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Solving multiobjective optimal reactive power dispatch using modified NSGA-II

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ABSTRACT

This paper addresses an application of modified NSGA-II (MNSGA-II) by incorporating controlled elitism and dynamic crowding distance (DCD) strategies in NSGA-II to multiobjective optimal reactive power dispatch (ORPD) problem by minimizing real power loss and maximizing the system voltage stability. To validate the Pareto-front obtained using MNSGA-II, reference Pareto-front is generated using multiple runs of single objective optimization with weighted sum of objectives. For simulation purposes, IEEE 30 and IEEE 118 bus test systems are considered. The performance of MNSGA-II, NSGA-II and multiobjective particle swarm optimization (MOPSO) approaches are compared with respect to multiobjective performance measures. TOPSIS technique is applied on obtained non-dominated solutions to determine best compromise solution (BCS). Karush–Kuhn–Tucker (KKT) conditions are also applied on the obtained non-dominated solutions to substantiate a claim on optimality. Simulation results are quite promising and the MNSGA-II performs better than NSGA-II in maintaining diversity and authenticates its potential to solve multiobjective ORPD effectively.

1. Introduction

The main purpose of ORPD problem is to minimize real power transmission losses of the network while maintaining the system voltage profile in an acceptable range, with control variables such as the generator voltages, tap ratios of transformers and reactive power generation of VAr sources. ORPD is usually modeled as a large-scale mixed integer nonlinear programming problem. Many classic optimization techniques such as linear programming [1], nonlinear programming [2], quadratic programming [3], Newton [4] and interior point methods [5] have been applied for solving ORPD problems.

However, these techniques have severe limitations like (i) need of continuous and differential objective functions, (ii) easily converge to local minima, and (iii) difficulty in handling discrete variables. To overcome these limitations, the robust and flexible evolutionary optimization techniques such as, simple genetic algorithms [6], evolutionary strategies [7], evolutionary programming [8], particle swarm optimization [9], differential evolution [10,11] and real coded genetic algorithms (RGA) [12] have been applied. These evolutionary algorithms have shown success in solving the ORPD problems since they do not need the objective and constraints as differentiable and continuous functions.

Recently, the ORPD problem is formulated as multiobjective optimization problem [13]. However, the multiobjective problem was converted into a single objective problem by weighted sum of objectives [14,15]. Inadequate choice of weight factors may cause the non-commensurable objectives to lose their significance on combining into a single objective function. Hence, this approach cannot be applied to find Pareto-optimal solutions of problems like ORPD which have non-convex Pareto-optimal front. Conventional optimization methods can at best find one solution in one simulation run, thereby making those methods inconvenient to solve multiobjective optimization problems. On the contrary, the multiobjective evolutionary algorithms (MOEAs) are getting immense popularity, mainly because of their ability to find a widespread of Pareto-optimal solutions in a single simulation run [16].

Some of the recent evolutionary approaches to multiobjective optimization are non-dominated sorting genetic algorithm (NSGA-II), strength Pareto evolutionary algorithm (SPEA), Pareto archived evolution strategy (PAES), multiobjective differential evolution (MODE) and others. Among these SPEA [13,17] have been applied to multiobjective ORPD problem and MODE [18] has been applied to multiobjective optimal power flow problem. Though NSGA-II [19] algorithm encompasses advanced concepts like elitism, fast non-dominated sorting approach and diversity maintenance along the Pareto-optimal front, it still falls short in maintaining lateral diversity and obtaining Pareto-front with high uniformity. To overcome this shortcoming, [16] proposed a technique called controlled elitism which can maintain the diversity of non-dominated front laterally. Also to obtain Pareto-front with high uniformity, DCD based diversity maintenance strategy is proposed recently [20].

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In this paper, NSGA-II algorithm has been modified by incorporating controlled elitism and DCD features to ensure better convergence and diversity and is termed as modified NSGA-II (MNSGA-II). MNSGA-II is applied to multiobjective ORPD problem. Multiobjective ORPD problem is formulated by considering real power loss minimization and the voltage stability improvement as competing objectives. Among the two considered objectives the significance of real power loss minimization is a well-known fact. Minimization of the system voltage stability index helps to enhance the security. Many analysis methods of system voltage stability determination have been developed on static analysis techniques based on the power flow model, since these techniques are simple, fast and convenient to use. The static voltage stability analysis involves determination of an index called as voltage collapse proximity indicator, which is an approximate measure of closeness to voltage collapse of the system. Among the different indices for voltage stability and voltage collapse prediction, a fast indicator of voltage stability, *Lindex*, presented by Kessel and Glavitsch [21] and developed by Tuanet et al. [22], is chosen as the objective for the voltage stability improvement.

