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Research Article

Reduction of Real Power Loss by Hybrid - Genetic Algorithm and Hooke-Jeeves Method

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Abstract

In this paper, a new Hybrid - genetic algorithm and Hooke-Jeeves method (HGAHJ) is proposed for solving reactive power dispatch problem. Hooke-Jeeves method is fine at local search and our projected method spectacularly improves the precision and convergence rate of genetic algorithm. In view of the derivative-free of Hooke-Jeeves technique, our method only requires information of objective function value which not only can trounce the computational difficulties caused by the ill-condition of the square penalty function, but also can handle the non-differentiability by the accurate penalty function. The projected HGAHJ algorithm has been tested on standard IEEE 57 bus test system and simulation results show clearly the best performance of the proposed algorithm in dipping the active power loss.

Keywords: Optimal Reactive Power; Transmission loss; Genetic Algorithm; Hooke-Jeeves

1. Introduction

Reactive power optimization places an important role in optimal operation of power systems. Various numerical methods like the gradient method (Alsac *et al*, 1973; Lee *et al*, 1985), Newton method (Monticelli *et al*, 1987) and linear programming (Deeb *et al*, 1990; Hobson, 1980; Lee *et al*, 1987; Mangoli, 1993) have been implemented to solve the optimal reactive power dispatch problem. Both the gradient and Newton methods have the intricacy in managing inequality constraints. The problem of voltage stability and collapse play a key role in power system planning and operation (Canizares *et al*, 1996). Evolutionary algorithms such as genetic algorithm have been already projected to solve the reactive power flow problem (Paranjothi *et al*, 2002; Devaraj *et al*, 2005; Berizzi *et al*, 2012). Evolutionary algorithm is a heuristic methodology used for minimization problems by utilizing nonlinear and non-differentiable continuous space functions. In (Yang *et al*, 2012), Hybrid differential evolution algorithm is projected to increase the voltage stability index. In

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(Roy *et al*, 2012) Biogeography Based algorithm is projected to solve the reactive power dispatch problem. In (Venkatesh *et al*, 2000), a fuzzy based method is used to solve the optimal reactive power scheduling method. In (Yan *et al*, 2004), an improved evolutionary programming is used to elucidate the optimal reactive power dispatch problem. In (Yan *et al*, 2006), the optimal reactive power flow problem is solved by integrating a genetic algorithm with a nonlinear interior point method. In (Yu *et al*, 2008), a pattern algorithm is used to solve ac-dc optimal reactive power flow model with the generator capability limits. In (Capitanescu, 2011) proposes a two-step approach to calculate Reactive power reserves with respect to operating constraints and voltage stability. In (Hu *et al*, 2010), a programming based approach is used to solve the optimal reactive power dispatch problem. In (Kargarian *et al*, 2012) present a probabilistic algorithm for optimal reactive power provision in hybrid electricity markets with uncertain loads. This paper proposes Hybrid - genetic algorithm and Hooke-Jeeves method (HGAHJ) algorithm to solve the optimal reactive power dispatch problem. In this paper, we will develop a new hybrid method in which a derivative-free method, Hooke-Jeeves method , and a stochastic method, say genetic algorithm (Bazaraa *et al*, 2006; Vasconcelos *et al*, 2001; Qiang Long *et al*, 2014) are combined together to solve optimal reactive power dispatch problem. The main idea is that during the implementation of genetic algorithm, apart from crossover operator, mutation operator and selection operator, we integrate another operator, called as acceleration operator which is premeditated from Hooke-Jeeves method. The acceleration is achieved through applying Hooke-Jeeves technique to some particular chromosomes. Thus, some genes are marked as outstanding ones in the novel generation. The proposed algorithm HGAHJ has been evaluated in standard IEEE 57 bus test system and the simulation results show that our proposed approach outperforms all the entitled reported algorithms in minimization of active power loss.

2. Problem Formulation

The optimal power flow problem is treated as a general minimization problem with constraints, and can be mathematically written in the following form:

$$\text{Minimize } f(x, u) \tag{1}$$

$$\text{subject to } g(x,u)=0 \tag{2}$$

and

$$h(x, u) \leq 0 \tag{3}$$

where f(x,u) is the objective function. g(x.u) and h(x,u) are respectively the set of equality and inequality constraints. x is the vector of state variables, and u is the vector of control variables.

