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REDUCTION OF ACTIVE POWER LOSS BY ADAPTIVE CHARGED SYSTEM SEARCH ALGORITHM

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Abstract

This paper presents a new optimization algorithm called Adaptive Charged System Search Algorithm (ACA) for solving optimal power problem. Coulomb law from electrostatics and the Newtonian laws of mechanics are forming the basics of the proposed algorithm. Adaptive Charged System Search Algorithm (ACA) is a multi-agent approach in which each agent is a Charged Particle (CP) & they affect each other based on their fitness values, separation of distances. The quantity of the resultant force is determined by using the electrostatics laws and the quality of the movement is determined using Newtonian mechanics laws. Proposed Adaptive Charged System Search Algorithm (ACA) has been tested in Standard IEEE 57,118 bus systems & real power loss has been comparatively reduced with voltage profiles are within the limits.

Keywords: Optimal Reactive Power; Transmission Loss; Charged Particle; Adaptive Charged System Search Algorithm.

1. Introduction

Optimal reactive power problem plays most important role in the stability of power system operation and control. In this paper the main aspect is to diminish the real power loss and to keep the voltage variables within the limits. Previously many mathematical techniques like gradient method, Newton method, linear programming [4-7] has been utilized to solve the optimal reactive power dispatch problem and those methods have many difficulties in handling inequality constraints. Voltage stability and voltage collapse play an imperative role in power system planning and operation [8]. Recently Evolutionary algorithms like genetic algorithm have been already utilized to solve the reactive power flow problem [9,10].In [11-20] Genetic algorithm, Hybrid differential evolution algorithm, Biogeography Based algorithm, fuzzy based methodology, improved evolutionary programming has been used to solve   optimal reactive power flow problem and all the algorithm successfully handled the reactive power problem. The Artificial Bee Colony (ABC) algorithm was introduced by Karaboga [21] as a technical report,

and then its performance was measured using benchmark optimization functions [22-33]. This paper presents a new optimization algorithm called Adaptive Charged System Search Algorithm (ACA) for solving optimal power problem. Coulomb law from electrostatics and the Newtonian laws of mechanics are forming the basics of the proposed algorithm. Adaptive Charged System Search Algorithm (ACA) is a multi-agent approach in which each agent is a Charged Particle (CP) [34-37] & they affect each other based on their fitness values, separation of distances. The quantity of the resultant force is determined by using the electrostatics laws and the quality of the movement is determined using Newtonian mechanics laws. Proposed Adaptive Charged System Search Algorithm (ACA) has been tested in Standard IEEE 57,118 bus systems & real power loss has been comparatively reduced with voltage profiles are within the limits.

2. Objective Function

2.1. Active Power Loss

The objective of the reactive power dispatch problem is to minimize the active power loss and can be defined in equations 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.

2.2. Voltage Profile Improvement

To minimize the voltage deviation in PQ buses, the objective function can be written as:

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

Where ω_v: is a weighting factor of voltage deviation.

VD is the voltage deviation given by:

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

2.3. Equality Constraint

The equality constraint of the problem is indicated by the power balance equation as follows:

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

Where the total power generation PG has to cover the total power demand PD and the power losses PL.

2.4. Inequality Constraints

The inequality constraint implies the limits on components in the power system in addition to the limits created to make sure 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:
$$V_i^{min} \leq V_i \leq V_i^{max} , i \in N \tag{7}$$

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

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

3. Adaptive Charged System Search Algorithm (ACA)

In this section, a new efficient optimization algorithm is established utilizing the aforementioned physics laws, which is called Adaptive Charged System Search Algorithm (ACA). In the Adaptive Charged System Search Algorithm (ACA), each solution candidate X i containing a number of decision variables i.e ($X_i = \{x_{i,j}\}$) is considered as a charged particle [34-37]. The charged particle is affected by the electrical fields of the other agents. The quantity of the resultant force is determined by using the electrostatics laws and the quality of the movement is determined using the Newtonian mechanics laws. It seems that an agent with good results must exert a stronger force than the bad ones, so the amount of the charge will be defined considering the objective function value, fit (i). In order to introduce ACA, the following rules are developed: Rule 1 Many of the natural evolution algorithms maintain a population of solutions which are evolved through random alterations and selection. Similarly, ACA considers a number of Charged Particles (CP). Each CP has a magnitude of charge (qi) and as a result creates an electrical field around its space. The magnitude of the charge is defined considering the quality of its solution, as follows:

$$qi = \frac{fit\ (i) - fitworst}{fitbest - fitworst}, \ i = 1,2,\ldots, N, \tag{10}$$

where, fitbest and fitworst are the so far best and the worst fitness of all particles; fit (i) represents the objective function value or the fitness of the agent i; and N is the total number of CPs. The separation distance rij between two charged particles is defined as follows:

$$r_{ij} = \frac{\|x_i - x_j\|}{\left\|\frac{(x_i + x_j)}{2} - x_{best}\right\| + \varepsilon}, \tag{11}$$

Where Xi and Xj are the positions of the i th and j th CPs, Xbest is the position of the best current CP, and ε is a small positive number to avoid singularities.

