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REDUCTION OF ACTIVE POWER LOSS BY COYOTE SEARCH ALGORITHM

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Abstract

This paper presents Coyote Search Algorithm (CSA) for solving optimal reactive power problem. Coyote Search Algorithm is a new bio – inspired heuristic algorithm which based on coyote preying behaviour. The way coyote search for food and survive by avoiding their enemies has been imitated to formulate the algorithm for solving the reactive power problem. And the specialty of coyote is possessing both individual local searching ability & autonomous flocking movement and this special property has been utilized to formulate the search algorithm. The proposed Coyote Search Algorithm (CSA) has been tested on standard IEEE 57 bus test system and simulation results shows clearly about the good performance of the proposed algorithm in reducing the real power loss.

Keywords: Coyote Search Algorithm; Optimal Reactive Power; Transmission Loss.

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1. Introduction

Reactive power optimization places an important role in optimal operation of power systems. Various numerical methods like the gradient method [1,2], Newton method [3] and linear programming [4-7] 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 [8] Evolutionary algorithms such as genetic algorithm have been already projected to solve the reactive power flow problem [9-11]. Evolutionary algorithm is a heuristic methodology used for minimization problems by utilizing nonlinear and non-differentiable continuous space functions. In [12], Hybrid differential evolution algorithm is projected to increase 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 elucidate the optimal reactive power dispatch problem. In [16], the optimal reactive power flow problem is solved by integrating a

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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 [18-20] proposes a two-step approach to calculate Reactive power reserves with respect to operating constraints and voltage stability. This paper presents Coyote Search Algorithm (CSA) for solving optimal reactive power problem. Coyote Search Algorithm is a new bio – inspired heuristic algorithm which based on coyote preying behaviour. The way coyote search for food and survive by avoiding their enemies has been imitated to formulate the algorithm for solving the reactive power problem. And the specialty of coyote possesses both individual local searching ability & autonomous flocking movement and this special property has been utilized to formulate the search algorithm. Coyote hunts independently by remembering its own trait and it will merge with its peer when the peer is in better position.The swarming behaviour of CSA has more advantage than that of algorithms like PSO [21], Fish [22] and Firefly [23]. CSA functions as multiple leaders swarming from multiple directions [24] to reach the best solution, ratherthan searching as a single flock. How the Coyote jumps far out of its hunter’s visual range to avoid being trapped like that algorithm design will jump away from the local optimal solution. The Coyotes in the nature have best memory capability for they can hide food in caches; also they sense and track down a prey from distances of miles away.They themselves do set markers in theirterritory in various methods like by urinating at the borders. Main assumption is that the Coyotes are functioning as searching agents in the CSA optimization algorithm are empowered by memory caches that can able to store thepreviously visited various positions. The proposed Coyote Search Algorithm (CSA) has been tested on standard IEEE 57 bus test system and simulation results shows clearly about the good performance of the proposed algorithm in reducing the real power loss.

2. Problem Formulation

Main objective of the reactive power problem is to minimize the real power loss.

2.1. Active Power Loss

The objective of the reactive power dispatch problem is to minimize the active power loss and can be written in equations as follows:

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

Where F- objective function, P_L – power loss, g_k- conductance of branch,V_i and V_j are voltages at buses i,j, Nbr- total number of transmission lines in power systems.

2.2. Voltage Profile Improvement

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

$$\mathrm{F} = P_L + \omega_{\mathrm{v}} \times \mathrm{VD} \quad (2)$$

Where VD - voltage deviation,ω_v- is a weighting factor of voltage deviation.
And the Voltage deviation given by:

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

Where Npq- number of load buses

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 P_G- total power generation, P_D - total power demand.

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 (P_g), and reactive power of generators (Q_g) 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) is given by:

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

Upper and lower bounds on the transformers tap ratios (T_i) is given by:

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

Upper and lower bounds on the compensators (Q_c) is given by:

