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DECREASE OF REAL POWER LOSS BY ADAPTED ALGORITHM

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Abstract

In this paper, Adapted Flower Pollination (AFP) algorithm is proposed to solve the optimal reactive power problem. Flower pollination algorithm has been improved by comprising of the elements of chaos theory, Shuffled frog leaping search and Levy Flight. In the AFP algorithm, the initial population is generated using the circle map, frog leaping local search is performed by each solution and when rand>p, modified Levy flight with integration of inertia weight in global pollination is performed on that particular solution. Proposed AFP algorithm has been tested in standard IEEE 57 bus test system and simulation results show clearly the better performance of the proposed algorithm in reducing the real power loss.

Keywords: Optimal Reactive Power; Transmission Loss; Flower Pollination Algorithm; Chaos Theory; Shuffled Frog Leaping Search and Levy Flight.

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1. Introduction

Optimal reactive power problem is to minimize the real power loss and bus voltage deviation. Various numerical methods like the gradient method [1-2], Newton method [3] and linear programming [4-7] have been adopted to solve the optimal reactive power dispatch problem. Both the gradient and Newton methods have the complexity in managing inequality constraints. If linear programming is applied then the input- output function has to be uttered as a set of linear functions which mostly lead to loss of accuracy.   The problem of voltage stability and collapse play a major role in power system planning and operation [8]. Evolutionary algorithms such as genetic algorithm have been already proposed to solve the reactive power flow problem [9-11].

Evolutionary algorithm is a heuristic approach used for minimization problems by utilizing nonlinear and non-differentiable continuous space functions. In [12], Hybrid differential evolution algorithm is proposed to improve the voltage stability index. In [13] Biogeography Based algorithm is projected to solve the reactive power dispatch problem. In [14], a fuzzy based method is used to solve the optimal reactive power scheduling method. In [15], an improved evolutionary

programming is used to solve the optimal reactive power dispatch problem. In [16], the optimal reactive power flow problem is solved by integrating a genetic algorithm with a nonlinear interior point method. In [17], a pattern algorithm is used to solve ac-dc optimal reactive power flow model with the generator capability limits. In [18], F. Capitanescu proposes a two-step approach to evaluate Reactive power reserves with respect to operating constraints and voltage stability.

In [19], a programming based approach is used to solve the optimal reactive power dispatch problem. In [20], A. Kargarian et al present a probabilistic algorithm for optimal reactive power provision in hybrid electricity markets with uncertain loads. This paper proposes Adapted Flower Pollination (AFP) algorithm is proposed to solve the reactive power problem. The basic idea of flower pollination process which leads to the formulation of flower pollination algorithm (FPA) [21] is first introduced and subsequently, chaos theory, Shuffled frog leaping search and Levy Flight are introduced. Proposed AFP algorithm has been evaluated in standard IEEE 118 & practical 191 bus test systems. Simulation results show that our proposed approach outperforms all the entitled reported algorithms in minimization of real power loss.

2. Problem Formulation

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:

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

Where g_k : is the conductance of branch between nodes i and j, Nbr: is the total number of transmission lines in power systems. P_d: is the total active power demand, P_{gi}: is the generator active power of unit i, and P_{gsalck}: is the generator active power of slack bus.

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

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

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 problem is represented by the power balance equation, where the total power generation must cover the total power demand and the power losses:

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

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

Inequality Constraints

The inequality constraints 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:

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

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

Upper and lower bounds on the bus voltage magnitudes:

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

Upper and lower bounds on the transformers tap ratios:

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

Upper and lower bounds on the compensators reactive powers:

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

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. Flower Pollination Algorithm

Generally we use the following systems in Flower Pollination Algorithm (FPA),
- System 1. Biotic and cross-pollination has been treated as global pollination process, and pollen-carrying pollinators travel in a way which obeys Levy flights.
- System 2. For local pollination, A- biotic and self-pollination has been utilized.
- System 3. Pollinators such as insects can develop flower reliability, which is equivalent to a reproduction probability and it is proportional to the similarity of two flowers implicated.
- System 4. The communication of local pollination and global pollination can be controlled by a control probability $p \in [0, 1]$, with a slight bias towards local pollination.