Rule 2 the initial positions of CPs are determined randomly in the search space
$$x_{i,j}^{(0)} = x_{i,min} + rand \cdot (x_{i,max} - x_{i,min}), i = 1,2,..,n \quad (12)$$

where $x_{i,j}^{(0)}$ determines the initial value of the i th variable for the j th CP; $x_{i,min}$ and $x_{i,max}$ are the minimum and the maximum allowable values for the i th variable; rand is a random number in the interval [0,1]; and n is the number of variables. The initial velocities of charged particles are zero

$$v_{i,j}^{(0)} = 0 \, , i = 1,2,..,n. \tag{13}$$

Rule 3 Three conditions could be considered related to the kind of the attractive forces: Any CP can affect another one; i.e., a bad CP can affect a good one and vice versa ($p_{ij} = 1$). A CP can attract another if its electric charge amount (fitness with revise relation in minimizing problems) is better than other. In other words, a good CP attracts a bad CP:

$$p_{ij} = \begin{cases} 1 & \text{fit(j)} > fit(i), \\ 0 & \text{else} \end{cases} \tag{14}$$

All good CPs can attract bad CPs and only some of bad agents attract good agents, considering following probability function:

$$p_{ij} = \begin{cases} 1 & \frac{\text{fit(i)}-\text{fitbest}}{\text{fit(j)}-\text{fit(i)}} > \text{rand} v \text{fit(j)} > \text{fit(i)} \\ 0 & \text{else} \end{cases} \tag{15}$$

According to the above conditions, when a good agent attracts a bad one, the exploitation ability for the algorithm is provided, and vice versa if a bad CP attracts a good CP, the exploration is provided. When a CP moves toward a good agent it improves its performance, and so the self-adaptation principle is guaranteed. Moving a good CP toward a bad one may cause losing the previous good solution or at least increasing the computational cost to find a good solution. To resolve this problem, a memory which saves the best-so-far solution can be considered. Therefore, it seems that the third kind of the above conditions is the best rule because of providing strong exploration ability and an efficient exploitation.
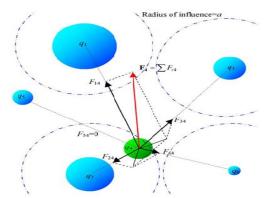

Figure 1: Determination of the resultant electrical force acting on a CP

Rule 4 the value of the resultant electrical force acting on a CP is

$$F_j = q_j \sum_{i,i\neq j} \left(\frac{q_i}{a^3} r_{ij} \cdot i_1 + \frac{q_i}{r_{ij}^2} \cdot i_2 \right) p_{ij}(X_i - X_j), \begin{cases} j = 1,2,..,N \\ i_1 = 1, i_2 = 0 \Leftrightarrow r_{ij} < a \\ i_1 = 0, i_2 = 1 \Leftrightarrow r_{ij} \geq a \end{cases} \tag{16}$$

Where Fj is the resultant force acting on the j th CP, as illustrated in Fig. 1.

In this algorithm, each CP is considered as a charged sphere with radius a, which has a uniform volume charge density. In this paper, the magnitude of set to unity; however, for more complex examples, the appropriate value for a must be defined considering the size of the search space. One can utilize the following equation as a general formula:

$$a = 0.10 \times \max(\{x_{i,max} - x_{i,min} |\, i = 1,2,..,n\}). \tag{17}$$

According to this rule, in the first iteration where the agents are far from each other the magnitude of the resultant force acting on a CP is inversely proportional to the square of the separation between the particles. Thus the exploration power in this condition is high because of performing more searches in the early iterations. It is necessary to increase the exploitation of the algorithm and to decrease the exploration gradually. After a number of searches where CPs are collected in a small space and the separation between the CPs becomes small, say 0.1, then the resultant force becomes proportional to the separation distance of the particles instead of being inversely proportional to the square of the separation distance. Therefore, the parameter a separates the global search phase and the local search phase, i.e., when majority of the agents are collected in a space with radius a, the global search is finished and the optimizing process is continued by improving the previous results, and thus the local search starts. Besides, using these principles controls the balance between the exploration and the exploitation. It should be noted that this rule considers the competition step of the algorithm. Since the resultant force is proportional to the magnitude of the charge, a better fitness (great qi) can create a stronger attracting force, so the tendency to move toward a good CP becomes more than toward a bad particle.

