A NOVEL MULTIOBJECTIVE EVOLUTIONARY ALGORITHM FOR OPTIMAL REACTIVE POWER DISPATCH PROBLEM

M. A. Abido *J. M. Bakhashwain*

Electrical Engineering Department
King Fahd University of Petroleum & Minerals
Dhahran 31261, Saudi Arabia

ABSTRACT

In this paper, a novel multiobjective evolutionary algorithm for optimal reactive power (VAR) dispatch problem is presented. The optimal VAR dispatch problem is formulated as a nonlinear constrained multiobjective optimization problem where the real power loss and the bus voltage deviations are to be minimized simultaneously. A new Strength Pareto Evolutionary Algorithm (SPEA) based approach is proposed to handle the problem as a true multiobjective optimization problem with competing and non-commensurable objectives. A hierarchical clustering algorithm is imposed to provide the decision maker with a representative and manageable Pareto-optimal set. The results demonstrate the capabilities of the proposed approach to generate true and well-distributed Pareto-optimal nondominated solutions in one single run. The results also show the superiority of the proposed approach and confirm its potential to solve the multiobjective VAR dispatch problem.

1. INTRODUCTION

In the past decade, the problem of reactive power control for improving economy and security of power system operation has received much attention. Generally, the load bus voltages can be maintained within their permissible limits by reallocating reactive power generations in the system. This can be achieved by adjusting transformer taps, generator voltages, and switchable VAR sources. In addition, the system losses can be minimized via redistribution of reactive power in the system. Therefore, the problem of the reactive power dispatch can be optimized to improve the voltage profile and minimize the system losses as well.

Several methods to solve the optimal reactive power dispatch problem have been proposed in the literature. Generally, there are three approaches to solve this complex problem. The *first* approach employs nonlinear programming technique [1]. However, nonlinear programming based procedures have many drawbacks, such as insecure convergence properties, long execution time, and algorithmic complexity. The *second* approach uses sensitivity analysis and gradient-based optimization algorithms by linearizing the objective function and the system constraints around an operating point [2]. However, the gradient-based methods are susceptible to be trapped in local minima and the solution obtained will not be the optimal one. The *third* approach utilizes the heuristic methods to search for the optimal solution in the problem space [3]. These heuristic methods have been applied to solve the optimal VAR dispatch problem with impressive success.

The multiobjective VAR dispatch problem was converted to a single objective problem by linear combination of different objectives as a weighted sum [4]. Unfortunately, this requires multiple runs as many times as the number of desired Pareto-optimal solutions. Furthermore, this method cannot be used to find Pareto-optimal solutions in problems having a non-convex Pareto-optimal front. To avoid this difficulty, the ε-constraint method for multiobjective optimization was presented in [5]. This method is based on optimization of the most preferred objective and considering the other objectives as constraints bounded by allowable levels ε. These levels are then altered to generate the entire Pareto-optimal set. The most obvious weaknesses of this approach are that it is time-consuming and tends to find weakly nondominated solutions.

On the contrary, the studies on evolutionary algorithms, over the past few years, have shown that these methods can be efficiently used to eliminate most of the difficulties of classical methods [6-7]. Since they use a population of solutions in their search, multiple Pareto-optimal solutions can, in principle, be found in one single run. The multiobjective evolutionary algorithms have been implemented to environmental/economic power dispatch problem with impressive success [8]

In this paper, the Strength Pareto Evolutionary Algorithm (SPEA) based approach is proposed for solving the multiobjective VAR dispatch optimization problem. The problem is formulated as a nonlinear constrained multiobjective optimization problem where the real power loss and the bus voltage deviations are treated as competing objectives. A hierarchical clustering technique is implemented to provide the power system operator with a representative and manageable Pareto-optimal set. The effectiveness and potential of the

0-7803-8163-7/03/$17.00 © 2003 IEEE ICECS-2003

proposed approach to solve the multiobjective VAR dispatch problem are demonstrated.

2. PROBLEM FORMULATION

The optimal VAR dispatch problem is to optimize the steady state performance of a power system in terms of one or more objective functions while satisfying several equality and inequality constraints. Generally the problem can be formulated as follows.

