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UNIQUE ALGORITHM FOR SOLVING OPTIMAL REACTIVE POWER DISPATCH PROBLEM

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Abstract

In this paper, a new algorithm based on krill herd actions, named as Antarctic krill Herd Algorithm (AKHA) is proposed for solving optimal reactive power dispatch problem. The AKHA algorithm is based on behavior of krill individuals. The minimum distance of each individual krill from food and from uppermost density of the herd are deliberated as the foremost mission for the krill movement. Projected AKHA algorithm has been tested in standard IEEE 30 bus test system and simulation results shows clearly about the good performance of the proposed algorithm in reducing the real power loss and voltage stability also improved.

Keywords: Antarctic Krill Herd; Bio-Inspired Algorithm; Optimal Reactive Power Dispatch; Transmission Loss.

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1. Introduction

Optimal reactive power dispatch problem is a multi-objective optimization problem that reduces the real power loss and bus voltage deviation by satisfying a set of physical and operational constraints enacted by apparatus limitations and security requirements. Numerous mathematical 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 has 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 accurateness. The problem of voltage stability and collapse play a major role in power system planning and operation [8]. Enhancing the voltage stability, voltage magnitudes within the limits alone will not be a reliable indicator to indicate that, how far an operating point is from the collapse point. The reactive power support and voltage problems are internally related to each other. This paper formulates by combining both the real power loss minimization and maximization of static voltage stability margin (SVSM) as the objectives. Global optimization has received extensive research awareness, and a great number of methods have been applied to solve this problem. Many evolutionary algorithms like genetic algorithm have been already proposed to solve the reactive power flow problem [9-20]. This paper proposes a new bio-inspired optimization called Antarctic krill Herd Algorithm (AKHA) for solving the optimal reactive power dispatch problem. This method is based on the simulation of the herd of the krill swarms [21] in response to specific biological and environmental processes. The proposed algorithm AKHA been evaluated in standard IEEE 30 bus test system & the simulation results shows that our proposed approach outperforms all reported algorithms in minimization of real power loss .

2. Voltage Stability Evaluation

2.1.Modal analysis for voltage stability evaluation

Modal analysis is one among best methods for voltage stability enhancement in power systems. The steady state system power flow equations are given by.

$$\begin{bmatrix}\Delta P\\ \Delta Q\end{bmatrix} = \begin{bmatrix}J_{p\theta} & J_{pv}\\ J_{q\theta} & J_{QV}\end{bmatrix} \begin{bmatrix}\Delta\theta\\ \Delta V\end{bmatrix} \quad (1)$$

Where
ΔP = Incremental change in bus real power.
ΔQ = Incremental change in bus reactive Power injection
$\Delta\theta$ = incremental change in bus voltage angle.
ΔV = Incremental change in bus voltage Magnitude

$J_{p\theta}$, J_{PV} , $J_{Q\theta}$, J_{QV} jacobian matrix are the sub-matrixes of the System voltage stability is affected by both P and Q.

To reduce (1), let $\Delta P = 0$, then.

$$\Delta Q = \left[J_{QV} - J_{Q\theta}J_{P\theta^{-1}}J_{PV}\right]\Delta V = J_R \Delta V \quad (2)$$

$$\Delta V = J^{-1} - \Delta Q \quad (3)$$

Where

$$J_R = \left(J_{QV} - J_{Q\theta}J_{P\theta^{-1}}JPV\right) \quad (4)$$

J_R is called the reduced Jacobian matrix of the system.

2.2.Modes of Voltage instability:

Voltage Stability characteristics of the system have been identified by computing the Eigen values and Eigen vectors.
Let

$$J_R = \xi \wedge \eta \quad (5)$$

Where,
ξ = right eigenvector matrix of JR

η = left eigenvector matrix of JR
∧ = diagonal eigenvalue matrix of JR and

$$J_{R^{-1}} = \xi \wedge^{-1} \eta \qquad (6)$$

From (5) and (8), we have

$$\Delta V = \xi \wedge^{-1} \eta \Delta Q \qquad (7)$$

or

$$\Delta V = \sum_I \frac{\xi_i \eta_i}{\lambda_i} \Delta Q \qquad (8)$$

Where ξi is the ith column right eigenvector and η the ith row left eigenvector of JR.
λi is the ith Eigen value of JR.

