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REDUCTION OF ACTIVE POWER LOSS BY IMPROVED FROG LEAPING ALGORITHM

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Abstract

This paper presents Improved Frog Leaping (IFL) algorithm for solving optimal reactive power problem. Comprehensive exploration capability of Particle Swarm Optimization (PSO) and good local search ability of Frog Leaping Algorithm (FLA) has been hybridized to solve the reactive power problem and it overcomes the shortcomings of premature convergence. In order to evaluate the validity of the proposed Improved Frog Leaping (IFL) algorithm, it has been tested in Standard IEEE 57,118 bus systems and compared to other standard algorithms. Simulation results show that proposed Improved Frog Leaping (IFL) algorithm has reduced the real power loss considerably and voltage profiles are within the limits.

Keywords: Optimal Reactive Power; Transmission Loss; Frog Leaping Algorithm; Particle Swarm Optimization.

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1. Introduction

Different numerical methods have been implemented to solve this optimal reactive power dispatch problem. These consist of the gradient method [1, 2], Newton method [3] and linear programming [4-7].The gradient and Newton methods suffer from the difficulty in handling inequality constraints. To apply linear programming, the input- output function is to be expressed as a set of linear functions which may lead to loss of accuracy. In recent times Global Optimization techniques such as genetic algorithms have been proposed to solve the reactive power flow problem [8.9]. In recent years, the problem of voltage stability and voltage collapse has become a major concern in power system planning and operation. To enhance the voltage stability, voltage magnitudes alone will not be a reliable indicator of how far an operating point is from the collapse point [10]. Particle Swarm Optimization (PSO) algorithm [11, 12] was originally an evolutionary computation technique, from observation and study of the predatory behaviour of birds. Frog Leaping Algorithm (FLA) [13] is swarm intelligence based sub-heuristic computation optimization algorithm used to solve discrete combinatorial optimization

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problem. The two algorithms are simple in concept, have less parameter, fast calculation speed, global search capability, and are easy to implement. This paper presents Improved Frog Leaping (IFL) algorithm for solving optimal reactive power problem. Global exploration capability of Particle Swarm Optimization (PSO) and good local search capability of Frog Leaping Algorithm (FLA) has been hybridized to solve the reactive power problem and it overcomes the shortcomings of premature convergence. In order to evaluate the validity of the proposed Improved Frog Leaping (IFL) algorithm, it has been tested in Standard IEEE 57,118 bus systems and compared to other standard algorithms. Simulation results show that proposed Improved Frog Leaping (IFL) algorithm has reduced the real power loss considerably and voltage profiles are within the limits.

2. Objective Function

Active power loss

Main aim of the reactive power dispatch problem is to reduce the active power loss in the transmission network, which can be described as:

$$F = PL = \sum_{k \in Nbr} g_k \left(V_i^2 + V_j^2 - 2V_iV_j cos\theta_{ij}\right) \tag{1}$$

Where g_k: is the conductance of branch between nodes i and j, Nbr: is the total number of transmission lines in power systems.

Voltage profile improvement

For minimization of the voltage deviation in PQ buses, the objective function turns into:

$$F = PL + \omega_v \times VD \tag{2}$$

Where ω_v: is a weighting factor of voltage deviation.

VD is the voltage deviation given by:

$$VD = \sum_{i=1}^{Npq} |V_i - 1| \tag{3}$$

Equality Constraint

The equality constraint of the Reactive power problem is represented by the power balance equation, and can be written as, where the total power generation must cover the total power demand and total power loss:

$$P_G = P_D + P_L \tag{4}$$

Where, P_G - Total Power Generation, P_D-Total Power Demand, P_L – Total Power Loss.