Rule 5 the new position and velocity of each CP is

$$X_{j,new} = rand_{j1} \cdot k_a \cdot \frac{F_j}{m_j} \cdot \Delta t^2 + rand_{j2} \cdot k_v \cdot V_{j,old} \cdot \Delta t + X_{j,old}, \tag{18}$$

$$V_{j,new} = \frac{X_{j,new} - X_{j,old}}{\Delta t}, \tag{19}$$

Where ka is the acceleration coefficient; kv is the velocity coefficient to control the influence of the previous velocity; and rand j1 and rand j2 are two random numbers uniformly distributed in the range of (0,1). Here, m j is the mass of the jth CP which is equal to qj · Δtis the time step and is set to unity. The effect of the pervious velocity and the resultant force acting on a CP can be decreased or increased based on the values of the kv and ka, respectively. Excessive search in the early iterations may improve the exploration ability; however, it must be decreased gradually, as described before. Since ka is the parameter related to the attracting forces, selecting a large value for this parameter may cause a fast convergence and vice versa a small value can increase the computational time. In fact ka t is a control parameter of the exploitation. Therefore, choosing an incremental function can improve the performance of the algorithm. Also, the direction of the pervious velocity of a CP is not necessarily the same as the resultant force. Thus, it can be concluded that the velocity coefficient kv controls the exploration process and therefore a decreasing function can be selected. Thus, kv and ka are defined as,

$$k_v = 0.5(1 - iter/iter_{max}), k_a = 0.5(1 + iter/iter_{max}) \tag{20}$$

Where iter is the actual iteration number and itermax is the maximum number of iterations. With this equation, kv decreases linearly to zero while ka increases to one when the number of iterations rises. In this way, the balance between the exploration and the fast rate of convergence is saved. Considering the values of these parameters, Eqs. (21) and (22) can be rewritten as

$$X_{j,new} = 0.5 rand_{j1} \cdot (1 + iter/iter_{max}) \cdot \sum_{i,i\neq j} \left(\frac{qi}{a^3} r_{ij} \cdot i_1 + \frac{qi}{r_{ij}^2} \cdot i_2 \right) p_{ij}(X_i - x_j) + 0.5 rand_{j2} \cdot$$

$$(1 + iter/iter_{max}) \cdot V_{j,old} + X_{j,old} \tag{21}$$

$$V_{j,new} = X_{j,new} - X_{j,old,} \tag{22}$$

Figure 5 illustrates the motion of a CP to its new position using this rule. The rules 5 and 6 provide the cooperation step of the CPs, where agents collaborate with each other by information transferring.

Rule 6 considering a memory which saves the best CP vectors and their related objective function values can improve the algorithm performance without increasing the computational cost. To fulfill this aim, Charged Memory (CM) is utilized to save a number of the best so far solutions. In this paper, the size of the CM (i.e. CMS) is taken as N/4. Another benefit of the CM consists of utilizing this memory to guide the current CPs. In other words, the vectors stored in the CM can attract current CPs according to Eq. (16). Instead, it is assumed that the same number of the current worst particles cannot attract the others.
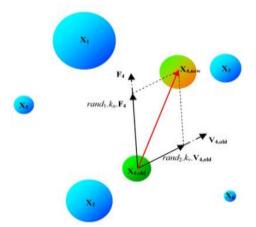

Figure 2: The movement of a CP to the new position

Rule 7 There are two major problems in relation to many meta-heuristic algorithms; the first problem is the balance between exploration and exploitation in the beginning, during, and at the end of the search, and the second is how to deal with an agent violating the limits of the variables. The first problem is solved naturally through the application of above-stated rules; however, in order to solve the second problem, one of the simplest approaches is utilizing the nearest limit values for the violated variable. Alternatively, one can force the violating particle to return to its previous position, or one can reduce the maximum value of the velocity to allow fewer particles to violate the variable boundaries. Although these approaches are simple, they are not sufficiently efficient and may lead to reduce the exploration of the search space. This problem has previously been addressed and solved using the harmony search-based handling

approach [38]. According to this mechanism, any component of the solution vector violating the variable boundaries can be regenerated from the CM as

$$x_{i,j} = \begin{cases} w.\,p.\,CMCR \\ w.\,p.\,(1-CMCR) \end{cases} \tag{23}$$

 Subject to
⇒Select a new value for a variable from CM
⇒w.p (1-PAR) do nothing
⇒w.p.PAR choose a neighbouring value
⇒select a new value

where "w.p." is the abbreviation for "with the probability"; xij is the i th component of the CP j ; The CMCR (the Charged Memory Considering Rate) varying between 0 and 1 sets the rate of choosing a value in the new vector from the historic values stored in the CM, and (1 – CMCR)sets the rate of randomly choosing one value from the possible range of values. The pitch adjusting process is performed only after a value is chosen from CM. The value (1−PAR) sets the rate of doing nothing, and PAR sets the rate of choosing a value from neighbouring the best CP.