2.1. Objective Functions

2.1.1. Real Power Loss (P_L)

This objective is to minimize the real power loss in transmission lines that can be expressed as

$$J_1 = P_L = \sum_{k=1}^{nl} g_k \left[V_i^2 + V_j^2 - 2V_iV_j\cos(\delta_i - \delta_j)\right] \quad (1)$$

where nl is the number of transmission lines; g_k is the conductance of the k^{th} line; $V_i\angle\delta_i$ and $V_j\angle\delta_j$ are the voltages at end buses i and j of the k^{th} line respectively.

2.1.2. Voltage Deviation (VD)

This objective is to minimize the deviations in voltage magnitudes at load buses that can be expressed as

$$VD = \sum_{k=1}^{NL} |V_k - 1.0| \quad (2)$$

where NL is the number of load buses.

2.2. Problem Constraints

2.2.1. Equality Constraints

These constraints represent load flow equations as: -

$$P_{G_i} - P_{D_i} - V_i\sum_{j=1}^{NB} V_j[G_{ij}\cos(\delta_i - \delta_j) + B_{ij}\sin(\delta_i - \delta_j)] = 0 \quad (3)$$

$$Q_{G_i} - Q_{D_i} - V_i\sum_{j=1}^{NB} V_j[G_{ij}\sin(\delta_i - \delta_j) - B_{ij}\cos(\delta_i - \delta_j)] = 0 \quad (4)$$

where i = 1,2,…,NB; NB is the number of buses; P_G and Q_G are the generator real and reactive power respectively; P_D and Q_D are the load real and reactive power respectively; G_{ij} and B_{ij} are the transfer conductance and susceptance between bus i and bus j respectively.

2.2.2. Inequality Constraints:

These constraints represent the system operating constraints such as generator voltages V_G; generator reactive power outputs Q_G; transformer tap T; Switchable VAR compensations Q_C; load bus voltages V_L; and transmission line loadings S_l. These constraints can be formulated as follows.

$$V_{G_i}^{\min} \le V_{G_i} \le V_{G_i}^{\max}, \quad i = 1,\ldots,NG \quad (5)$$

$$Q_{G_i}^{\min} \le Q_{G_i} \le Q_{G_i}^{\max}, \quad i = 1,\ldots,NG \quad (6)$$

$$T_i^{\min} \le T_i \le T_i^{\max}, \quad i = 1,\ldots,NT \quad (7)$$

$$Q_{ci}^{\min} \le Q_{ci} \le Q_{ci}^{\max}, \quad i = 1,\ldots,NC \quad (8)$$

$$V_{L_i}^{\min} \le V_{L_i} \le V_{L_i}^{\max}, \quad i = 1,\ldots,NL \quad (9)$$

$$S_{l_i} \le S_{l_i}^{\max}, \quad i = 1,\ldots,nl \quad (10)$$

where NG, NT, and NC are the number of generators, transformers, and switchable VAR sources, respectively.

Aggregating the objectives and constraints, the problem can be mathematically formulated as a nonlinear constrained multiobjective optimization problem as follows.

$$\textit{Minimize}\ [P_L(\mathbf{x},\mathbf{u}),\ VD(\mathbf{x},\mathbf{u})] \quad (11)$$

Subject to:

$$g(\mathbf{x},\mathbf{u}) = 0 \quad (12)$$

$$h(\mathbf{x},\mathbf{u}) \le 0 \quad (13)$$

where:

x: is the vector of dependent variables consisting of load bus voltages V_L, generator reactive power outputs Q_G, and transmission line loadings S_l. Hence, **x** can be expressed as

$$\mathrm{x}^T = [V_{L_1}\ldots V_{L_{NL}}, Q_{G_1}\ldots Q_{G_{NG}}, S_{l_1}\ldots S_{l_{nl}}] \quad (14)$$

u: is the vector of control variables consisting of generator voltages V_G, transformer tap settings T, and shunt VAR compensations Q_c. Hence, **u** can be expressed as

$$\mathrm{u}^T = [V_{G_1}\ldots V_{G_{NG}}, T_1\ldots T_{NT}, Q_{c1}\ldots Q_{c_{NC}}] \quad (15)$$

g: is the equality constraints.

h: is the inequality constraints.