System 1 and flower reliability can be represented mathematically as

$$x_i^{t+1} = x_i^t + \gamma L(\lambda)(x_i^t - g_*) \tag{10}$$

Where x_i^t is the pollen i or solution vector x_i at iteration t, and g_* is the current best solution found among all solutions at the current generation/iteration. Here γ is a scaling factor to control the step size. $L(\lambda)$ is the parameter that corresponds to the strength of the pollination, which essentially is

also the step size. Since insects may move over a long distance with various distance steps, we can use a Levy flight to mimic this characteristic efficiently. We draw $L > 0$ from a Levy distribution

$$L \sim \frac{\lambda \Gamma(\lambda sin(\Pi \lambda/2))}{\Pi} \frac{1}{s^{1+\lambda}} , (s \gg s_0 > 0) \tag{11}$$

Here, $\Gamma(\lambda)$ is the standard gamma function, and this distribution is valid for large steps $s > 0$. Then, to model the local pollination, for both system 2 and system 3 can be represented as

$$x_i^{t+1} = x_i^t + \in \left(x_j^t - x_k^t\right) \tag{12}$$

Where x_j^t and x_k^t are pollen from different flowers of the same plant species. This essentially mimics the flower reliability in a limited neighbourhood. Mathematically, if x_j^t and x_k^t comes from the same species or selected from the same population, this equivalently becomes a local random walk if we draw $\in$ from a uniform distribution in [0,1]. Though Flower pollination performance can occur at all balance, local and global, neighbouring flower patch or flowers in the not-so-far-away neighbourhood are more likely to be pollinated by local flower pollen than those far away. In order to mimic this, we can effectively use a control probability (system 4) or proximity probability p to switch between common global pollination to intensive local pollination. To start with, we can use a raw value of $p = 0.8$ as an initially value.

The simplest method is to use a weighted sum to combine all multiple objectives into a composite single objective

$$f = \sum_{i=1}^{m} w_i f_i \ \sum_{i=1}^{m} w_i = 1 , w_i > 0 \tag{13}$$

Where m is the number of objectives and $w_i (i = 1, ...,m)$ are non-negative weights.

FP Algorithm for solving optimal reactive power optimization

Step 1. Objective min of (x), x = (x_1, x_2, ..., x_d)
Step 2. Initialize a population of n flowers
Step 3. Find the best solution g_* in the initial population
Step 4. Define a control probability p $\in$ [0, 1]
Step5. Define a stopping criterion (a fixed number of   generations/iterations)
Step6. while (t < Max Generation)
Step6. for i = 1: n (all n flowers in the population)
Step7. if rand < p,
Step8. Draw a (d-dimensional) step vector L which obeys a Levy distribution Global pollination through $x_i^{t+1} = x_i^t + L(x_i^t - g_*)$
else
step9. Draw $\in$ from a uniform distribution in [0,1]
step 10. Do local pollination through $x_i^{t+1} = x_i^t + \in \left(x_j^t - x_k^t\right)$
end if
step10. Evaluate new solutions
step11. If new solutions are better, update them in the population

end for
step12. Find the current best solution g_*
end while
Output - best solution has been found

4. Chaotic Maps

Chaos is a random state found in the non-linear dynamical deterministic system, possesses non-period, non-converging and bounded properties. The use of chaotic sequences is more beneficial than the random sequences due to its non-repetition and ergodicity properties. Borrowing the advantages of ergodicity, non-repetition and randomness of the chaotic sequences, the chaotic map is replacing the random sequences in generating the initial population in the FPA in this study. This is to ensure that the diversity of the initial population can be improved, where the distribution of the initial population is more uniform. Ten different chaotic maps are and circle map is selected for the integration with FPA.

$$x_{n+1} = \left(x_n + 0.2 - \left(\frac{0.5}{2\pi}\right)sin(2\pi x_n)\right) \times mod(1) \tag{14}$$

5. Shuffled Frog Leaping Algorithm

Shuffled 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:

$$D = rand(\ ) * (P_b - P_\omega) \tag{15}$$

$$P_{new\_-\omega} = P_\omega + D_i, -D_{max} \leq D_i \leq D_{max} \tag{16}$$

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 (15) 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.