The state variables are the load buses (PQ buses) voltages, angles, the generator reactive powers and the slack active generator power:

$$x = \left(P_{g1}, \theta_2, .., \theta_N, V_{L1}, ., V_{LNL}, Q_{g1}, .., Q_{gng}\right)^T \tag{4}$$

The control variables are the generator bus voltages, the shunt capacitors/reactors and the transformers tap-settings:

$$u = \left(V_g, T, Q_c\right)^T \quad (5)$$

or

$$u = \left(V_{g1}, \dots, V_{gng}, T_1, .., T_{Nt}, Q_{c1}, .., Q_{cNc}\right)^T \quad (6)$$

where ng, nt and nc are the number of generators, number of tap transformers and the number of shunt compensators respectively.

3. Objective Function

3.1 Active Power Loss

The objective of the reactive power dispatch is to minimize the active power loss in the transmission network, which can be described as follows:

$$F = PL = \sum_{k \in Nbr} g_k \left(V_i^2 + V_j^2 - 2V_iV_j\cos\theta_{ij}\right) \quad (7)$$

or

$$F = PL = \sum_{i \in Ng} P_{gi} - P_d = P_{gslack} + \sum_{i \neq slack}^{Ng} P_{gi} - P_d \quad (8)$$

where gk : is the conductance of branch between nodes i and j, Nbr: is the total number of transmission lines in power systems. Pd: is the total active power demand, Pgi: is the generator active power of unit i, and Pgsalck: is the generator active power of slack bus.

3.2 Voltage Profile Improvement

For minimizing the voltage deviation in PQ buses, the objective function becomes:

$$F = PL + \omega_v \times VD \quad (9)$$

where ωv: is a weighting factor of voltage deviation.

VD is the voltage deviation given by:

$$VD = \sum_{i=1}^{Npq} |V_i - 1| \quad (10)$$

3.3 Equality Constraint

The equality constraint g(x,u) of the ORPD problem is represented by the power balance equation, where the total power generation must cover the total power demand and the power losses:

$$P_G = P_D + P_L \quad (11)$$

This equation is solved by running Newton Raphson load flow method, by calculating the active power of slack bus to determine active power loss.

3.4 Inequality Constraints

The inequality constraints h(x,u) reflect the limits on components in the power system as well as the limits created to ensure system security. Upper and lower bounds on the active power of slack bus, and reactive power of generators:

$$P_{gslack}^{min} \leq P_{gslack} \leq P_{gslack}^{max} \quad (12)$$

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max}, i \in N_g \quad (13)$$

Upper and lower bounds on the bus voltage magnitudes:

$$V_i^{min} \leq V_i \leq V_i^{max}, i \in N \quad (14)$$

Upper and lower bounds on the transformers tap ratios:

$$T_i^{min} \leq T_i \leq T_i^{max}, i \in N_T \quad (15)$$

Upper and lower bounds on the compensators reactive powers:

$$Q_c^{min} \leq Q_c \leq Q_C^{max}, i \in N_C \quad (16)$$

where N is the total number of buses, NT is the total number of Transformers; Nc is the total number of shunt reactive compensators.

4. Hybrid - Genetic Algorithm and Hooke-Jeeves Method

HGAHJ is a hybrid technique combining genetic algorithm and Hooke-Jeeves method. In order to perk up the local search of genetic algorithm, an acceleration operator based on Hooke-Jeeves technique is embedded into genetic algorithm. During the execution of genetic algorithm, the acceleration operator generates some outstanding chromosomes, which dramatically encourage the convergence rate and accuracy of optimal solution.

4.1 *Initial Population Generator*

During the implementation of genetic algorithm, the primary population is arbitrarily generated from X, and the number of chromosomes in the early population equals population size.

Step 1: key in population size: pop_size, upper bound u and lower bound l, correspondingly. Set k=1.

Step 2: if $k \leq$ pop_ size, then generate the kth initial chromosome by $x_i = l_i + \alpha_i(u_i - l_i)$ where $i = 1,2,3,..,n$ are arbitrarily chosen number in [0, 1].