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

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

3. Coyote Search Algorithm

Coyotes are social predators that hunt in packs and uses stealth when huntingprey together. In behaviour of ants it utilizes pheromones to communicate with their peers to know about food source which decreases the run time of thesearch. Coyotes are unique, partially cooperative characteristics and usually move in a group in coupled formation, but have tendency to take down the prey individually. Coyote Search Algorithm (CSA) naturally balances scouting theproblem space in random groups and individual. During hunting, Coyotes will group themselvesas they approach their prey. This peculiar characteristic prompts the searching agents in CSA to move for abetter position,like the same way Coyotes continuouslychange their positions for better ones. When hunting, Coyotessearch for prey and also keenly watch the threats from hunters or other animals like tigers etc. Each Coyotein the pack chooses itsown way & position continuously moving to a better state for the prey andalso for threats in all directions. When Coyotes' bumping into their enemies it is well equipped with a threat probability and it dashes a greatdistance away from its present position. The same way in CSA avoids the deadlock of getting trapped in local optimal solution. The direction and distance the Coyote moving away from a threat are random, and is similar to mutation and crossover in Genetic algorithm.Coyotes have very high sense of smell and it can easily locateprey by scent. Similarly, in the CSA each Coyote has a sensing distance that creates visual distance. This visual distance is applied to search the global optimum and in moving to a better position and for jumping out of visual range. In search mode, the Coyotes are move in Brownian motion (BM), which imitates the random drifting of particles suspended in fluid.

Basic logics of Coyote Search

There are three rules that act as basic logics of the CoyoteSearch Algorithm (CSA)

Rule 1: Each Coyote has visual area as a fixed one and with a radius defined by v for X as a set of continuous possible solutions. Each Coyote can sense companions who are all appear within its visual circle. The footstep expanse by which the Coyote moves at a time is normally smaller than its visual distance.

Rule 2: The fitness of the objective function represents the Coyotes current position. If there is more options the Coyote will chose the best terrain inhabited by another Coyote from the given options. If not, the Coyotewillcontinue to move randomly in BM.

Rule 3: if the Coyote will sense an enemy then the Coyote will immediately escape to a random position far from the threat and beyond its visual range.

CSA implementation in based on the fitness of the objective function and it reflects the quality of a terrain position which will eventually lead to food.

Coyote often changes in position in search of food and also to safeguard form the enemies. Coyote trust with other Coyotes in movement because they never prey each other. The movement done by one Coyote will be watched by other Coyotes simultaneously and they position themselves in chance of finding food also with care of them by continuously moving. If the current coyotes location is greater the distance of the companion location, then that new location will be less attractive one even though the new position may be good one. Coyotes willingness to move is decreased means, and then that movement will obey the inverse square law. The formula is $(r) = \frac{I_o}{r^2}$, where Io is the origin of food and r is the distance between the food or we can denote that distance between the new terrain and the Coyote.

This is the similar formula in the firefly algorithm, for the calculation of attractiveness. The incentive formula for the Coyote search by using absorption coffeicient and gaussian equation , can be written as ,

$$\beta(r) = \beta_o e^{-r^2} \tag{10}$$

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Normally all the Coyotes want to move better position based on colonized by their peers position and it depends on many factors like visual distance and how the initial Coyote covers the area. Coyote will visualize the other Coyotes location each other i.e. it will compare the range of distance and set by itself in best position for preying and also from enemies. The movement can be written as

$$x(i) = x(i) + \beta_o e^{-r^2}\big(x(j) - x(i)\big) + \text{escape}(\,) \tag{11}$$

Where, escape ( ) is a function that calculates a random position to jump to with a constraint of minimum length; v, x is the Coyote, which represents a candidate solution; and x(j) is the peer with a better position as represented by the value of the fitness function. The second term of the above equation represents the change in value or gain achieved by progressing to the new position. r is the distance between the Coyote and its peer with the better location.

There are three types of preying that takes place in sequence,

Preying Initiatively

Coyote feed on prey it represents the optimization function as objective. By using the visual boundary Coyote will have step by step movement on constantly seeing the prey and it will have random movement from the current step to forward or backward depending on the prey position. If it thinks particular position as best one then it will omit other Coyotes movements. Then it will move in own direction.

Prey Passively

In passive mode the Coyote will compare the position with its peers and will improve the current position. Coyotewill move to passive mode when its own movement does not find food or insecurity for its movement.

