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Optimal Reactive Power Dispatch Using Differential Evolution Bat Algorithm for Reduction of Voltage Deviation

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Abstract: *In power engineering society, sinking the power loss in transmission lines and/or minimizing the voltage deviation at the load buses by controlling the reactive power is referred to as optimal reactive power dispatch (ORPD). ORPD is necessary for safe operation of power systems with regard to voltage stability. In this paper, the nature inspired Differential Evolutionary based Bat Algorithm (DEBA) is introduced to solve optimal reactive power flow problem in power systems. Generator bus voltages, transformer tap positions and switchable shunt capacitor banks are used as variables to control the reactive power flow. DEBA was tested on standard IEEE 30 bus system and the results are compared with further methods to prove the effectiveness of the new algorithm. The results are quite encouraging and the algorithm is found to be simple and easy to employ.*

Keywords: *Differential Evolutionary based Bat Algorithm, Optimal Reactive Power Dispatch, Active Power LossMinimization.*

I. Introduction

The augmentedinsist for electric power and the inadequate power generation and transmission facility forces the power system networks is being operated under stressed conditions. The security of a power system is under threat when it is operated at stressed conditions and may result in voltage instability. Nowadays voltage instability has become a new challenge to power system planning and operation. Insufficient reactive power availability or non-optimized reactive power flow may lead a power system to insecure operation under heavily loaded conditions [1]-[2]. By reallocating reactive power generations in the system by adjusting transformer taps, generator voltages and switchable VAR sources, the problem can be solved to a far extent.

Apart from the aforementioned methods, the system losses can also be minimized via redistribution of reactive power in the system for improving the stability of a power system. Large amount of reactive power flow in a system is indicated by the real power loss in the system. Therefore minimizing the real power loss ensures optimized reactive power flow (ORPF) through the lines. Reactive power optimization by real power loss minimization increases the power system economics to some extent. Reactive power optimization by minimization of real power loss has long been attempted for voltage stability improvement [3]-[4].

Optimal reactive power flow is an important tool in terms of secure and operation of power system. It is a powerful concept for power system operation and planning [5]-[6]. In ORPF, the network active power loss is reduced and voltage profile is improved while satisfying a given set of operating and physical constraints [7]-[8]. Reactive power flow is optimized by properly setting the values ofcontrol parameters. A number of conventional optimization methodshave been exploited for this objective. Techniques such as non linear programming technique [9], gradient based optimization algorithm are used to solve ORPF problem algorithms [10] are used to solve ORPF problem. But it has several disadvantages like large numerical iteration, insufficient convergence properties; which leads to large computation and more execution time.

The recently developed meta-heuristics based algorithms are proving better performance than the conventional methods. They find global best or nearly global best solutions for engineering problems. These algorithms are better utilised for power system optimization. Some of them are Tabu Search [11], Simulated Annealing (SA) [12], Genetic Algorithm (GA) [13], Evolutionary Programming (EP) [14]-[15] Hybrid Evolutionary Programming (HEP) [16], Particle Swarm Optimization PSO [17]-[19], Chaotic Ant Swarm Optimization (CASO) [20], Bacterial Foraging Optimization (BFO) [21], Ant Colony Optimization (ACO) [22], Differential Evolution (DE) [23] and Quantum Genetic Algorithm (QGA) [24] are developed which provides fast and optimal solution.

Conventional methods are sensitive to initial guess of the search point where functions have multiple local minima and not efficient in handling problems of discrete variables [25]. In addition to this a lot of algorithms have been presented to solve optimal reactive power dispatch. Chien-Feng Yang proposed a system for limiting voltage variations by means of switchable shunt reactive compensation and transformer tap setting

[26]. Other new optimization techniques are based on using fuzzy logic [27], lagrangian decomposition method [28].

DEBA is a recent development and it very simple and easy to implement [29]. This algorithm has not as much of number of parameters and has good convergence characteristics. The performance of this method is compared with other algorithms to prove its competence.

II. Problem Formulation

The objective of this work is to optimize the reactive power flow in a power system by minimizing the real power loss. An improved objective function is formed.

1.1 Objective Function

The objective function of this work is to find the optimal settings of reactive power control variables including the rating shunt of var compensating devices which minimizes the real power loss.

