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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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