6. Levy Flight

Levy flight is a rank of non-Gaussian random processes whose arbitrary walks are drawn from Levy stable distribution. This allocation is a simple power-law formula $L(s) \sim |s|^{-1-\beta}$ where $0 < \beta < 2$ is an index. Mathematically exclamation, a easy version of Levy distribution can be defined as ,

$$L(s, \gamma, \mu) = \begin{cases} \sqrt{\frac{\gamma}{2\pi}} \ exp\left[-\frac{\gamma}{2(s-\mu)}\right]\frac{1}{(s-\mu)^{3/2}} & if \ 0 \ < \mu < s < \infty \\ 0 \quad if \ s \leq 0 \end{cases} \qquad (17)$$

Where $\gamma > 0$ parameter is scale (controls the scale of distribution) parameter, μ parameter is location or shift parameter. In general, Levy distribution should be defined in terms of Fourier transform

$$F(k) = exp[-\alpha|k|^\beta], 0 < \beta \leq 2, \qquad (18)$$

Where α is a parameter within [-1,1] interval and known as scale factor. An index of o stability $\beta \in [0, 2]$ is also referred to as Levy index. In particular, for $\beta = 1$, the integral can be carried out analytically and is known as the Cauchy probability distribution. One more special case when $\beta = 2$, the distribution correspond to Gaussian distribution. β and α parameters take a key part in determination of the distribution. The parameter β controls the silhouette of the probability distribution in such a way that one can acquire different shapes of probability distribution, especially in the tail region depending on the parameter β. Thus, the smaller β parameter causes the distribution to make longer jumps since there will be longer tail. It makes longer jumps for smaller values whereas it makes shorter jumps for bigger values. By Levy flight, new-fangled state of the particle is designed as,

$$X^{t+1} = X^t + \alpha \oplus Levy \ (\beta) \qquad (19)$$

α is the step size which must be related to the scales of the problem of interest. In the proposed method α is random number for all dimensions of particles.

$$X^{t+1} = X^t + random \ (size(D)) \oplus Levy(\beta) \qquad (20)$$

The product $\oplus$ means entry-wise multiplications.

A non-trivial scheme of generating step size s samples are summarized as follows,

$$X^{t+1} = X^t + random \ (size(D)) \oplus Levy(\beta) \sim 0.01\frac{u}{|v|^{1/\beta}}(x_j^t - gb) \qquad (21)$$

Where u and v are drawn from normal distributions. That is

$$u \sim N(0, \sigma_u^2) \quad v \sim N(0, \sigma_v^2) \tag{22}$$

With

$$\sigma_u = \left\{ \frac{\Gamma(1+\beta)\sin(\pi\beta/2)}{\Gamma[(1+\beta)/2]\beta 2^{(\beta-1)/2}} \right\}^{1/\beta} , \sigma_v = 1 \tag{23}$$

Here Γ is standard Gamma function. One of the important points to be considered while performing distribution by Levy flights is the value taken by the β parameter and it substantially affects distribution.

7. Adapted Flower Pollination (AFP) algorithm

In the AFP algorithm, the initial population is generated using the circle map, frog leaping local search is performed by each solution and when rand>p, modified Levy flight with integration of inertia weight in global pollination is performed on that particular solution. The steps involved in the AFP are as follows:

Step 1: Parameter Initialization
Initialize the relevant parameters of population size, n, dimension of search space, d, maximum iteration, max_iter, switch probability, p, range of search space [Lb, Ubm] , number of memeplexes, m and iterations within each memeplex, it.
Step 2: create Initial Population using the chaotic map
Step 3: Find the Best Solution
The fitness value of each solution is calculated and the best solution is determined.
Step 4: Perform the Frog Leaping Search - For each solution, search is performed.
Step 5: Perform the Global Search of Flower Pollination Algorithm
Step 6: Update the Solution
The fitness value of each new solution is evaluated. The historical position is updated through comparison with the new solution. Subsequently, the best solution is updated.
Step 7: Check Termination Condition or else, Step 4 is repeated.