In the first stage of this paper, reference Pareto-front is generated using multiple runs of single objective optimization with weighted sum of objectives to validate the Pareto-front obtained using MNSGA-II. To select the suitable single objective evolutionary algorithm (SOEA) for generating reference Pareto-front, ORPD problem is first solved using RGA and covariance matrix adopted evolutionary strategy (CMAES) [23]. In the subsequent stage, the Pareto-front obtained from MOPSO, NSGA-II and MNSGA-II is compared with the reference Pareto-front obtained from the multiple runs of single objective CMAES algorithm. The performance of MNSGA-II, NSGA-II and MOPSO [24] approaches are carried out with respect to multiobjective performance measures. Post-optimality analysis is carried out on the best non-dominated front obtained from MNSGA-II. The analysis makes use of a TOPSIS technique to obtain a best compromise solution [25]. Deb et al. [26] have proposed a systematic procedure of analyzing a representative set of Pareto-optimal solutions for their closeness to satisfying KKT points, which every optimal solution must satisfy. To confirm a claim on optimality, KKT conditions [27] are also applied to the best non-dominated solutions obtained from MNSGA-II. The suitability of the proposed algorithm has been tested on the IEEE 30 bus and IEEE 118 bus test systems.

The rest of this paper is organized as follows: Section 2 presents the mathematical formulation of the multiobjective ORPD problem. In Section 3, MNSGA-II is described in detail. Implementation of MNSGA-II for reactive power dispatch is presented in Section 4. Section 5 presents the numerical results and discussions. Final conclusions are outlined in Section 6.

2. Problem formulation

2.1. Objective functions

The multiobjective ORPD problem is formulated as a true multiobjective problem by considering minimization of transmission losses and improvement of voltage stability as objectives while satisfying system and unit constraints.

2.1.1. Real power loss (Ploss) [11]

$$f_1 = Ploss = \sum_{k=1}^{N_L} \text{Loss}_k, \tag{1}$$

where *Ploss* is the system real (active) power losses, N_L is the number of transmission lines.

2.1.2. Voltage stability index (Lindex)

In this work, voltage stability enhancement is achieved through minimizing the voltage stability indicator Lindex. The indicator values varies in the range between 0 (the no load case) and 1 which corresponds to voltage collapse [28]. For multi-node system,

$$\mathbf{I}_{bus} = \mathbf{Y}_{bus} \times \mathbf{V}_{bus} \tag{2}$$

By segregating the load buses (PQ) from generator buses (PV), we obtain as

$$\begin{bmatrix} I_L \\ I_G \end{bmatrix} = \begin{bmatrix} Y_1 Y_2 \\ Y_3 Y_4 \end{bmatrix} \begin{bmatrix} V_L \\ V_G \end{bmatrix} \tag{3}$$

$$\begin{bmatrix} V_L \\ I_G \end{bmatrix} = \begin{bmatrix} H_1 H_2 \\ H_3 H_4 \end{bmatrix} \begin{bmatrix} I_L \\ V_G \end{bmatrix} \tag{4}$$

where V_L and I_L are the voltages and currents for PQ buses. V_G and I_G are the voltages and currents for PV buses. H_1, H_2, H_3, H_4, are the sub matrices generated from $\mathbf{Y}_{bus}$ partial inversion. Let

$$\overline{V}_{ok} = \sum_{i=1}^{n_G} H_{2ki} \cdot \overline{V}_i \tag{5}$$

where n_G is the number of generators.

$$H_2 = -Y_1 \times Y_2 \tag{6}$$

$$L_k = \left| 1 + \frac{V_{ok}}{V_k} \right| \tag{7}$$

where L_k is the index value for bus k. For stabilized system the index value is less than 1 and must not be violated. Hence a global system indicator describing the stability of the complete system is, $L_{\max}$ = -max{L_k}, where in {L_k} all load bus indices are listed. The objective is to minimize $L_{\max}$, is given as,

$$f_2 = Lindex = \max\{L_k\}, \quad k = 1, 2, \ldots, N_{PQ} \tag{8}$$

where N_{PQ} is the number of load buses.

The minimization of the objective functions (1) and (8) are subjected to a number of equality and inequality constraints.

2.2. System constraints

The equality constraints are the power balance equations which guarantee that the load demand is met by considering the transmission losses of the system and is given by,

$$P_i - V_i \sum_{j=1}^{N_B} V_j (G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}) = 0, \quad i = 1, \ldots, N_B \tag{9}$$

$$Q_i - V_i \sum_{j=1}^{N_B} V_j (G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij}) = 0, \quad i = 1, \ldots, N_B \tag{10}$$

where N_B is the total number of buses, G_{ij} is the real part of (i, j)th entry of bus admittance matrix, B_{ij} is the imaginary part of (i, j)th entry of bus admittance matrix, P_i is the net real power injection at bus i, and Q_i is the net reactive power injection at bus i.

2.3. Unit constraints

2.3.1. Inequality constraints on dependent variables

The unit constraints considered are (i) the voltage magnitude limits of load buses, (ii) the generator reactive power capability limits of generators, and (iii) the line flow limits in MVA of transmission lines.

$$V_i^{\min} \leqslant V_i \leqslant V_i^{\max}, \quad i = 1, \ldots, N_{PQ} \tag{11}$$