3. THE PROPOSED APPROACH

3.1. Overview

Recently, the studies on evolutionary algorithms have shown that these algorithms can be efficiently used to eliminate most of the difficulties of classical methods that can be summarized as:

- An algorithm has to be applied many times to find multiple Pareto-optimal solutions.
- Most algorithms demand some knowledge about the problem being solved.
- Some algorithms are sensitive to the shape of the Pareto-optimal front.
- The spread of Pareto-optimal solutions depends on efficiency of the single objective optimizer.

In general, the goal of a multiobjective optimization algorithm is not only guide the search towards the Pareto-optimal front but also maintain population diversity in the set of the nondominated solutions.

3.2. Strength Pareto Evolutionary Algorithm (SPEA)

The SPEA algorithm has the following steps [7].

Step 1 (Initialization): Generate an initial population and create an empty external Pareto-optimal set.

Step 2 (External set updating): The external Pareto-optimal set is updated as follows.

(a) Search the population for the nondominated individuals and copy them to the external Pareto set.

(b) Search the external Pareto set for the nondominated individuals and remove all dominated solutions.

(c) If the size of the Pareto set exceeds the maximum size, reduce the set by means of clustering. The average linkage based hierarchical clustering algorithm [9] is implemented in this study.

Step 3 (Fitness assignment): Calculate the fitness values of individuals in both external Pareto set and the population as follows.

(a) Assign a real value $s \in [0,1)$ called strength for each individual in the Pareto optimal set. The strength of an individual is proportional to the number of individuals covered by it. The strength of a Pareto solution is at the same time its fitness.

(b) The fitness of each individual in the population is the sum of the strengths of all external Pareto solutions by which it is covered. In order to guarantee that Pareto solutions are most likely to be produced, a small positive number is added to the resulting value.

Step 4 (Selection): Combine the population and the external set individuals. Select two individuals at random and copy the better one to the mating pool.

Step 5 (Crossover and Mutation): Perform the crossover and mutation operations according to their probabilities to generate the new population.

Step 7 (Termination): Check for stopping criteria. If any one is satisfied *then* stop *else* copy new population to old population and go to Step 2. In this study, the search will terminate if the generation counter exceeds its maximum.

4. RESULTS AND DISCUSSIONS

In this study, the proposed approach was tested on the standard IEEE 30-bus 6-generator test system. The single-line diagram of the IEEE test system is shown in Fig. 1 and the detailed data are given in [10]. The system has 6 generators and 4 transformers and, therefore, the number of the optimized variables is 10 in this prolem. The lower voltage magnitude limits at all buses are 0.95 pu and the upper limits are 1.1 pu for generator buses 2, 5, 8, 11, and 13, and 1.05 pu for the remaining buses including the reference bus 1. The lower and upper limits of the transformer tappings are 0.9 and 1.1 pu respectively. The initial settings of the control variables and the initial values of objective functions are given in Table 1.

At first, the P_L and VD objectives are optimized individually in order to explore the extreme points of the trade-off surface and evaluate the diversity characteristics of the Pareto optimal solutions obtained by the proposed approach. The best results of P_L and VD functions when optimized individually are given in Table 1.

The problem was handled as a multiobjective optimization problem where both power loss and voltage deviations were optimized simultaneously with the proposed approach. The diversity of the Pareto optimal set over the trade-off surface is shown in Fig. 2. It is worth mentioning that the Pareto optimal set has 30 nondominated solutions generated by a single run. Out of them, two nondominated solutions that represent the best P_L and best VD are given in Table 2.