Rule 8 the terminating criterion is one of the following:
Maximum number of iterations: the optimization process is terminated after a fixed number of iterations, for example, 1,000 iterations. Number of iterations without improvement: the optimization process is terminated after some fixed number of iterations without any improvement. Minimum objective function error: the difference between the values of the best objective function and the global optimum is less than a pre-fixed anticipated threshold. Difference between the best and the worst CPs: the optimization process is stopped if the difference between the objective values of the best and the worst CPs becomes less than a specified accuracy. Maximum distance of CPs: the maximum distance between CPs is less than a pre-fixed value. Now we can establish a new optimization algorithm utilizing the above rules.

Adaptive Charged System Search Algorithm (ACA) For Solving Optimal Power Problem

Level 1: Initialization
Step 1: Initialization. Initialize ACA algorithm parameters; Initialize an array of Charged Particles with random positions and their associated velocities (Rules 1 and 2).
Step 2: CP ranking. Evaluate the values of the fitness function for the CPs, compare with each other and sort increasingly.
Step 3: CM creation. Store the CMS number of the first CPs and their related values of the objective function in the CM.
Level 2: Search
Step 1: Attracting force determination. Determine the probability of moving each CP toward others (Rule 3), and calculate the attracting force vector for each CP (Rule 4).
Step 2: Solution construction. Move each CP to the new position and find the velocities (Rule 5).
Step 3: CP position correction. If each CP exits from the allowable search space, correct its position using Rule 7.

Step 4: CP ranking. Evaluate and compare the values of the objective function for the new CPs, and sort them increasingly.

Step 5: CM updating. If some new CP vectors are better than the worst ones in the CM, include the better vectors in the CM and exclude the worst ones from the CM (Rule 6)

Level 3: Terminating criterion controlling

Repeat search level steps until a terminating criterion is satisfied (Rule 8).

4. Simulation Results

At first Adaptive Charged System Search Algorithm (ACA) 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} = 12.118 p.u. Q_{load} = 3.074 p.u.

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

$\sum P_G$ = 12.462 p.u. $\sum Q_G$ = 3.3152 p.u.

P_{loss} = 0.25848 p.u. Q_{loss} = -1.2062 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	ACA
V1	1.10
V2	1.038
V3	1.037
V6	1.026
V8	1.025
V9	1.004

V12	1.010
Qc18	0.0663
Qc25	0.200
Qc53	0.0472
T4-18	1.001
T21-20	1.049
T24-25	0.868
T24-26	0.877
T7-29	1.056
T34-32	0.875
T11-41	1.014
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 [39]	0.25902	0.30854	0.27858
2	CGA [39]	0.25244	0.27507	0.26293
3	AGA [39]	0.24564	0.26671	0.25127
4	PSO-w [39]	0.24270	0.26152	0.24725
5	PSO-cf [39]	0.24280	0.26032	0.24698
6	CLPSO [39]	0.24515	0.24780	0.24673
7	SPSO-07 [39]	0.24430	0.25457	0.24752
8	L-DE [39]	0.27812	0.41909	0.33177
9	L-SACP-DE [39]	0.27915	0.36978	0.31032
10	L-SaDE [39]	0.24267	0.24391	0.24311
11	SOA [39]	0.24265	0.24280	0.24270
12	LM [40]	0.2484	0.2922	0.2641
13	MBEP1 [40]	0.2474	0.2848	0.2643
14	MBEP2 [40]	0.2482	0.283	0.2592
15	BES100 [40]	0.2438	0.263	0.2541
16	BES200 [40]	0.3417	0.2486	0.2443
17	Proposed ACA	0.22058	0.23012	0.22236

Then Adaptive Charged System Search Algorithm (ACA) has been tested in standard IEEE 118-bus test system [41].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 Adaptive Charged System Search Algorithm (ACA) in reducing the real power loss.

Table 5: Comparison results

Active power loss (MW)	BBO [42]	ILSBBO/ strategy1 [42]	ILSBBO/ strategy1 [42]	Proposed ACA
Min	128.77	126.98	124.78	116.04
Max	132.64	137.34	132.39	120.98
Average	130.21	130.37	129.22	118.76

5. Conclusion

In this paper a novel approach Adaptive Charged System Search Algorithm (ACA) used to solve optimal reactive power problem, by considering various generator constraints. To handle the mixed variables a flexible representation scheme was proposed. Adaptive Charged System Search Algorithm (ACA) is a multi-agent approach in which each agent is a Charged Particle (CP) & they affect each other based on their fitness values, separation of distances. The quantity of the resultant force is determined by using the electrostatics laws and the quality of the movement is determined using Newtonian mechanics laws. Proposed Adaptive Charged System Search Algorithm (ACA) has been tested in Standard IEEE 57,118 bus systems & real power loss has been comparatively reduced with voltage profiles are within the limits.

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