The ith modal reactive power variation is,

$$\Delta Q_{mi} = K_i \xi_i \qquad (9)$$

where,

$$K_i = \sum_j \xi_{ij^2} - 1 \qquad (10)$$

Where
ξji is the jth element of ξi

The corresponding ith modal voltage variation is

$$\Delta V_{mi} = [1/\lambda_i] \Delta Q_{mi} \qquad (11)$$

If | λi | =0 then the ith modal voltage will collapse .
In (10), let ΔQ = ek where ek has all its elements zero except the kth one being 1. Then,

$$\Delta V = \sum_i \frac{\eta_{1k}\ \xi_1}{\lambda_1} \qquad (12)$$

η_{1k} k th element of η_1
V –Q sensitivity at bus k

$$\frac{\partial V_K}{\partial Q_K} = \sum_i \frac{\eta_{1k}\ \xi_1}{\lambda_1} = \sum_i \frac{P_{ki}}{\lambda_1} \qquad (13)$$

3. Problem Formulation

The objectives of the reactive power dispatch problem is to minimize the system real power loss and maximize the static voltage stability margins (SVSM).

3.1.Minimization of Real Power Loss

Minimization of the real power loss (Ploss) in transmission lines is mathematically stated as follows.

$$P_{loss} = \sum_{\substack{k=1 \\ k=(i,j)}}^{n} g_{k(V_i^2 + V_j^2 - 2V_i V_j \cos\theta_{ij})} \qquad (14)$$

Where n is the number of transmission lines, gk is the conductance of branch k, Vi and Vj are voltage magnitude at bus i and bus j, and θij is the voltage angle difference between bus i and bus j.

3.2.Minimization of Voltage Deviation

Minimization of the voltage deviation magnitudes (VD) at load buses is mathematically stated as follows.

Minimize VD = $\sum_{k=1}^{nl} |V_k - 1.0|$ (15)

Where nl is the number of load busses and Vk is the voltage magnitude at bus k.

3.3.System Constraints

Objective functions are subjected to these constraints shown below.
Load flow equality constraints:

$$P_{Gi} - P_{Di} - V_{i \sum_{j=1}^{nb} V_j} \begin{bmatrix} G_{ij} & \cos\theta_{ij} \\ +B_{ij} & \sin\theta_{ij} \end{bmatrix} = 0, i = 1,2 \ldots., nb \quad (16)$$

$$Q_{Gi} - Q_{Di} - V_{i \sum_{j=1}^{nb} V_j} \begin{bmatrix} G_{ij} & \sin\theta_{ij} \\ +B_{ij} & \cos\theta_{ij} \end{bmatrix} = 0, i = 1,2 \ldots., nb \quad (17)$$

where, nb is the number of buses, PG and QG are the real and reactive power of the generator, PD and QD are the real and reactive load of the generator, and Gij and Bij are the mutual conductance and susceptance between bus i and bus j.

Generator bus voltage (VGi) inequality constraint:

$V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{max}, i \in ng$ (18)

Load bus voltage (VLi) inequality constraint:

$V_{Li}^{min} \leq V_{Li} \leq V_{Li}^{max}, i \in nl$ (19)

Switchable reactive power compensations (QCi) inequality constraint:

$Q_{Ci}^{min} \leq Q_{Ci} \leq Q_{Ci}^{max}, i \in nc$ (20)

Reactive power generation (QGi) inequality constraint:

$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max}, i \in ng$ (21)

Transformers tap setting (Ti) inequality constraint:

$T_i^{min} \leq T_i \leq T_i^{max}, i \in nt$ (22)

Transmission line flow (SLi) inequality constraint:

$S_{Li}^{min} \leq S_{Li}^{max}, i \in nl$ (23)

Where, nc, ng and nt are numbers of the switchable reactive power sources, generators and transformers.