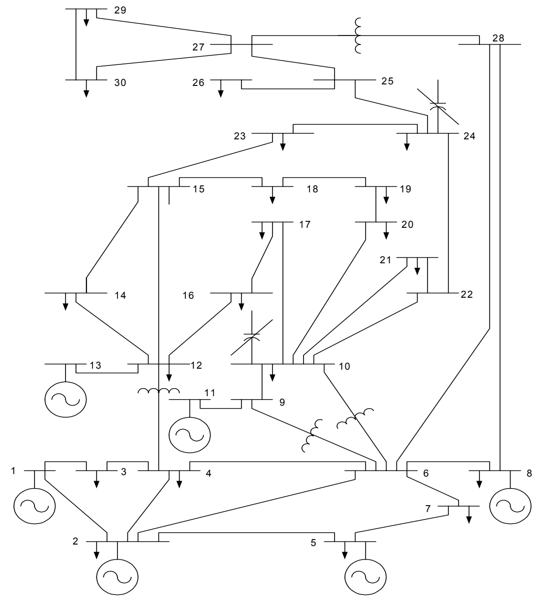

Figure 1: Single-line diagram of IEEE 30-bus test system

Table 1: The best solutions for P_L and VD optimized individually

	Initial [10]	*Best P_L*	*Best VD*
V_{G1}	1.050	1.050	1.009
V_{G2}	1.045	1.041	1.006
V_{G5}	1.010	1.018	1.021
V_{G8}	1.010	1.017	0.998
V_{G11}	1.050	1.084	1.066
V_{G13}	1.050	1.079	1.051
$T_{6\text{-}9}$	0.978	1.002	1.093
$T_{6\text{-}10}$	0.969	0.951	0.904
$T_{4\text{-}12}$	0.932	0.990	1.002
$T_{27\text{-}28}$	0.968	0.940	0.941
P_L (MW)	5.3786	**5.1167**	5.8889
VD (pu)	0.4993	0.7438	**0.1435**

For completeness and comparison purposes, the problem was also treated as a single objective optimization problem by linear combination of P_L and VD objectives as follows:-

$$Minimize \;\; w \times P_L + (1-w) \times \lambda \times VD \qquad (16)$$

where the scaling factor λ was selected as 0.25 and w is a weighting factor. To generate 30 nondominated solutions, the algorithm was applied 30 times with varying w as a random number w = rand[0,1]. The best P_L and best VD solutions are given in Table 2. It is clear that the proposed approach gives better results in one single run.

Table 3 gives a comparison between the results of single objective optimization and that of the proposed multiobjective approach. It is clear that the results of the proposed approach are almost identical to that of individual optimization. It can be concluded that the proposed approach is capable of exploring more efficient and non-inferior solutions. This demonstrates that the search of the proposed approach span over the entire trade-off surface. In addition, the close agreement of the results shows clearly the capability of the proposed approach to handle multiobjective optimization problems as the best solution of each objective along with a manageable set of nondominated solutions can be obtained in one single run.

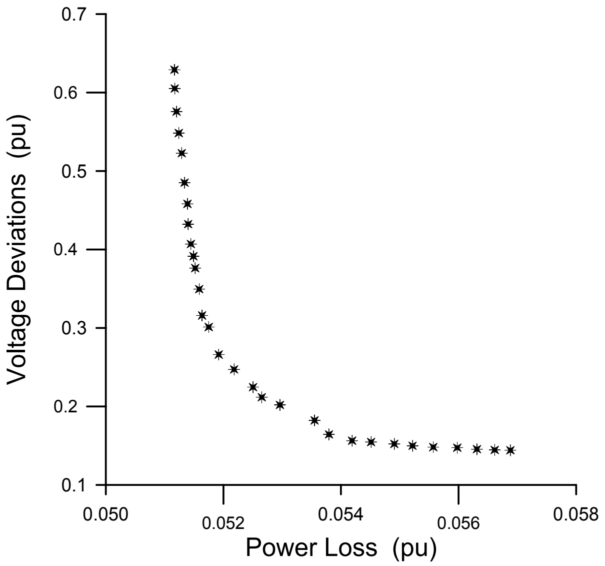

Figure 2: Pareto-optimal front of the proposed approach in a single run

Table 2: Test results of best P_L and VD of the proposed approach

	Proposed Multiobjective Approach		*Single Objective*	
	Best P_L	***Best VD***	***Best*** P_L	***Best VD***
V_{G1}	1.050	1.016	1.045	1.021
V_{G2}	1.045	1.012	1.042	1.021
V_{G5}	1.024	1.018	1.020	1.021
V_{G8}	1.025	1.003	1.022	1.002
V_{G11}	1.073	1.061	1.057	1.025
V_{G13}	1.088	1.034	1.061	1.030
$T_{6\text{-}9}$	1.053	1.090	1.074	1.045
$T_{6\text{-}10}$	0.921	0.907	0.931	0.909
$T_{4\text{-}12}$	1.014	0.970	1.019	0.964
$T_{27\text{-}28}$	0.964	0.943	0.966	0.941
P_L (MW)	**5.1168**	5.6882	**5.1630**	5.6474
VD (pu)	0.6291	**0.1442**	0.3142	**0.1446**