Inequality Constraints

Inequality constraints define the limitations in power system components and power system security. Upper and lower bounds on the active power of slack bus, and reactive power of generators are written as follows:

$$P_{gslack}^{min} \leq P_{gslack} \leq P_{gslack}^{max} \tag{5}$$

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max}, i \in N_g \tag{6}$$

Upper and lower bounds on the bus voltage magnitudes are described as follows:

$$V_i^{min} \leq V_i \leq V_i^{max}, i \in N \tag{7}$$

Upper and lower bounds on the transformers tap ratios are given as follows:

$$T_i^{min} \leq T_i \leq T_i^{max}, i \in N_T \tag{8}$$

Upper and lower bounds on the compensators reactive powers are written as follows:

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$$Q_c^{min} \leq Q_c \leq Q_C^{max}, i \in N_C \tag{9}$$

Where N is the total number of buses, N_T is the total number of Transformers; N_c is the total number of shunt reactive compensators.

3. Particle Swarm Optimization Algorithm

Particle swarm optimization algorithm is an optimization algorithm based on group and fitness. The system initializes particles (representing potential solutions) as a set of random solutions, which has two features of position and velocity. The fitness values of particles are decided by particle positions. Particles move in the solution space; the moving direction and distance are determined by the speed vector and new speed , position are updated from personal best position pbest, global best position gbest and the current particle velocity; particles search and pursue the optimal particle based on fitness values in the solution space, and gradually converge to the optimal solution. Assuming in a d-dimensional search space, there is a group composed of n particles, where of generation t particle i(i = 1, 2, ... , n), position coordinates $x_i^t = (x_{i1}, x_{i2}, .., x_{id})$, velocity $v_i^t = (v_{i1}, v_{i2}, ... v_{id})$ personal best position $p_i^t = (p_{i1}, p_{i2}, .., p_{id})$ and global best position $p_g^t = \left(p_{g1}, p_{g2}, .., p_{gd}\right)$.For particle i dimension d generation t, its iterative formula can be expressed as:

$$v_{id}^{t+1} = \omega \vartheta_{id}^t + c_1 r_1 (p_{id}^t - x_{id}^t) + c_2 r_2 \left(p_{gd}^t - x_{id}^t\right) \tag{10}$$

$$x_{id}^{t+1} = x_{id}^t + \vartheta_{id}^{t+1} \tag{11}$$

Where, ϑ_{id}^t - current velocity,
ϑ_{id}^{t+1} - New speed of particle r after iteration t,
ω- Inertia weight,
$c_{1,} c_2$ - Acceleration (learning) factors,
$r_{1,} r_2$ – Uniformly distributed random numbers between 0 and 1,
x_{id}^t -current position of particle i ,
x_{id}^{t+1}-new position of particle i after iteration t.

4. Frog Leaping Algorithm

Frog leaping algorithm is a biological evolution algorithm based on swarm intelligence. The algorithm simulates a group of frogs in the wetland passing thought and foraging by classification of ethnic groups. In the execution of the algorithm, F frogs are generated at first to form a group, for N-dimensional optimization problem, frog i of the group is represented as $X_i = (x_i^1, x_i^2, .., x_i^N)$ then individual frogs in the group are sorted in descending order according to fitness values, to find the global best solution P_x. The group is divided into m ethnic groups, each ethnic group including n frogs, satisfying the relation F = m × n. The rule of ethnic group division is: the first frog into the first sub-group, the second frog into the second sub-group, frog m into sub-group m, frog m + 1 into the first sub-group again, frog m + 2 into the second sub-group, and so on, until all the frogs are divided, then find the best frog in each sub-group, denoted by P_b; get a worst frog correspondingly, denoted by P_w. Its iterative formula can be expressed as:

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$$D = rand(\,) * (P_b - P_\omega) \tag{12}$$

$$P_{new\_-\omega} = P_\omega + D_i, -D_{max} \le D_i \le D_{max} \tag{13}$$

Where rand ( ) represents a random number between 0 and 1,
P_b represents the position of the best frog,
P_w represents the position of the worst frog,
D represents the distance moved by the worst frog,
$P_{new\_-\omega}$ is the improved position of the frog,
D_{max} represents the step length of frog leaping.