4. Antarctic krill Herd Algorithm (AKHA)

The Antarctic krill Herd Algorithm (AKHA) imitates the systematic activities of krill. When predators, such as seals, penguins or seabirds, attack krill, they eliminate individual krill. This results in dropping the krill density. The configuration of the krill herd after predation depends on many parameters. The herding of the krill individuals is a multi-objective process including two key goals: (a) escalating krill density, and (b) attainment food. In the present study, this process is taken into account to propose a new metaheuristic algorithm for solving global optimization problems. Thickness-dependent hold of krill (increasing density) and finding food (areas of high food concentration) are used as objectives which finally lead the krill to herd around the global minima. In this process, an individual krill moves toward the best solution when it searches for the highest density and food. They are i. progress induced by other krill individuals; ii. Foraging activity; and iii. Random diffusion. The krill individuals try to maintain a high density and move due to their mutual effects [22]. The direction of motion induced, α_i , is estimated from the local swarm density (local effect), a target swarm density (target effect), and a repulsive swarm density (repulsive effect) . For a krill individual, this movement can be defined as:

$$N_i^{new} = N^{max}\alpha_i + \omega_n N_i^{old} \tag{24}$$

Where

$$\alpha_i = \alpha_i^{local} + \alpha_i^{target} \tag{25}$$

And N^{max} is the maximum induced speed, ω_n is the inertia weight of the motion induced in the range [0, 1], N_i^{old} is the last motion induced, α_i^{local} is the local effect provided by the neighbours and α_i^{target} is the target direction effect provided by the best krill individual. According to the measured values of the maximum induced speed.
The effect of the neighbours in a krill movement individual is determined as follows:

$$\alpha_i^{local} = \sum_{j=1}^{NN} \widehat{K}_{ij} \widehat{X}_{ij} \tag{26}$$

$$\widehat{X}_{i,j} = \frac{X_j - X_i}{\|X_j - X_i\| + \varepsilon} \tag{27}$$

$$\widehat{K}_{i,j} = \frac{K_i - K_j}{K^{worst} - K^{best}} \tag{28}$$

where K^{best} and K^{worst} are the best and the worst fitness values of the krill individuals so far; K_i represents the fitness or the objective function value of the ith krill individual; K_j is the fitness of jth (j = 1,2,. . .,NN) neighbour; X represents the related positions; and NN is the number of the neighbours. For avoiding the singularities, a small positive number,ε, is added to the denominator.

The sensing distance for each krill individual can be determined by using the following formula for each iteration:

$$d_{s,i} = \frac{1}{5N} \sum_{j=1}^{N} \|X_i - X_j\| \tag{29}$$

Where $d_{s,i}$ the sensing distance for the ith krill is individual and N is the number of the krill individuals. The factor 5 in the denominator is empirically obtained. Using Eq. (29), if the distance of two krill individuals is less than the defined sensing distance, they are neighbours.

The effect of the individual krill with the best fitness on the ith individual krill is taken into account by using the formula

$$\alpha_i^{target} = C^{best}\widehat{K}_{i,best}\widehat{X}_{i,best} \quad (30)$$

Where, C^{best} is the effective coefficient of the krill individual with the best fitness to the ith krill individual. This coefficient is defined since α_i^{target} leads the solution to the global optima and it should be more effective than other krill individuals such as neighbours. Herein, the value of C^{best} is defined as:

$$C^{best} = 2\left(rand + \frac{I}{I_{max}}\right) \quad (31)$$

Where rand is a random value between 0 and 1 and it is for enhancing exploration, "I" is the actual iteration number and I_{max} is the maximum number of iterations.
The Foraging motion can be expressed for the ith krill individual as follows:

$$F_i = V_f\beta_i + \omega_f F_i^{old} \quad (32)$$

Where

$$\beta_i = \beta_i^{food} + \beta_i^{best} \quad (33)$$

And V_f is the foraging speed, ω_f is the inertia weight of the foraging motion in the range [0, 1], is the last foraging motion, $\beta_i^{food}$is the food attractive and β_i^{best} is the effect of the best fitness of the ith krill so far. According to the measured values of the foraging speed.

The centre of food for each iteration is formulated as:

$$X^{food} = \frac{\sum_{i=1}^{N}\frac{1}{K_i}X_i}{\sum_{i=1}^{N}\frac{1}{K_i}} \quad (34)$$

Therefore, the food attraction for the ith krill individual can be determined as follows:

$$\beta_i^{food} = C^{food}\widehat{K}_{i,food}\widehat{X}_{i,food} \quad (35)$$

Where C^{food} is the food coefficient. Because the effect of food in the krill herding decreases during the time, the food coefficient is determined as:

$$C^{food} = 2\left(1 - \frac{I}{I_{max}}\right) \quad (36)$$

The food attraction is defined to possibly attract the krill swarm to the global optima. Based on this definition, the krill individuals normally herd around the global optima after some iteration. This can be considered as an efficient global optimization strategy which helps improving the globalist of the Krill Herd Algorithm. The effect of the best fitness of the ith krill individual is also handled using the following equation:

$$\beta_i^{best} = \widehat{K}_{i,ibest}\widehat{X}_{i.ibest} \qquad (37)$$

Where $K_{i.ibest}$ is the best previously visited position of the ith krill individual.