Table 3: Comparison of best solutions of P_L and VD

	Individual Optimization	***Proposed Multiobjective***	***Single Objective***
$\boldsymbol{P_L}$ ***(MW)***	5.1167	5.1168	5.1630
VD (pu)	0.1435	0.1442	0.1446

5. CONCLUSION

In this paper, a novel approach based on the Strength Pareto Evolutionary algorithm has been presented and applied to multiobjective VAR dispatch optimization problem. The problem has been formulated as multiobjective optimization problem with competing real power loss and bus voltage deviations objectives. A hierarchical clustering technique is implemented to provide the operator with a representative and manageable Pareto-optimal set without destroying the characteristics of the trade-off front. The results show that the proposed approach is efficient for solving multiobjective VAR dispatch problem where multiple Pareto-optimal solutions can be found in one simulation run. In addition, the nondominated solutions obtained are well distributed and have satisfactory diversity characteristics as the proposed approach has an embedded diversity-preserving mechanism. Since the proposed approach does not impose any limitation on the number of objectives, its extension to include more objectives is a straightforward process.

6. ACKNOWLEDGMENT

The authors acknowledge the support of King Fahd University of Petroleum & Minerals.

7. REFERENCES

[1] M. O. Mansour and T. M. Abdel-Rahman, "Non-Linear VAR Optimization Using Decomposition and Coordination," *IEEE Trans. on Power Apparatus and Systems*, Vol. PAS-103, No. 2, 1984, pp. 246-255.

[2] K. R. C. Mamandur and R. D. Chenoweth, "Optimal Control of Reactive Power Flow for Improvements in Voltage profiles and for Real Power Loss Minimization," *IEEE Trans. on Power Apparatus and Systems*, Vol. PAS-100, No. 7, 1981, pp. 3185-3193.

[3] K. Iba, "Reactive Power Optimization by Genetic Algorithm," *IEEE Trans. on Power Systems*, Vol. 9, No. 2, 1994, pp. 685-692.

[4] N. Grudinin, "Reactive Power Optimization Using Successive Quadratic Programming Method," *IEEE Trans. on PWRS*, Vol. 13, No. 4, 1998, pp. 1219-1225.

[5] Y. T. Hsaio, H. D. Chaing, C. C. Liu, and Y. L. Chen, “A Computer Package for Optimal Multi-objective VAR Planning in Large Scale Power Systems,” *IEEE Trans. on PWRS*, Vol. 9, No. 2, 1994, pp. 668-676.

[6] C. M. Fonseca and P. J. Fleming, “An Overview of Evolutionary Algorithms in Multiobjective Optimization,” *Evolutionary Computation*, Vol. 3, No. 1, 1995, pp. 1-16.

[7] E. Zitzler and L. Thiele, “An Evolutionary Algorithm for Multiobjective optimization: The Strength Pareto Approach,” *Swiss Federal Institute of Technology*, *TIK-Report*, No. 43, 1998.

[8] M. A. Abido, “A Niched Pareto Genetic Algorithm for Multiobjective Environmental/Economic Dispatch,” *International Journal of Electrical Power and Energy Systems*, Vol. 25, No. 2, February 2003, pp. 79-105.

[9] J. N. Morse, “Reducing the Size of Nondominated Set: Pruning by Clustering,” *Computers and Operations Research*, Vol. 7, No. 1-2, 1980, pp. 55-66.

[10] O. Alsac and B. Stott, “Optimal Load Flow with Steady State Security,” *IEEE Trans. on Power Apparatus and Systems*, Vol. PAS-93, 1974, pp. 745-751.