In the execution of the algorithm, if the updated $P_{new\_-\omega}$ is in the feasible solution space, calculate the corresponding fitness value of $P_{new\_-\omega}$, if the corresponding fitness value of $P_{new\_-\omega}$ is worse than the corresponding fitness value of P_w, then use P_w to replace P_b in equation (12) and re-update $P_{new\_-\omega}$; if there is still no improvement, then randomly generate a new frog to replace P_w; repeat the update process until satisfying stop conditions.

5. Improved Frog Leaping (IFL) Algorithm

Exploration and exploitation has been a contradiction in the search process of swarm intelligence algorithms. Exploration stresses searching for a new search region in the global range, and exploitation is focused on fine search in local search area. Although particle swarm optimization algorithm is simple and its optimization performance is good, in the entire iterative process, exploration capability is strong and exploitation capability is weak in early period, at this time if particles fall on the neighbourhood of the best particle, they may flee the neighbourhood of the best particle, due to too strong exploration capability; exploration capability is weak and exploitation capability is strong in later period, at this time if particles encounter local optima, the speed of all particles may be rapidly reduced to zero instead of flying, leading to convergence of particle swarm to local optima; the iterative mechanism and ethnic group division lead to strong exploitation and weak exploration in early period, and strong exploration and weak exploitation in later period. Based on the above analysis, in the update process of the algorithm, in order to ensure the diversity of particles, particle swarm and frog group sharing part of the particles, we propose particle sharing based particle swarm frog leaping hybrid optimization algorithm. The idea is as follows: divide the total number of particles N into two sub-groups of numbers N1 and N2, where the first sub-group uses shuffled frog leaping algorithm to optimize, the second sub-group uses the standard particle swarm optimization algorithm to optimize, and N, N1 and N2 satisfy $N \le N1 + N2$, so the number of shared particles is N1 + N2 - N.

1) Initialize groups and parameters. Initialize group total number of particles N, total number of frogs N1, number of sub-groups m, number of frogs in each sub-group n (parameters satisfying $N_1 = m \times n$), number of updates It within frog group sub-group, number of particles N_2 of particle swarm (parameters satisfying $N \le N1 + N2$), inertia weight ω, acceleration factor c_1, deceleration factor c_2, the maximum number of iterations Iter Max and other parameters.
2) Evaluate the initial fitness values of the particles, save the initial best positions and the initial best fitness values, and sort all N particles in ascending order according to fitness

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values; N_1 particles counted from front to back belong to the frog group, and N_2 particles counted from back to front belong to the particle swarm.

3) Sort N_1 frogs in ascending order and divide them into sub-groups according to the sub-group division rule.
4) Determine the best fitness individual P_b and the worst fitness individual P_w of each subgroup in frog group, and the group best individual P_x, improve the worst solution within a specified number of iterations It according to equations (12) and (13).
5) Sort particles of the group in ascending order according to fitness values, re-mix the particles to form a new group, and sort the N particles in ascending order according to fitness values; N_1 particles counted from front to back belong to the frog group, and N2 particles counted from back to front belong to the particle swarm. Calculate the new speed of each particle according to equation (10), calculate the new position of each particle according to equation (11), limiting the maximum values of the new speed and position of each particle; update each particle's personal best fitness value and personal best position; update the global best fitness value and the global best position.
6) Sort particles of the group in ascending order according to fitness values, and re-mix the particles to form a new group.
7) If stop conditions are satisfied (the number of iterations exceeds the maximum allowable number of iterations or the optimal solution is obtained), the search stops, and output the position and fitness value of the first particle of the group; otherwise, return to step (c) to continue the search.

6. Simulation Results

At first Improved Frog Leaping (IFL) algorithm has been tested in standard IEEE-57 bus power system. The 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. The system variable limits are given in Table 1.
The preliminary conditions for the IEEE-57 bus power system are given as follows:
P_{load} = 12.129 p.u. Q_{load} = 3.060 p.u.
The total initial generations and power losses are obtained as follows:
$\sum P_G$ = 12.470 p.u. $\sum Q_G$ = 3.3161 p.u.
P_{loss} = 0.25870 p.u. Q_{loss} = -1.2071 p.u.
Table 2 shows the various system control variables i.e. generator bus voltages, shunt capacitances and transformer tap settings obtained after optimization which are within the acceptable limits. In Table 3, shows the comparison of optimum results obtained from proposed methods with other optimization techniques. These results indicate the robustness of proposed approaches for providing better optimal solution in case of IEEE-57 bus system.

