Diminution of Active Power Loss by Cooperative Animal Performance Algorithm

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Abstract; This work presents Cooperative Animal Performance Algorithm (CAPF) for solving optimal reactive power problem. In the proposed algorithm, each individual, confess three dissimilar actions; attraction, repulsion, or arbitrary and clutch two kinds of positions: conserve the position or struggle for a determined position. In this representation, the progression, which is accomplished by every individual, is determined arbitrarily (according to an inner inspiration). On the other hand, the states follow an unchanging criterion position. Consequently, it is achievable to model multifaceted cooperative behaviors with easy individual regulations and set a common memory. Projected Cooperative Animal Performance Algorithm (CAPF) has been tested in standard IEEE 14,300 bus test system and simulation results show the projected algorithm reduced the real power loss extensively.

Key words; optimal reactive power, Transmission loss, cooperative animal behavior

1. Introduction

Reactive power problem plays a key role in secure and economic operations of power system. Optimal reactive power problem has been solved by variety of types of methods [1-6]. Nevertheless numerous scientific difficulties are found while solving problem due to an assortment of constraints. Evolutionary techniques [7-16] are applied to solve the reactive power problem, but the main problem is many algorithms get stuck in local optimal solution & failed to balance the Exploration & Exploitation during the search of global solution. This research work presents Cooperative Animal Performance Algorithm (CAPF) for solving optimal reactive power problem. Projected Cooperative Animal Performance Algorithm (CAPF) reveals about how animals create group behaviors and scrutinize their evolution transversely as a variety of species. Process followed as (a) maintaining the present position for most excellent individuals, (b) progression from or to close by neighbors may be local pull or revulsion, (c) progression in arbitrarily mode (d) contend for the space inside a determined space. Every entity, therefore, confess three dissimilar actions viz. attraction, repulsion, or arbitrary and clutch two kinds of positions: conserve the position or struggle for a determined position. In this representation, the progression, which is accomplished by every individual, is determined arbitrarily (according to an inner inspiration). Projected Cooperative Animal Performance Algorithm (CAPF) has been tested in standard IEEE 14,300 bus test system and simulation results show the projected algorithm reduced the real power loss extensively.

2. Problem Formulation

Objective of the problem is to reduce the true power loss:

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

Voltage deviation given as follows:

$$\mathbf{F = P_L + \omega_v \times \text{Voltage Deviation}} \quad (2)$$

Voltage deviation given by:

$$\textbf{Voltage Deviation} = \mathbf{\sum_{i=1}^{Npq} |V_i - 1|} \quad (3)$$

Constraint (Equality)

$$\mathbf{P_G = P_D + P_L} \quad (4)$$

Constraints (Inequality)

$$\mathbf{P_{gslack}^{min}} \leq \mathbf{P_{gslack}} \leq \mathbf{P_{gslack}^{max}} \qquad (5)$$

$$\mathbf{Q_{gi}^{min}} \leq \mathbf{Q_{gi}} \leq \mathbf{Q_{gi}^{max}}, \mathbf{i} \in \mathbf{N_g} \qquad (6)$$

$$\mathbf{V_i^{min}} \leq \mathbf{V_i} \leq \mathbf{V_i^{max}}, \mathbf{i} \in \mathbf{N} \qquad (7)$$

$$\mathbf{T_i^{min}} \leq \mathbf{T_i} \leq \mathbf{T_i^{max}}, \mathbf{i} \in \mathbf{N_T} \qquad (8)$$

$$\mathrm{Q_c^{min}} \leq \mathrm{Q_c} \leq \mathrm{Q_C^{max}}, \mathrm{i} \in \mathrm{N_C} \qquad (9)$$