Escape

Coyotes normally have enemies in nature and threat will be there always. If any threat is found, it will relocate very quickly form the current position to new position which will be normally greater distance than that of the normal visual range. This can be written in equation as,

$$\text{if moving} = \begin{cases} x(i) = x(i) + \alpha \cdot r \cdot \text{rand}(\,)\text{prey} \\ x(i) = x(i) + \alpha \cdot s \cdot \text{escape}\ (\,)\text{escape} \end{cases} \tag{12}$$

Where x(i) is the Coyotes location; a is the velocity; v is the visual distance; rand() is a random function whose mean value distributed in [-1,1], s is the step size, which must be smaller than v; and escape() is a custom function that randomly generates a position greater than v and less than half of the solution boundary.

Coyote algorithm for solving optimal reactive power dispatch problem

Step 1: Objective function f(x), $x=(x_1,x_2,..x_d)T$
Step 2: Initialize the population, $x_i(i=1,2,..,W)$
Step 3: initialize parameters

r = radius of the visual range
s = step size by which a Coyote moves at a time
α= velocity factor of Coyote
p_a= a user-defined threshold [0-1], determines how often foe appears
Step 4: WHILE (t<generations and also for stopping criteria is not met)
step5: FOR i=1: W // each Coyote
step6: Prey new food initiatively();
step7: Generation of new location();
step8:To check whether the next location suggested bythe random number generator is newone .
step8: If not, repeat generating random location.
Step9:IF($dist(x_i,x_j)<r$ and x_j is better as $f(x_i)<f(x_j)$)x_i moves towards x_j // x_j is a better than x_i
Step 10: ELSE IF
x_i= Prey new food passively();
Step 11: END IF
Generation of new location();
IF(rand () > pa)
$x_i = x_i$ + rand() + v; Coyote escape to a new position.
END IF
END FOR
END WHILE

4. Simulation Results

Proposed Coyote Search Algorithm (CSA) 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}= 12.019 p.u. Q_{load} = 3.014 p.u.
The total initial generations and power losses are obtained as follows:
$\sum P_G$ = 12.5526 p.u. $\sum Q_G$ = 3.3202 p.u.
P_{loss}= 0.25709 p.u. Q_{loss} = -1.2025 p.u.
Table 2 shows the various system control variables i.e. generator bus voltages, shunt capacitances and transformer tap settings obtained after CSA based optimization which are within the acceptable limits. In Table 3, shows the comparison of optimum results obtained from proposed CSA with other optimization techniques. These results indicate the robustness of proposed CSA approach 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		

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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	**CSA**
V1	1.10
V2	1.039
V3	1.042
V6	1.033
V8	1.035
V9	1.017
V12	1.021
Qc18	0.0669
Qc25	0.200
Qc53	0.0464
T4-18	1.012
T21-20	1.064
T24-25	0.886
T24-26	0.882
T7-29	1.060
T34-32	0.880
T11-41	1.021
T15-45	1.044
T14-46	0.916
T10-51	1.020
T13-49	1.061
T11-43	0.911
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 [25]	0.25902	0.30854	0.27858
2	CGA [25]	0.25244	0.27507	0.26293
3	AGA [25]	0.24564	0.26671	0.25127
4	PSO-w [25]	0.24270	0.26152	0.24725
5	PSO-cf [25]	0.24280	0.26032	0.24698
6	CLPSO [25]	0.24515	0.24780	0.24673
7	SPSO-07 [25]	0.24430	0.25457	0.24752
8	L-DE [25]	0.27812	0.41909	0.33177

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9	L-SACP-DE [25]	0.27915	0.36978	0.31032
10	L-SaDE [25]	0.24267	0.24391	0.24311
11	SOA [25]	0.24265	0.24280	0.24270
12	LM [26]	0.2484	0.2922	0.2641
13	MBEP1 [26]	0.2474	0.2848	0.2643
14	MBEP2 [26]	0.2482	0.283	0.2592
15	BES100 [26]	0.2438	0.263	0.2541
16	BES200 [26]	0.3417	0.2486	0.2443
17	Proposed CSA	0.22106	0.23124	0.22138

5. Conclusion

In this paper, Coyote Search Algorithm (CSA) has been successfully solved optimal reactive power problem. The way coyote search for food and survive by avoiding their enemies has been imitated to formulate the algorithm for solving the reactive power problem. And the specialty of coyote is possessing both individual local searching ability & autonomous flocking movement and this special property has been utilized to formulate the search algorithm. The proposed Coyote Search Algorithm (CSA) has been tested on standard IEEE 57 bus test system and simulation results shows clearly about the good performance of the proposed algorithm in reducing the real power loss.

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