Step 3: Set k = k + 1 and go back to Step2.

4.2 *Arithmetic Crossover Operator*

For the crossover operator, we employ arithmetic crossover. Suppose that x_1 and x_2 are two chromosomes arbitrarily selected to crossover, then the following rule is used to generate their offspring's

$$x'_1 = \beta x_1 + (1 - \beta)x_2 \tag{17}$$

$$x'_2 = \beta x_2 + (1 - \beta)x_1 \tag{18}$$

where $\beta \in [0,1]$ is a arbitrary number. The procedure of arithmetic crossover operator is given as follows.

Step 1: key in crossover rate: cross_rate, and population size: pop_size. Let counter k = 1.

Step 2: When $k \leq$ pop_size, generate a number $\alpha \in [0, 1]$, if $\alpha \leq$ cross_rate, then the kth chromosome is marked as a candidate to crossover; or else, set k = k + 1 and go back to Step 2.

Step 3: Sequently pick two chromosomes which were marked as candidates for crossover, and crossover them using the approach (Vasconcelos *et al*, 2001). The chromosomes obtained are stored as offspring.

Chromosomes created by arithmetic crossover are really convex combinations of x1 and x2. This crossover operator, on one hand, sufficiently searches the local area, on the other hand, assurance global exploration. Additionally, this approach is simple, direct and easy to implement. The drawback of this crossover is that only those points between x1 and x2 are considered, which decreases search area of crossover operator. To overcome it, we enlarge the arbitrary number β from [0, 1] to [-1, 1].

4.3 *Non-Uniform Mutation Operator*

Non-uniform mutation is applied in mutation operator. For a given parent x, if its component xk (here, subscript represents the kth element of vector x) was selected to mutate, then the offspring should be

$$x' = (x_1, \ldots, x'_k, \ldots, x_n) \tag{19}$$

Here, x'_k is randomly chosen from the following two options

$$x_k = x_k + d\left(t, x_k^U - x_k\right) \text{ if } \gamma \leq 0.5 \tag{20}$$

or

$$x'_k = x_k + d\left(t, x_k - x_k^L\right) \text{ if} \gamma > 0.5 \tag{21}$$

where $\gamma \in [0,1]$ is a randomly chosen number, x_k^U and x_k^L are upper bound and lower bound of x_k, respectively.

Step 1: Input the mutation rate: mutate_rate, population size: pop_size, dimension of the problem: n, upper bound u, lower bound l and the maximal generation time: T = max_gene. Set counter i = 1 for chromosomes, set counter k = 1 for elements of every chromosome.

Step 2: For the ith chromosome (denoted as x), when k ≤ n, generate a number $\alpha \in [0; 1]$, if $\alpha \leq$ mutate_rate, then the element xk mutates according to the strategies provided in (20, 21); otherwise, set k = k + 1 and go back to Step 2.

Step 3: If i < pop_size, then, let i = i + 1 and k = 1, go back to Step 2; or else, stop the loop.

4.4 Acceleration Operator

Acceleration operator is based on Hooke-Jeeves method (Long and Wu, 2014) which is a derivative-free method. Hooke-Jeeves method includes two types of search: exploratory search and pattern search.

Step 1: key in the starting point x0, an initial step length t0 and a tolerance parameter ϵ.
Step 2: perform initial exploratory search: starting from x1(= x0), run line search along the coordinate axes with the initial step length t0, set the point obtained as xn and the direction d = xn - x1. Let y = xn.

Step 3: perform pattern search: starting from y, run a line search along the direction d with an initial step size t0, set the obtained point as x1.

Step 4: Exploratory search: starting from x1, using initial step length t0, run a line search along the coordinate axes. Set point obtained as xn and denote the direction d = xn - y. let y = xn.

Step 5: If $|f(y) - f(x_n)| < \epsilon$, then stop; otherwise, go back to Step 3.

