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Application of NSGA-II Algorithm to Multi-Objective Reactive Power Dispatch

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Abstract— *This paper discusses the application of Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) to multi-objective Reactive Power dispatch (RPD) problem. The objectives considered are minimization of transmission line losses and bus voltage profile improvement. The standard IEEE 30-bus test system is considered to analyze the performance of NSGA-II. The results show the effectiveness of NSGA-II and confirm its potential to solve the multi-objective RPD problem.*

Index Terms-Reactive Power Dispatch (RPD), Non-dominated Sorting Genetic Algorithm-II(NSGA-II), Multi-objective Reactive Power Dispatch(MORPD).

I. Introduction

The RPD problem is the important problem in power system operational planning. The objective of the RPD problem is to minimize the transmission line losses and improve the voltage profiles. The objective can be achieved by employing various reactive power compensation devices such as automatic voltage regulators (continuous variable), tap changing transformers and shunt capacitors/reactors (discrete variables) (Mamundur and Chenoweth 1981).Due to the presence of continuous and discrete control variables, the problems of RPD are complex combinatorial optimization problems involving non-linear functions having multiple local minima. The RPD problem is an important power system operational control problem which adjusts all kinds of existing controllable devices, such as generator voltages, transformer taps, shunt capacitors/reactors, etc., and handles a given set of physical and operating constraints to minimize transmission losses, to improve voltage profile and to maintain system stability.

II. REACTIVE POWER DISPATCH (RPD) PROBLEM

Reactive power dispatch (RPD) in electric power system means an injection of reactive power into the system on the generators for improving voltage stability condition when the system experienced a heavily loaded situation.

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Additional load connected to a particular load Bus could cause system to be under stressed condition and reduction in voltage which may lead to cascading blackout in the entire system. An attempt should be taken in order to improve the voltage stability condition of the system by performing RPD. As a result the voltage profile is improved and secure power delivery to the utilities is maintained. The development of conventional and non-conventional optimization techniques and their applications to solve optimal RPD (ORPD) problem are briefed here.

To solve the RPD problem, a number of conventional optimization techniques have been proposed in the literature. They include LP, NLP, Gradient-based method, QP and IP methods.

Recently, the RPD problem is formulated as a multi-objective optimization problem. In the case of multi-objective optimization also conventional and non-conventional methods are reported in the literature. However, the problem is not treated as a true multi-objective problem by Durairaj et al (2005) and Hsaio et al (1994). It was converted to a single objective problem by linear combination of different objectives as a weighted sum by Durairaj et al (2005). The ε-constraint method for multi-objective optimization was presented by Hsaio et al (1994). This method is based on optimization of the most preferred objective and considering the other objectives as constraints bounded by some allowable levels of 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 non-dominated solutions. In contrast, EAs can find multiple optimal solutions in single simulation run due to their population approach. Recently, some successful application of EAs to ORPD have been reported by Abido and Bakhashwain (2003) where minimizing voltage differences have been considered as an objective in addition to loss minimization. A three objective RPD problem can be found in Zhang and Liu (2008) where a fuzzy system is employed to adaptively adjust the parameters of PSO such as the inertia weight and learning factors during the evolutionary process. Zhihuan et al (2010) presented a Pareto based solution set to solve ORPD problem using NSGA-II approach which is insensitive to the load disturbances or load drifts. Jeyadevi et al (2011) discussed the concept of controlled elitism and dynamic crowding distance (DCD) in NSGA-II for solving multi-objective RPD (MORPD) problem by considering minimization of real power loss and voltage stability enhancement as objectives.