2.1 Real power loss minimization (PL)

The total real power of the system can be calculated as follows

$$P_{loss} = \sum_{K=1}^{N_L} G_k[V_i^2 + V_j^2 - 2|V_i||V_j|\cos\delta_i - \delta_j] \quad (1)$$

Where, N_L is the total number of lines in the system; G_k is the conductance of the line 'k', V_i and V_j are the magnitudes of the sending end and receiving end voltages of the line; δ_i and δ_j are angles of the end voltages.

2.2 Constraints

The minimization problem is subject to the following equality and inequality constraints

2.2.1 Equality constraints

Load Flow Constraints:

The equality constraints represent the load flow equations, which are given below for i_{th} bus:

$$P_{gi} - P_{Di} = \sum_{j=1}^{NB} V_i V_j Y_{ij} cos(\delta_{ij} + \gamma_j - \gamma_i) \qquad (2)$$

$$Q_{gi} - Q_{Di} = \sum_{j=1}^{NB} V_i V_j Y_{ij} sin(\delta_{ij} + \gamma_i - \gamma_j) \qquad (3)$$

wherePgi , Qgi are the active and reactive power of i_{th} generator, P_{Di} , Q_{Di} the active and reactive power of i_{th} load bus.

2.2.2 Inequality constraints

Generator constraints.

Generator voltage and reactive power of i_{th} bus lies between their upper and lower limits as given below:

$$V_{gi}^{min} \le V_{gi} \le V_{gi}^{max} \qquad i= 1,2,....NG \qquad (4)$$

$$Q_{g1}^{min} \le Q_{g1} \le Q_{g1}^{max} \qquad i= 1,2,....NG \qquad (5)$$

Where V_{gi}^{min}, V_{gi}^{max} are the minimum and maximum voltage of i_{th} generating unit and Qmingi , Qmaxgi are the minimum and maximum reactive power of i_{th} generating unit.

Load bus constraints.

$$V_{L1}^{min} \le V_{L1} \le V_{L1}^{max} \qquad i= 1,2,....NL \qquad (6)$$

Where V_{L1}^{min}, V_{L1}^{max} are the minimum and maximum load voltage of i_{th} unit.

Transmission line constraints.

$$S_{L1} \le S_{L1}^{max} \qquad i= 1,2,...,NTL \qquad (9)$$

Where S_{L1} is the apparent power flow of i_{th} branch and S_{L1}^{max} is the maximum apparent power flow limit of i_{th}branch.

Transformer tap constraints.

Transformer tap settings are bounded between upper and lower limit as given below:

$T_i^{max} \leq T_i \leq T_i^{max}$ i= 1,2,...,NT (10)

Where T_i^{max}, T_i^{max} are the minimum and the minimum and maximum tap setting limits of i_{th}transformer.

Shunt compensator constraints.

Shunt compensation are restricted by their limits as follows:

$Q_{C_1}^{min} \leq Q_{C_1} \leq Q_{C_1}^{max}$, i=1,2....,NC (11)

Where $Q_{C_1}^{min}$, $Q_{C_1}^{max}$ are the minimum and maximum VAR injection limits of i_{th}shunt capacitor.

III. Differential Evolutionary Based Bat Algorithm About Deba

Bats use echolocation to detect prey and discriminate different types of insects even in the dark. Hence bats are sensitive to the sounds. Bats usually feed on insects, which can emit sound. In a specific habitat, there exist a group of bats, some of which may simultaneously forage for food. Thus bats may be subjected to the noise and interference induced by their prey and their partners. Comprehensive study has suggested that bats seem to be able to discriminate targets by the variations of the Doppler Effect induced by the wing-flutter rates of the targeted insects.

As the simplification of the bats‟ behaviors, the other bats‟ and insects‟ interferences for the bats are not considered in the basic BA. To make the virtual bats resemble the realistic bats is the main idea in this work. In this paper, the living environments the bats inhabit would be integrated into the BA.

Through integration of the mutation operator in the DE/rand/1/bin scheme with the BA, the insects‟ interferences for the bats can be visually simulated as a stochastic decision. The insects‟ interferences for the bats only exists when rand (0, 1), a uniform random number in [0, 1], is smaller than CR. Here CR is the crossover rate in DE. Consider three different individuals interfere with the virtual bats. If the interference is strong enough that the virtual bats cannot distinguish the targets by themselves, they will follow the clues suggested by the interference. Otherwise, they will continue searching for their targets using their ownstrategies.

For simplicity, the swarm's mean velocity is simulated as the other bats effects on thebats. Figure 1 is a good case to illustrate that it may contribute to help the virtual bats to find the prey by considering the swarm's mean velocity.