Line search plays an amazingly important role in Hooke-Jeeves method. It is necessary both in pattern search and exploratory search. In common, an optimal line search is applied in Hooke-Jeeves method, but this may cause some practical issues for problems whose derivative is time consuming or unfeasible to achieve. In addition, optimal line search is time consuming itself and not global convergence. So in our replication, we use discrete step length to shorten the computational process and avoid the computation of derivative. More accurately, a double step size approach is introduced instead of optimal line search. At each iteration, this method starts from a small given step size. If the current step size reduces objective function value along the considered direction, we accept it and further test its double. Otherwise, we stop line search and take the last accepted step size as a solution. The primary step size at every generation is chosen according to the following rule:

$$t_0 = \alpha \underbrace{\min}_{x_i, x_j \in P} \left\| x_i - x_j \right\| \tag{22}$$

where $\alpha \in [0, 1]$ is a parameter and P is the current generation. Clearly, the preference of initial step size is self-adaptive in this approach. At the early stage, the diversity of population is great. So the step sizes should be bigger to assurance enough decrease of the objective function value. At the latter stage, the population gradually converges to an estimated solution, the decrease of objective function becomes minute vibration of individuals, which needs the step size to be lesser.

4.5 Hybrid - Genetic Algorithm and Hooke-Jeeves Algorithm for Solving Reactive Power Dispatch

Implanting the acceleration operator to the general process of genetic algorithm, we can add some improved chromosomes to the offspring, which, in return, creates more outstanding points in the next generation. Yet, if the acceleration operator is often called during the iterations, the process becomes time consuming and a lot of calculations are actually needless although it can provide better chromosomes to the next generation. Thus, the acceleration operator must be applied as less as possible. In HGAHJ, we run acceleration operator when the current generation reduces the objective function value, i.e., the best point of the current generation is superior to the current best point. For the selection operator, we maintain the better chromosomes to the next generation so as to promise the local exploitation. On the other hand, it is still very significant to maintain the diversity of the next generation which guarantees the global exploration. Therefore, Instead of keeping all the better points in the next generation or arbitrarily choosing points to the next generation, we construct it by half choosing from the best chromosomes and half choosing arbitrarily. In the method HGAHJ in which P (t) and O (t) stand for parents and offspring in the t^{th} generation, respectively.

1: Initialization
1.1: create the initial population P (0),

1.2: position crossover rate, mutation rate, and maximal generation number,
1.3: position t ← 0.

2: While generation counter have not arrive at the maximal generation number, do
2.1: Arithmetic crossover operator: create O (t),
2.2: Non-uniform mutation operator: create O (t),
2.3: calculate P (t) and O (t): compute their value of fitness function,
2.4: Selection operator: build the next generation by choosing half population size of best chromosomes from P (t) and O (t), the other half is selected arbitrarily.
2.5: Acceleration operator: renew the best point so far, if the best objective function value decreases, then acceleration operator is activated with the updated best point as s starting point.
2.6: Set t ← t + 1, go to 2.1
End

5. Simulation Results

The proposed Hybrid - genetic algorithm and Hooke-Jeeves algorithm (HGAHJ) for solving ORPD problem is tested in standard IEEE-57 bus power system. The IEEE 57-bus system data consists of 80 branches, seven generator-buses and 17 branches under load tap setting transformer branches. The possible reactive power compensation buses are 18, 25 and 53. Bus 2, 3, 6, 8, 9 and 12 are PV buses and bus 1 is selected as slack-bus. In this case, the search space has 27 dimensions, i.e., the seven generator voltages, 17 transformer taps, and three capacitor banks. The system variable limits are given in Table 1. The initial conditions for the IEEE-57 bus power system are given as follows:

Pload = 12.352 p.u. Qload = 3.336 p.u.

The total initial generations and power losses are obtained as follows:

$\sum P_G$ = 12.7789 p.u. $\sum Q_G$ = 3.4589 p.u.

Ploss = 0.27592 p.u. Qloss = -1.2259 p.u.

Table 1 Variables limits for ieee-57 bus power system (p.u.)

reactive power generation limits							
bus no	1	2	3	6	8	9	12
Qgmin	-1.1	-.012	-.02	-0.03	-1.2	-0.03	-0.2
qgmax	2	0.3	0.3	0.24	2	0.03	1.52

voltage and tap setting limits					
vgmin	vgmax	vpqmin	vpqmax	tkmin	tkmax
0.5	1.3	0.93	1.03	0.3	1.3

shunt capacitor limits			
bus no	18	25	53
qcmin	0	0	0
qcmax	10	5.3	6.5

Table 2 shows the various system control variables i.e. generator bus voltages, shunt capacitances and transformer tap settings obtained after HGAHJ based optimization which are within their acceptable limits. In Table 3, a comparison of optimum results obtained from proposed HGAHJ with other optimization techniques for Optimal Reactive Power Dispatch problem .These results indicate the robustness of proposed HGAHJ approach for providing better optimal solution in case of IEEE-57 bus system.