Table 1: Variable Limits

Reactive Power Generation Limits							
Bus no	1	2	3	6	8	9	12
Qgmin	-1.4	-.015	-.02	-0.04	-1.3	-0.03	-0.4
Qgmax	1	0.3	0.4	0.21	1	0.04	1.50
Voltage And Tap Setting Limits							
vgmin	**Vgmax**	**vpqmin**	**Vpqmax**	**tkmin**	**tkmax**		

0.9	1.0	0.91	1.05	0.9	1.0
Shunt Capacitor Limits					
Bus no	18	25	53		
Qcmin	0	0	0		
Qcmax	10	5.2	6.1		

Table 2: Control variables obtained after optimization

Control Variables	IFL
V1	1.1
V2	1.030
V3	1.032
V6	1.020
V8	1.021
V9	1.006
V12	1.011
Qc18	0.0660
Qc25	0.200
Qc53	0.0471
T4-18	1.006
T21-20	1.041
T24-25	0.860
T24-26	0.871
T7-29	1.051
T34-32	0.872
T11-41	1.012
T15-45	1.030
T14-46	0.910
T10-51	1.020
T13-49	1.060
T11-43	0.910
T40-56	0.900
T39-57	0.950
T9-55	0.950

Table 3: Comparison results

S.No.	Optimization Algorithm	Finest Solution	Poorest Solution	Normal Solution
1	NLP [14]	0.25902	0.30854	0.27858
2	CGA [14]	0.25244	0.27507	0.26293
3	AGA [14]	0.24564	0.26671	0.25127
4	PSO-w [14]	0.24270	0.26152	0.24725
5	PSO-cf [14]	0.24280	0.26032	0.24698
6	CLPSO [14]	0.24515	0.24780	0.24673
7	SPSO-07 [14]	0.24430	0.25457	0.24752
8	L-DE [14]	0.27812	0.41909	0.33177
9	L-SACP-DE [14]	0.27915	0.36978	0.31032

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10	L-SaDE [14]	0.24267	0.24391	0.24311
11	SOA [14]	0.24265	0.24280	0.24270
12	LM [15]	0.2484	0.2922	0.2641
13	MBEP1 [15]	0.2474	0.2848	0.2643
14	MBEP2 [15]	0.2482	0.283	0.2592
15	BES100 [15]	0.2438	0.263	0.2541
16	BES200 [15]	0.3417	0.2486	0.2443
17	Proposed IFL	0.22064	0.23016	0.22248

Then Improved Frog Leaping (IFL) algorithm has been tested in standard IEEE 118-bus test system [16].The system has 54 generator buses, 64 load buses, 186 branches and 9 of them are with the tap setting transformers. The limits of voltage on generator buses are 0.95 -1.1 per-unit., and on load buses are 0.95 -1.05 per-unit. The limit of transformer rate is 0.9 -1.1, with the changes step of 0.025. The limitations of reactive power source are listed in Table 4, with the change in step of 0.01.

Table 4: Limitation of reactive power sources

BUS	5	34	37	44	45	46	48
QCMAX	0	14	0	10	10	10	15
QCMIN	-40	0	-25	0	0	0	0
BUS	74	79	82	83	105	107	110
QCMAX	12	20	20	10	20	6	6
QCMIN	0	0	0	0	0	0	0

The statistical comparison results of 50 trial runs have been list in Table 5 and the results clearly show the better performance of proposed Improved Frog Leaping (IFL) algorithm in reducing the real power loss.