3. Cooperative Animal performance Algorithm

Projected Cooperative Animal Performance Algorithm (CAPF) reveals about how animals create group behaviors and scrutinize their evolution transversely as a variety of species. Process followed as (a) maintaining the present position for most excellent individuals, (b) progression from or to close by neighbors may be local pull or revulsion, (c) progression in arbitrarily mode (d) contend for the space inside a determined space. Every entity, therefore, confess three dissimilar actions viz. attraction, repulsion, or arbitrary and clutch two kinds of positions: conserve the position or struggle for a determined position. In this representation, the progression, which is accomplished by every individual, is determined arbitrarily (according to an inner inspiration). On the other hand, the states follow an unchanging criterion position. Consequently, it is achievable to model multifaceted cooperative behaviors with easy individual regulations and set a common memory.
Memory is alienated into two diverse elements, one for preserving the most excellent locations at each creation (N_g) and the other to store the most excellent historical positions in the period of the absolute evolutionary progression (N_h). main formulations based on a. Maintain the position of the most excellent individuals , b. Shift from or to close by neighbors (local pull and revulsion) , c. Shift arbitrarily, d. Contend for the space inside for a resolute distance (modernize the memory). At first initialize a set B of Np (number of population) animal positions ($\mathbf{B} = \{\mathbf{b}1, \mathbf{b}2, \ldots, \mathbf{b}N_p\}$). Every animal location $\mathbf{b}i$ is a *D*-dimensional vector which contains the parameter values. Such values are arbitrarily and consistently dispersed between the specific lower preliminary parameter bound b_j^{low} and the higher preliminary parameter bound b_j^{high}.

$$\mathrm{b\,j,i} = b_j^{low} + \mathrm{random}\ (0,1) \, . (b_j^{high} - b_j^{low});\ \mathrm{j} = 1,2,\ldots\ldots,\mathrm{D}\ ;\ \mathrm{i} = 1,2,\ldots.,\mathrm{Np} \qquad (10)$$

All the preliminary positions **B** are arranged according to the fitness function value to figure out a new-fangled individual set $\mathbf{Y} = \{\mathbf{y}1, \mathbf{y}2, \ldots, \mathbf{y}N_p\}$, and the most excellent *B* positions can be stored them in the memory $\mathbf{N}_g$ and $\mathbf{N}_h$. The reality is that t both memories share the similar information that will be allowed in the preliminary stage. Specific animal group is employed as an evolutionary procedure in the approach. In this procedure, the first *B* elements ($\{\mathbf{b}1, \mathbf{b}2, \ldots, \mathbf{b}_B\}$), of the new-fangled animal position set **B**, are engendered. Such positions are calculated by the value restricted within the historical memory $\mathbf{N}_h$, in view of a small arbitrary perturbation in the region around. This process is indicated by:

$$\mathrm{b_l} = n_h^l + v \qquad (11)$$

While $\boldsymbol{n_h^l}$ symbolize the *l*-element of the historical memory $\mathbf{N}_h$. **v** is a arbitrary vector with a miniature enough length. A consistent arbitrary number r_m is engendered inside the range [0, 1]. If r_m is smaller than the threshold T*H*, then a resolute individual position is attracted or repelled by taking into account the adjoining most excellent historical position within the group (adjoining position in $\mathbf{N}_h$); or else, it is attracted or repelled to/from the adjoining most excellent location within the group for the present generation (adjoining position in $\mathbf{N}_g$). Consequently such operation can be represented by:

$$\mathrm{b_i} = \begin{cases} y_i \pm r\,.(n_h^{nearest} - y_i) & with\ probability\ TH \\ y_i \pm r\,.\left(n_g^{nearest} - y_i\right) & with\ probability\ (1-TH) \end{cases} \qquad (12)$$

Where $i \in \{B+1, B+2, \ldots, N_p\}$, $n_h^{nearest}$ and $n_g^{nearest}$ represent the adjoining elements of $\mathbf{N}_h$ and $\mathbf{N}_g$ to $\mathbf{y}_i$, while r is a arbitrary number [−1, 1]. Consequently, if $r > 0$, the individual position $\mathbf{y}i$ is attracted to the position $n_h^{nearest}$ or $n_g^{nearest}$ or else such progression is measured as a revulsion. Under probability Py, one animal arbitrarily change its position and denoted by

$$b_i = \begin{cases} r & with\ probability\ Py \\ y_i & with\ probability\ (1-Py) \end{cases} \quad (13)$$

