviation. Based on the hypervolume comparison, it has been shown that MOGWO is superior to the other MOEAs according to the measures of a convergance rate and a search consistency for both design cases. This investigation is said to be one of the very first studies on MOORPD using MOEAs. The obtained results can be used as the starting baseline for performance comparison of MOEAs for MOORPD.

7. Acknowledgements

The authors thank research group at Robotic Engineering. Department of Electrical Engineering, Sustainable Infrastructure Research and Development Center, Department of Mechanical Engineering, Faculty of Engineering, Khon Kaen University. Scholarships from Rajamangala University of Technology Isan, Khon Kaen Campus, Thailand, and Thailand Research Funds (TRF).

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