Table 2 Control variables obtained after optimization by HGAHJ method for ieee-57 bus system (p.u.).

Control Variables	HGAHJ
V1	1.1
V2	1.082
V3	1.071
V6	1.061
V8	1.072
V9	1.053
V12	1.061
Qc18	0.0842
Qc25	0.332
Qc53	0.0621
T4-18	1.012
T21-20	1.073
T24-25	0.971
T24-26	0.942
T7-29	1.091
T34-32	0.952
T11-41	1.013
T15-45	1.071
T14-46	0.941
T10-51	1.053
T13-49	1.071
T11-43	0.921
T40-56	0.911
T39-57	0.973
T9-55	0.983

Table 3: comparative optimization results for ieee-57 bus power system (p.u.)

S.No.	Optimization Algorithm	Best Solution	Worst Solution	Average Solution
1	NLP (Chaohua Dai, Weirong Chen, Yunfang Zhu, and Xuexia Zhang (2009))	0.25902	0.30854	0.27858
2	CGA (Chaohua Dai, Weirong Chen, Yunfang Zhu, and Xuexia Zhang (2009))	0.25244	0.27507	0.26293
3	AGA (Chaohua Dai, Weirong Chen, Yunfang Zhu, and Xuexia Zhang (2009))	0.24564	0.26671	0.25127
4	PSO-w (Chaohua Dai, Weirong Chen, Yunfang Zhu, and Xuexia Zhang (2009))	0.24270	0.26152	0.24725

5	PSO-cf (Chaohua Dai, Weirong Chen, Yunfang Zhu, and Xuexia Zhang (2009))	0.24280	0.26032	0.24698
6	CLPSO (Chaohua Dai, Weirong Chen, Yunfang Zhu, and Xuexia Zhang (2009))	0.24515	0.24780	0.24673
7	SPSO-07(Chaohua Dai, Weirong Chen, Yunfang Zhu, and Xuexia Zhang (2009))	0.24430	0.25457	0.24752
8	L-DE (Chaohua Dai, Weirong Chen, Yunfang Zhu, and Xuexia Zhang (2009))	0.27812	0.41909	0.33177
9	L-SACP-DE (Chaohua Dai, Weirong Chen, Yunfang Zhu, and Xuexia Zhang (2009))	0.27915	0.36978	0.31032
10	L-SaDE (Chaohua Dai, Weirong Chen, Yunfang Zhu, and Xuexia Zhang (2009))	0.24267	0.24391	0.24311
11	SOA (Chaohua Dai, Weirong Chen, Yunfang Zhu, and Xuexia Zhang (2009))	0.24265	0.24280	0.24270
12	LM (J. R. Gomes and 0. R. Saavedra (1999))	0.2484	0.2922	0.2641
13	MBEP1 (J. R. Gomes and 0. R. Saavedra (1999))	0.2474	0.2848	0.2643
14	MBEP2 (J. R. Gomes and 0. R. Saavedra (1999))	0.2482	0.283	0.2592
15	BES100 (J. R. Gomes and 0. R. Saavedra (1999))	0.2438	0.263	0.2541
16	BES200 (J. R. Gomes and 0. R. Saavedra (1999))	0.3417	0.2486	0.2443
17	Proposed HGAHJ	0.22299	0.23397	0.23015

6. Conclusion

HGAHJ has been successfully applied for Optimal Reactive Power Dispatch problem. The HGAHJ based Optimal Reactive Power Dispatch is tested in standard IEEE-57 bus system. Performance comparisons with well-known population-based algorithms give hopeful results. HGAHJ emerge to find good solutions when compared to that of other algorithms. The simulation results presented in previous section prove the ability of IGAABC approach to arrive at near global optimal solution.

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