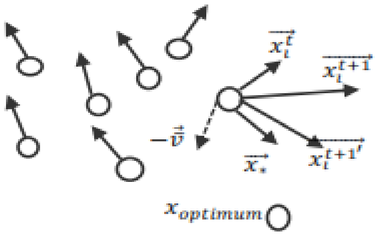

Figure 1 Swarm's Trajectory

Without considering the swarm's mean velocity, the bat i will be located at $\overrightarrow{X_t^{t+1}}$. However, following this direction, bat i will be far away from the optimal solution. If the opposite swarm's mean velocity is considered, the situation will be improved. Compared with $\overrightarrow{X_t^{t+1}}$ optimal solution than $\overrightarrow{X_t^{t+1'}}$ the new location (solution) $\overrightarrow{X_t^{t+1}}$ can be closer to the solution.

$\overrightarrow{X_t^{t+1}}$ = W x ($V_i^t - W_2 \; x \; v$) + ($X_i^t - X_*$) x f_i

Where W $\in (0,1), W_2 \in (-1,1)$are two random vectors drawn from a uniformdistribution.Moreover, consider a following situation. Bats would not find a better food than theirprevious ones during several time step (G), and they have eaten up their food. Then they maygo to another place to forage for food. For simplicity, this situation can be simulated asfollows. All the bats‟ loudness would be initialized again. Their pulse rates can be temporarilyset to a high value, hence the bats can search globally. Using the criteria above, the virtual bats in the proposed algorithm can be more lifelikethan the ones in basic BA, thus helping them escape from the local optima.

3.1 Implementation of DEBA for ORPF problem.

Step 1: Initialize the population, position, velocity in D-dimensional space and initialize the associated parameters, such as frequency, loudness and pulse rates.

Step 2: Evaluate the fitness value of each bat by the objective function f(x) and the constraint value of each bat by the constrained functions.

Step 3: Update solutions.

Step 4: Generate offspring (solutions)$\overrightarrow{X_t^{t+1}}$

Step 5:Select a solution among the best solutions. Generate a local solution $\overrightarrow{X_t^{t+1}}$ around the selected best solution.

Step 6: Evaluate the fitness values and constraint values of the offspring$\overrightarrow{X_t^{t+1}}$.

Step 7: Generate offspring (solutions)$\overrightarrow{X_t^{t+1'}}$

Step 8: Evaluate the fitness values and constraint values of the offspring$\overrightarrow{X_t^{t+1'}}$.

Step 9: Select the final offspring $\overrightarrow{X_t^{t+1}}$ by comparing the fitness value and constraint value of $\overrightarrow{X_t^{t+1}}$with those of $\overrightarrow{X_t^{t+1'}}$ according to the feasibility-based rules.

Step 10: Rank the bats and find the current best X_*.

Step 11: If X_* does not improve in G generations. Reinitialize the loudness Ai, and set the pulse rates r_i which is a uniform random number between [0.85, 0.9].

Step 12: Update the best X_*.

3.2. The Feasibility-based Rules

The feasibility-based rules used in this paper are illustrated as follows.

(1) Any feasible solution is superior to any infeasible solution.

(2) Between two feasible solutions, the one having a better objective function value ispreferred.

(3) Between two infeasible solutions, the one having a smaller constraint value is preferred.

To summarize, these rules are to choose a solution that lies closer to the feasible region.

IV. Numerical Results And Discussions

The performance of the proposed DEBAbased reactive power optimization method is tested in the medium size IEEE 30 bus system. The algorithm is coded in MATLAB environment and a Core 2 Duo, 2.8 MHz, 2GB RAM based PC is for the simulation purpose.

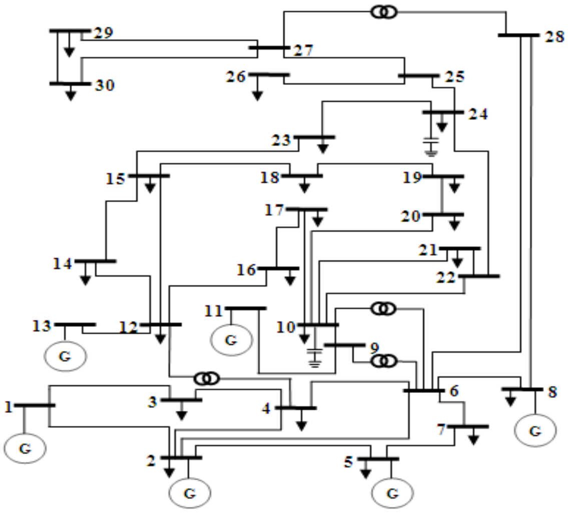

Figure 2.Single line diagram of IEEE-30 bus system.