The physical diffusion of the krill individuals is considered to be a random process. This motion can be express in terms of a maximum diffusion speed and a random directional vector. It can be formulated as follows:

$$D_i = D^{max}\delta \qquad (38)$$

Where D^{max} is the maximum diffusion speed, and δ is the random directional vector and its arrays are random values between -1 and 1. This term linearly decreases the random speed with the time and works on the basis of a geometrical annealing schedule:

$$D_i = D^{max}\left(1 - \frac{I}{I_{max}}\right)\delta \qquad (39)$$

The physical diffusion performs a random search in the proposed method. Using different effective parameters of the motion during the time, the position vector of a krill individual during the interval t to t + Δt is given by the following equation

$$X_i(t + \Delta t) = X_i(t) + \Delta t\frac{dX_i}{dt} \qquad (40)$$

It should be noted that Δt is one of the most important constants and should be carefully set according to the optimization problem. This is because this parameter works as a scale factor of the speed vector. Δt Completely depends on the search space and it seems it can be simply obtained from the following formula:

$$\Delta t = C_t \sum_{j=1}^{NV}\left(UB_j - LB_j\right) \qquad (41)$$

Where NV is the total number of variables, LB_j and UB_j are lower and upper bounds of the jth variables (j = 1,2,. . .,NV),respectively. Therefore, the absolute of their subtraction shows the search space. It is empirically found that C_t is a constant number between [0, 2]. It is also obvious that low values of C_t let the krill individuals to search the space carefully.

To improve the performance of the algorithm, genetic reproduction mechanisms are integrated into the algorithm.

a. Crossover

The binomial scheme performs crossover on each of the d components or variables/parameters. By generating a uniformly distributed random number between 0 and 1, the mth component of X_i , $X_{i,m}$, is manipulated as:

$$X_{i,m} = \begin{cases} X_{r,m} \ rand_{i,m} < Cr \\ X_{i,m} \quad else \end{cases} \tag{42}$$

$$C_r = 0.2\hat{K}_{i,best} \tag{43}$$

Where r ∈ {1, 2,. ..,N}. Using this new crossover probability, the crossover probability for the global best is equal to zero and it increases with decreasing the fitness.

b. Mutation

The mutation process used here is formulated as:

$$X_{i,m} = \begin{cases} X_{gbes,m} + \mu(X_{p,m} - X_{q,m}) rand_{i,m} < Mu \\ X_{i,m} \qquad\qquad else \end{cases} \tag{44}$$

$$Mu = 0.05/\hat{K}_{i,best} \tag{45}$$

Where p, q ∈{1, 2, .,K} and l is a number between 0 and 1. It should be noted in $\hat{K}_{i,best}$the nominator is K_i-$K^{best.}$

Antarctic krill Herd Algorithm (AKHA) for solving optimal reactive power dispatch problem.

Describing the modest limits & algorithm constraint

Initialize: Arbitrarily generate the preliminary population in the exploration space.

Fitness appraisal: Assessment of each krill individual rendering to its position.

Motion calculation:

a) Motion tempted by the existence of other individuals,
b) Foraging motion
c) Physical diffusion

Applying the genetic operators

Apprising: modernizing the krill individual position in the exploration space.

Reiterating: go to step fitness assessment until the end criteria is reached.

Termination

5. Simulation Results

The efficiency of the proposed Antarctic krill Herd Algorithm (AKHA) is demonstrated by testing it on standard IEEE-30 bus system. The IEEE-30 bus system has 6 generator buses, 24 load buses and 41 transmission lines of which four branches are (6-9), (6-10) , (4-12) and (28-27) - are with the tap setting transformers. The lower voltage magnitude limits at all buses are 0.95 p.u. and the upper limits are 1.1 for all the PV buses and 1.05 p.u. for all the PQ buses and the reference bus. The simulation results have been presented in Tables 1, 2, 3 &4. And in the Table

5 shows the proposed algorithm powerfully reduces the real power losses when compared to other given algorithms. The optimal values of the control variables along with the minimum loss obtained are given in Table 1. Corresponding to this control variable setting, it was found that there are no limit violations in any of the state variables.