III. PROBLEM FORMULATION FOR MULTI-OBJECTIVE RPD (MORPD)

The problem of MORPD is to optimize the steady state performance of a power system while satisfying several equality and inequality constraints. It is concerned with the attempt to minimize each objective function simultaneously. Meanwhile, the equality and inequality constraints of the system must be satisfied. Generally the problem can be represented as follows:

1. Minimization of Transmission Losses

This objective is to minimize the real power loss in transmission lines that can be expressed through the following equation:

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

2. Minimization of Voltage Deviation

The objective of ORPD is not only to minimize the real power loss but also to improve the voltage profile of the system. Bus voltage is one of the most important security and service quality indices. Considering only loss-based objectives in RPD problem may result in a feasible solution that has unattractive voltage profile. So, in this case a two-fold objective function (Abido 2002) will be considered in order to minimize the loss and improve the voltage profile by minimizing the load bus voltage deviations from 1.0 per unit. This objective is to minimize the deviations in voltage magnitudes at load buses that can be expressed through Equation.

$$f_2(x,u) = VD = \sum_{K=1}^{N_L} \left|V_K - 1.0\right| \quad (2)$$

Equality Constraints

The equality constraints are power flow equations and these constraints seek to find the set of voltages that satisfy the system conditions which can be represented by Equation.

$$0 = P_i - V_i \sum_{j\in N_i} V_j \left(G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}\right) \quad i \in NB-1$$
$$0 = Q_i - V_i \sum_{j\in N_i} V_j \left(G_{ij}\sin\theta_{ij} - B_{ij}\cos\theta_{ij}\right) \quad i \in N_{PQ} \quad (3)$$

Inequality Constraints

The inequality constraints are similar one which has been considered in the Equations.

Continuous control variables

$$V_{G_i}^{\min} \le V_{G_i} \le V_{G_i}^{\max} \qquad i \in N_G \quad (4)$$

Discrete control variables:

$$T_K^{\min} \le T_K \le T_K^{\max} \qquad K \in N_T$$
$$B_{sh_i}^{\min} \le B_{sh_i} \le B_{sh_i}^{\max} \qquad i \in N_{sh} \quad (5)$$

State variables:

$$V_{PQ_i}^{\min} \le V_{PQ_i} \le V_{PQ_I}^{\max} \qquad i \in N_{PQ}$$
$$Q_{G_i}^{\min} \le Q_{G_i} \le Q_{G_i}^{\max} \qquad i \in N_G \quad (6)$$

The constraints violations are checked by using NR load flow method with the above-mentioned equality and inequality constraints.

IV. NON-DOMINATED SORTING GENETIC ALGRITHM-II (NSGA-II)

In NSGA-II, SBX and polynomial mutation are used to generate new offspring and tournament is then used to select the population for next iteration.

1. Simulated Binary Crossover (SBX)

In general, SBX puts the stress on generating offspring near the parents (Deb 2001). This crossover guarantees that the extent of the children or offspring is proportional to the extent of the parents and also favors that near parent individuals are monotonically more likely to be chosen as children than individuals distant from the parents in the solution space. The procedure for finding the offspring solutions xi (1, t+1) and xi (2, t+1) from parent solutions xi (1, t) and xi (2, t) is given below:

First a random number u_i between 0 and 1 is created. Thereafter, from a specified probability distribution function, the ordinate β_{qi} is found as follows:

$$\beta_{qi} = \begin{cases} \left(2u_i\right)^{\frac{1}{\eta_c+1}} & if\ u_i \le 0.5; \\ \left(\dfrac{1}{2\left(1-u_i\right)}\right)^{\frac{1}{\eta_c+1}} & otherwise \end{cases} \quad (7)$$

In the above Equation, the distribution index η_c is any positive real number. After obtaining β_{qi} the children solutions are calculated as follows:

$$X_i^{(1,t+1)} = 0.5\left[\left(1+\beta_{qi}\right)X_i^{(1,t)} + \left(1-\beta_{qi}\right)X_i^{(2,t)}\right]$$
$$X_i^{(2,t+1)} = 0.5\left[\left(1-\beta_{qi}\right)X_i^{(1,t)} + \left(1+\beta_{qi}\right)X_i^{(2,t)}\right] \quad (8)$$

The steps followed for the creation of offspring are briefly given as follows:

Step 1 : Choose a random number $u_i \in [0,1]$.