Table 5: Comparison results

Active power loss (MW)	**BBO [17]**	**ILSBBO/ strategy1 [17]**	**ILSBBO/ strategy1 [17]**	**Proposed IFL**
Min	128.77	126.98	124.78	117.86
Max	132.64	137.34	132.39	119.54
Average	130.21	130.37	129.22	118.42

7. Conclusion

In this paper a novel approach Improved Frog Leaping (IFL) algorithm used to solve reactive power problem, considering various generator constraints, has been successfully applied.The performance of the proposed Improved Frog Leaping (IFL) algorithm has been has been tested in standard IEEE 57,118 bus systems and simuation results reveal about the reduction of real power loss when compared with other standard reported algorithms and volatge profiles are within the limits.

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DOI: 10.5281/zenodo.999199

References

[1] O.Alsac,and B. Scott, "Optimal load flow with steady state security",IEEE Transaction. PAS -1973, pp. 745-751.

[2] Lee K Y ,Paru Y M , Oritz J L –A united approach to optimal real and reactive power dispatch , IEEE Transactions on power Apparatus and systems 1985: PAS-104 : 1147-1153

[3] A.Monticelli , M .V.F Pereira ,and S. Granville , "Security constrained optimal power flow with post contingency corrective rescheduling" , IEEE Transactions on Power Systems :PWRS-2, No. 1, pp.175-182.,1987.

[4] Deeb N ,Shahidehpur S.M ,Linear reactive power optimization in a large power network using the decomposition approach. IEEE Transactions on power system 1990: 5(2) : 428-435

[5] E. Hobson ,'Network consrained reactive power control using linear programming, ' IEEE Transactions on power systems PAS -99 (4) ,pp 868=877, 1980

[6] K.Y Lee ,Y.M Park , and J.L Oritz, "Fuel –cost optimization for both real and reactive power dispatches" , IEE Proc; 131C,(3), pp.85-93.

[7] M.K. Mangoli, and K.Y. Lee, "Optimal real and reactive power control using linear programming" , Electr.Power Syst.Res, Vol.26, pp.1-10,1993.

[8] K.Anburaja, "Optimal power flow using refined genetic algorithm", Electr.Power Compon.Syst , Vol. 30, 1055-1063,2002.

[9] D. Devaraj, and B. Yeganarayana, "Genetic algorithm based optimal power flow for security enhancement", IEE proc-Generation.Transmission and. Distribution; 152, 6 November 2005.

[10] C.A. Canizares , A.C.Z.de Souza and V.H. Quintana , " Comparison of performance indices for detection of proximity to voltage collapse ,'' vol. 11. no.3 , pp.1441-1450, Aug 1996 .

[11] Kennedy J, Eberhart R C. "Particle swarm optimization", In Proceedings of IEEE International Conference on Neural Network, pages 1942 – 1948, 1995.

[12] Shi Y, Eberhart R C. "A modified particle swarm optimizer", In Proceedings of the IEEE International Conference on Evolutionary Computation, pages 69 – 73, 1998.

[13] Eusuff, Lansey. "Optimization of Water Distribution Network Design Using Shuffled Frog Leaping Algorithm", Journal of Water Resources Planning and Management, 129 (3): 210 – 225, 2003.

[14] Chaohua Dai, Weirong Chen, Yunfang Zhu, and Xuexia Zhang, "Seeker optimization algorithm for optimal reactive power dispatch," IEEE Trans. Power Systems, Vol. 24, No. 3, August 2009, pp. 1218-1231.

[15] J. R. Gomes and 0. R. Saavedra, "Optimal reactive power dispatch using evolutionary computation: Extended algorithms," IEE Proc.-Gener. Transm. Distrib.. Vol. 146, No. 6. Nov. 1999.

[16] IEEE, "The IEEE 30-bus test system and the IEEE 118-test system", (1993), http://www.ee.washington.edu/trsearch/pstca/.

[17] Jiangtao Cao, Fuli Wang and Ping Li, "An Improved Biogeography-based Optimization Algorithm for Optimal Reactive Power Flow" International Journal of Control and Automation Vol.7, No.3 (2014), pp.161-176.

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