In the projected algorithm, the historical memory $\mathbf{N}_h$ is modernized by taking into account of the subsequent process; Step a. $\mathbf{N}_h$, $\mathbf{N}_g$ elements are combined into $\mathbf{N}_U$ ($\mathbf{N}_U = \mathbf{N}_h \cup \mathbf{N}_g$). Step b. Every element m_u^i of the memory $\mathbf{N}_U$ is compared couple wise to the left over memory elements ($\{n_u^1, n_u^2, \ldots n_u^{2B-1},\}$). When the distance between both elements is less than ρ, then the element receiving an improved performance in the fitness function evaluation and others will be removed. Step c. Commencing from the ensuing elements of $\mathbf{N}_U$ (from Step b), it is chosen the B as most excellent value to construct the new-fangled $\mathbf{N}_h$. Memory elements are considered with solutions that clutch the most excellent fitness value inside the area "ρ" distance. Process perks up the exploration capability by integrating the information of the previously established probable solutions throughout the algorithm's development. Most common, the value of ρ depends on the dimension of the exploration space. A gigantic value of ρ perks up the exploration capability of the algorithm even though it yields an inferior convergence rate and ρ value, calculated by:

$$\rho = \frac{\Pi_{j=1}^{D}\ (b_j^{high} - b_j^{low})}{10\ .\ D} \quad (14)$$

Step a. Initialize the parameters

Step b. Engender arbitrarily the position of set B by equation $b\ j, i = b_j^{low} + \text{random}\ (0,1) . (b_j^{high} - b_j^{low})$
Step c. Arrange B with reference to the objective function to construct Y = {y1, y2, . . . yNp}. By using the objective function Fitness evaluations of the animals of the problem has been done based on the results of Newton–Raphson power flow analysis

Step d. Pick the primary B positions of Y and accumulate them into the memory N_g.

Step e. Modernize the value of N_h and in the first iteration it is maintained that : $N_h = N_g$).

Step f. Engender the first B positions from the new-fangled solution set B ({b1, b2, . . . , b_B}).Such position match up to the elements of N_h creating a small arbitrary perturbation in the region, $b_l = n_h^l + v$

Step g. Engender the remaining B elements by using attraction, repulsion and arbitrary movements.
Step h. Modernize the parameter values
Step i. Check for the constraints of the problem

Step j. When Number of Iterations is completed the procedure will be stopped; or else, go back to Step c.
Step k . Most excellent value in N_h symbolizes the global solution.

4. Simulation results

At first in standard IEEE 14 bus system the validity of the proposed Cooperative Animal Performance Algorithm (CAPF) has been tested & comparison results are presented in Table 1.

Control variables	ABCO [19]	IABCO [19]	CAPF
V1	1.06	1.05	1.02
V2	1.03	1.05	1.01
V3	0.98	1.03	1.04

V6	1.05	1.05	1.00
V8	1.00	1.04	0.90
Q9	0.139	0.132	0.100
T56	0.979	0.960	0.900
T47	0.950	0.950	0.900
T49	1.014	1.007	1.000
Ploss (MW)	5.92892	5.50031	4.1896

Then IEEE 300 bus system [18] is used as test system to validate the performance of the Cooperative Animal Performance Algorithm (CAPF).Table 2 shows the comparison of real power loss obtained after optimization.

Table 2 Comparison of Real Power Loss

Parameter	Method EGA [21]	Method EEA [21]	Method CSA [20]	CAPF
PLOSS (MW)	646.2998	650.6027	635.8942	619.9982

5. Conclusion

In this work Cooperative Animal Performance Algorithm (CAPF) has been successfully solved the optimal reactive power problem. Memory elements are considered with solutions that clutch the most excellent fitness value inside the area "ρ" distance. Process perks up the exploration capability by integrating the information of the previously established probable solutions throughout the algorithm's development. Projected Cooperative Animal Performance Algorithm (CAPF) has been tested in standard IEEE 14,300 bus test system and simulation results show the projected algorithm reduced the real power loss extensively.

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