Table 1: Results of AKHA – ORPD optimal control variables

Control variables	**Variable setting**
V1	1.041
V2	1.040
V5	1.046
V8	1.031
V11	1.001
V13	1.034
T11	1.00
T12	1.00
T15	1.01
T36	1.01
Qc10	3
Qc12	3
Qc15	2
Qc17	0
Qc20	2
Qc23	3
Qc24	3
Qc29	2
Real power loss	4.2872
SVSM	0.2486

Optimal Reactive Power Dispatch problem together with voltage stability constraint problem was handled in this case as a multi-objective optimization problem where both power loss and maximum voltage stability margin of the system were optimized simultaneously. Table 2 indicates the optimal values of these control variables. Also it is found that there are no limit violations of the state variables. It indicates the voltage stability index has increased from 0.2486 to 0.2492, an advance in the system voltage stability. To determine the voltage security of the system, contingency analysis was conducted using the control variable setting obtained in case 1 and case 2. The Eigen values equivalents to the four critical contingencies are given in Table 3. From this result it is observed that the Eigen value has been improved considerably for all contingencies in the second case.

Table 2: Results of AKHA -Voltage Stability Control Reactive Power Dispatch Optimal Control Variables

Control Variables	**Variable Setting**
V1	1.044
V2	1.048
V5	1.045
V8	1.031
V11	1.004
V13	1.031
T11	0.090
T12	0.090
T15	0.090
T36	0.090
Qc10	3
Qc12	3
Qc15	2
Qc17	3
Qc20	0
Qc23	2

Qc24	2
Qc29	3
Real power loss	4.9889
SVSM	0.2492

Table 3: Voltage Stability under Contingency State

Sl.No	Contingency	ORPD Setting	VSCRPD Setting
1	28-27	0.1419	0.1434
2	4-12	0.1642	0.1650
3	1-3	0.1761	0.1772
4	2-4	0.2022	0.2043

Table 4: Limit Violation Checking Of State Variables

State variables	limits		ORPD	VSCRPD
	Lower	upper		
Q1	-20	152	1.3422	-1.3269
Q2	-20	61	8.9900	9.8232
Q5	-15	49.92	25.920	26.001
Q8	-10	63.52	38.8200	40.802
Q11	-15	42	2.9300	5.002
Q13	-15	48	8.1025	6.033
V3	0.95	1.05	1.0372	1.0392
V4	0.95	1.05	1.0307	1.0328
V6	0.95	1.05	1.0282	1.0298
V7	0.95	1.05	1.0101	1.0152
V9	0.95	1.05	1.0462	1.0412
V10	0.95	1.05	1.0482	1.0498
V12	0.95	1.05	1.0400	1.0466
V14	0.95	1.05	1.0474	1.0443
V15	0.95	1.05	1.0457	1.0413
V16	0.95	1.05	1.0426	1.0405
V17	0.95	1.05	1.0382	1.0396
V18	0.95	1.05	1.0392	1.0400
V19	0.95	1.05	1.0381	1.0394
V20	0.95	1.05	1.0112	1.0194
V21	0.95	1.05	1.0435	1.0243
V22	0.95	1.05	1.0448	1.0396
V23	0.95	1.05	1.0472	1.0372
V24	0.95	1.05	1.0484	1.0372
V25	0.95	1.05	1.0142	1.0192
V26	0.95	1.05	1.0494	1.0422
V27	0.95	1.05	1.0472	1.0452

V28	0.95	1.05	1.0243	1.0283
V29	0.95	1.05	1.0439	1.0419
V30	0.95	1.05	1.0418	1.0397

Table 5: Comparison of Real Power Loss

Method	**Minimum loss**
Evolutionary programming [23]	5.0159
Genetic algorithm [24]	4.665
Real coded GA with Lindex as SVSM [25]	4.568
Real coded genetic algorithm [26]	4.5015
Proposed AKHA method	4.2872

6. Conclusion

In this paper, the Antarctic krill Herd Algorithm (AKHA) has been efficaciously applied to solve optimal reactive power dispatch problem. The chief benefits of AKHA to the given problem is optimization of different type of objective function, real coded of both continuous and discrete control variables, and easily handling nonlinear constraints. Projected AKHA method has been tested in standard IEEE 30-bus system .simulation results reveals about the minimization of real power loss & voltage stability index also augmented when compared to other reported standard algorithms.

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