Step 2 : Calculate β_{qi} using Equation (7).

Step3 : A pair of mutated parents $\left(X_i^{(1,t)} and\ X_i^{(2,t)}\right)$ is selected randomly to create offspring solutions $(X_i^{(1,t+1)} and\ X_i^{(2,t+1)})$ by using Equation (8).

2. Polynomial mutation

The probability of creating a solution near to the parent is higher than the probability of creating one distant from it. The shape of the probability distribution is directly controlled by an external parameter η_m and the distribution remains unchanged throughout the iterations. Like in the SBX operator, the probability distribution can also be a polynomial function, instead of a normal distribution (Deb 2001).

$$y_i^{(1,t+1)} = x_i^{(1,t+1)} + \left(x_i^{(U)} - x_i^{(L)}\right)\delta_i \qquad (9)$$

where the parameter δ is calculated from the polynomial probability distribution

$$P(\delta_i) = 0.5(\eta_m + 1)(1 - |\delta|)^{\eta_m}$$

$$\delta_i = \begin{cases} (2r_i)^{\frac{1}{\eta_m - 1}} - 1 & \text{if } r_i \langle 0.5 \\ 1 - \left[2(1 - r_i)\right]^{\frac{1}{\eta_m + 1}} & \text{if } r_i \geq 0.5 \end{cases} \qquad (10)$$

For handling the bounded decision variables, the mutation operator is modified for two regions $\left[X_i^{(L)}, X_i\right]$ and $\left[X_i, X_i^{(U)}\right]$.

3. Tournament Selection

Selection is made using tournament between two individuals. The individual with the lowest front number is selected if the two individuals are from different fronts. The individual with the highest CD is selected if they are from the same front. i.e., a higher fitness is assigned to individuals located on a sparsely populated part of the front. In each iterations, the N existing individuals (parents) generate N new individuals (offspring). Both parents and offspring compete with each other for inclusion in the next iteration.

4. NSGA-II Implementation

The following steps can be adopted for the implementation of NSGA-II algorithm. Figure 3.1 shows the flowchart for NSGA-II algorithm.

Step 1: Identify the control variables for the MOOP.

Step 2: Select the parameters like number of population, maximum number of iteration, crossover and mutation probabilities.

Step 3: Generate initial population

Step 4: Evaluation of objective functions (i.e., f1, f2) for initial population

Step 5: Set the iteration count

Step 6: Perform SBX and polynomial mutation for the set of individuals

Step 7: Perform non-dominated sorting. (i.e., sorting the population according to each of the objective function value in ascending order of magnitude)

Step 8: Calculate CD between the solutions.

Step 9: Perform selection based on tournament selection thereby a higher fitness is assigned to individuals located on a sparsely populated part of the front.

Step 10: Increment the iteration count and repeat the steps from 6 to 9 until the count reaches the specified maximum number of iterations.

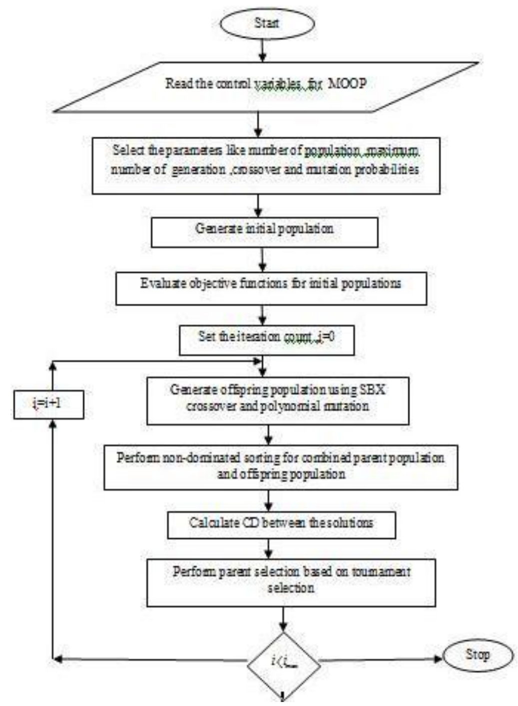

Fig. 1 Flowchart for NSGA-II Algorithm

V. TEST SYSTEM DESCRIPTION

To analyze the performance of MOEAs the problem of MORPD is tested in IEEE 30-bus test system. The relevant data for 30-bus Indian utility system is given.