8. Simulation results

Adapted Flower Pollination (AFP) algorithm has been tested in standard IEEE-57 bus power system. 18, 25 and 53 are reactive power compensation buses. PV buses are 2, 3, 6, 8, 9 and 12 and slack-bus is bus 1. In Table 1 system variable limits are given.

IEEE-57 preliminary conditions for the bus power system are given as follows:
P_{load} = 12.102 p.u. Q_{load} = 3.020 p.u.

Complete sum of initial generations and power losses are attained as follows:
$\sum P_G$ = 12.410 p.u. $\sum Q_G$ = 3.3120 p.u.
P_{loss} = 0.25841 p.u. Q_{loss} = -1.2032 p.u.

Control variables values obtained after optimization is given in Table 2. Comparisons of results are shown in Table 3.

Table 1: Variable Limits

Reactive Power Generation Limits							
Bus no	1	2	3	6	8	9	12
Qgminimum	-1.4	-.015	-.02	-0.04	-1.3	-0.03	-0.4
Qgmaximum	1	0.3	0.4	0.21	1	0.04	1.50

Voltage And Tap Setting Limits					
vgminimum	Vgmaximum	vpqminimum	Vpqmaximum	tkminimum	tkmaximum
0.9	1.0	0.91	1.05	0.9	1.0

Shunt Capacitor Limits			
Bus no	18	25	53
Qcminimum	0	0	0
Qcmaximum	10	5.2	6.1

Table 2: Control variables obtained after optimization

List of Control Variables	AFP
V1	1.100
V2	1.03120
V3	1.03110
V6	1.02000
V8	1.02000
V9	1.00110
V12	1.01010
Qc18	0.06500
Qc25	0.20010
Qc53	0.04520
T4-18	1.00020
T21-20	1.04110
T24-25	0.86010
T24-26	0.87000
T7-29	1.05000
T34-32	0.87090
T11-41	1.01000
T15-45	1.03000
T14-46	0.91000
T10-51	1.02000
T13-49	1.06000
T11-43	0.91000
T40-56	0.90000
T39-57	0.95000
T9-55	0.95000

Table 3: Comparison results

S.No.	Optimization Algorithm	Finest Solution	Poorest Solution	Average Solution
1	NLP (Chaohua Dai et al .,2009)	0.25902	0.30854	0.27858
2	CGA (Chaohua Dai et al .,2009)	0.25244	0.27507	0.26293
3	AGA (Chaohua Dai et al .,2009)	0.24564	0.26671	0.25127
4	PSO-w (Chaohua Dai et al .,2009)	0.24270	0.26152	0.24725
5	PSO-cf (Chaohua Dai et al .,2009)	0.24280	0.26032	0.24698
6	CLPSO (Chaohua Dai et al .,2009)	0.24515	0.24780	0.24673
7	SPSO-07 (Chaohua Dai et al .,2009)	0.24430	0.25457	0.24752
8	L-DE (Chaohua Dai et al .,2009)	0.27812	0.41909	0.33177
9	L-SACP-DE (Chaohua Dai et al .,2009)	0.27915	0.36978	0.31032
10	L-SaDE (Chaohua Dai et al .,2009)	0.24267	0.24391	0.24311
11	SOA (Chaohua Dai et al .,2009)	0.24265	0.24280	0.24270
12	LM (Gomes et al .,1999)	0.2484	0.2922	0.2641
13	MBEP1 (Gomes et al .,1999)	0.2474	0.2848	0.2643
14	MBEP2 (Gomes et al .,1999)	0.2482	0.283	0.2592
15	BES100 (Gomes et al .,1999)	0.2438	0.263	0.2541
16	BES200 (Gomes et al .,1999)	0.3417	0.2486	0.2443
17	Proposed AFP	0.22001	0.23002	0.22200

9. Conclusion

Adapted Flower Pollination (AFP) algorithm has been effectively applied for solving reactive power problem. And it has been tested in standard 57 bus test system. Performance comparisons with well-known population-based algorithms give improved results. Adapted Flower Pollination (AFP) algorithm emerges to find good solutions when compared to that of other reported algorithms. The simulation results presented in previous section prove the capability of AFP approach to arrive at near to global optimal solution.

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