The test system taken has six generating units connected to buses 1,2,5,8,11 and 13. There are 4 regulating transformers connected between bus numbers 6-9, 6-10, 4-12 and 27-28. Two shunt compensators are connected in bus numbers 10 and 24. The system is interconnected by 41 transmission lines. The control variables are generator's voltages, tap settings of the regulating transformers and var injection of shunt capacitors.

The upper and lower bounds of the different control variables are given in table 1.

Table 1. Control variable limits

S. No	Control Variable	Limit
1.	Generator voltage (V_G)	(0.9-1.1) p.u.
2.	Tap setting(T_P)	(0.9 -1.1) p.u.
3.	Static Var compensators (Q_{svc})	(0-25) MVAR

4.1 Reduction of voltage deviation

The voltage deviation reduction is the major component of reactive power optimization and it needs more attention. This case takes only the voltage deviation reduction as the objective function. The optimal control variables of the overall system obtained by DEBAfor this case are shown in table 2.

Table 2.Optimal parameter values.

Sl no.	Parameter	Initial value	Optimal Value [DEBA]
1	V_{G1}	1.05	1.1000
2	V_{G2}	1.04	1.1000
3	V_{G5}	1.01	1.0913
4	V_{G8}	1.01	1.0834
5	V_{G11}	1.05	1.0875
6	V_{G13}	1.05	1.1000
7	T_{6-9}	1.078	1.0873
8	T_{6-10}	1.069	1.1000
9	T_{4-12}	1.032	1.0534
10	T_{27-28}	1.068	0.9850
11	Q_{10}	0.0	6.3884
12	Q_{24}	0.0	3.2034

The strength of DEBA in reducing the voltage deviation is compared with the performance of bat algorithm (BA) and differential evolution (DE) algorithm.

4.2.Minimization Of Objective Function:

In this case the DEBAbetter optimizes voltage deviation as shown in table 3. The reduction in deviation indicated by DEBA algorithm is highly encouraging and it is only 0.1488 volts.

Table 3. Minimization of objective term

Sl. No	Parameter	Initial value	DEBA	BA	DE
1.	Voltage deviation	0.232	0.1488	0.1596	0.1620

The good convergence characteristics of DEBA In the objective of voltage deviation reductionis plotted in figure 3.

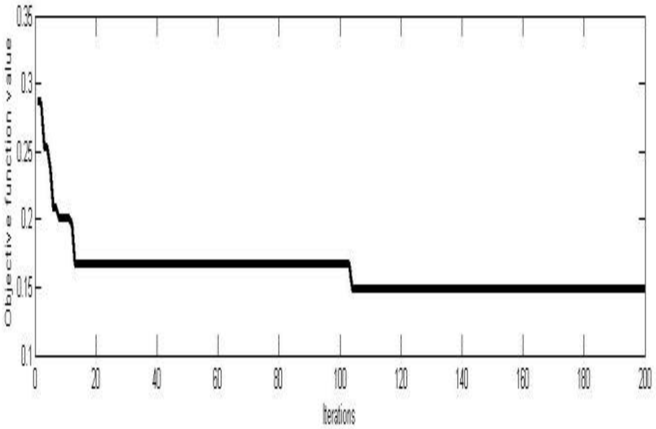

Figure 3. Convergence characteristics of DEBA

V. Conclusions

In this paper, a novel DEBA Based optimization algorithm is proposed to solve optimal reactive power flow problem. The performance of the proposed algorithm for solving ORPF problems is demonstrated using IEEE-30 bus system. The results are compared to those of other algorithms like DE and BA. The test results clearly demonstrate that DEBAoutperforms other reported methods in terms of solution quality. The superiority of the proposed DEBAmethod is more pronounced for large system as is evident from IEEE-30 bus system. From all simulation results it may finally be concluded that among all the algorithms, DEBAbased optimization method is capable of achieving large-scale optimal solution. This paper shows that such excellent results with different objective functions shows that makes the proposed DEBAoptimization technique is good in dealing with power system optimization problems.

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