1. IEEE 30-bus Test System

The representation of the IEEE 30-bus test system and the detailed data are given in Lee et al (1985). The system has 6 generators, 4 transformers and 9 shunt compensators. Therefore, the number of variables to be optimized is 19. The bus numbers 1, 2, 5, 8, 11, and 13 are generator bus. The lower and upper limits for voltage magnitude of these bus are 0.95 p.u. and 1.1 p.u. and for the remaining bus lower and upper limits for voltage magnitudes of bus are 0.95 p.u. and 1.05 p.u. respectively. The transformer tap settings are varied between 0.9 p.u. and 1.1 p.u. with the step size of 0.0001 and the shunt capacitors have the rating between 0 and 5 MVAr with the step size of 1 MVAr for each capacitor. The shunt capacitors are installed at buses 10, 12, 15, 17, 20, 21, 23, 24 and 29.

2. IMPLEMENTATION OF NSGA-II TO RPD

The objective function is subjected to power flow constraints, control variable (continuous and discontinuous) limits and state variables. A penalty parameter-less constraint-handling scheme is employed, in which all feasible solutions have zero constraint violation and all infeasible solutions are evaluated according to their constraint violations alone. Hence, both the objective function value and constraint violation are not combined in the population. Thus there is no need to have any penalty parameter for this approach (Deb 2000). The NR load flow calculation method is used for checking constraint violations.

In all the three algorithms, uniform population size of 40 and iteration size of 200 are used to perform effective comparison of solutions. For NSGA-II algorithm, based on 50 trials of various combinations of parameters, it is concluded that crossover probability of 0.9, mutation probability of (1/number of control variables), crossover index of 5 and mutation index of 10 yield better results for RPD problem.

VI. SIMULATION RESULTS

Fifteen independent trials are conducted using NSGA-II algorithm. Figure 2 shows the Pareto optimal front of Optimal Loss and Voltage Deviation Values obtained using NSGA-II.

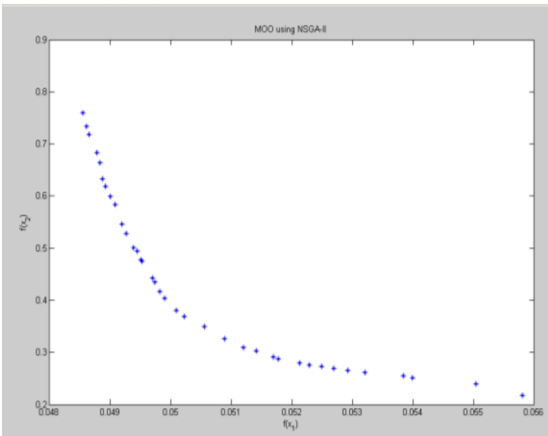

Fig. 2 Pareto optimal front of Optimal Loss and Voltage Deviation Values obtained using NSGA-II

VII. CONCLUSION

In this work, the Non-dominated Sorting Genetic Algorithm-II (NSGA-II) has been applied to solve the multi objective Reactive Power Dispatch (RPD) problem. In the RPD problem, the conflicting objectives are considered: i) minimization of real power loss and ii) improvement of voltage profile. The NSGA-II is successfully implemented to solve the RPD problem for IEEE 30 bus test system. The simulation results clearly show that the NSGA-II algorithm is certainly more suitable for solving multi-objective reactive power dispatch problems.

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