



Science

**ANTELOPE ALGORITHM FOR SOLVING OPTIMAL REACTIVE  
POWER DISPATCH PROBLEM****Dr.K.Lenin** <sup>\*1</sup><sup>\*1</sup> Professor, Prasad V.Potluri Siddhartha Institute of Technology, Kanuru, Vijayawada, Andhra Pradesh -520007, India**Abstract**

In this paper, Antelope Algorithm (AA) is proposed for solving optimal reactive power dispatch problem. A population of candidate solution move toward as a herd of Antelope out a sequence of jumps through the exploration space in order to find the most outstanding solution. The main idea of this algorithm is fairly different from the population based algorithms, as the individual solutions are stirred collectively in a herd-like approach. Projected Antelope Algorithm (AA) algorithm has been tested in standard IEEE 30 bus test system and simulation results show clearly about the superior performance of the projected algorithm in reducing the real power loss.

**Keywords:** Modal Analysis; Optimal Reactive Power; Transmission Loss; Antelope Algorithm.

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**1. Introduction**

Optimal reactive power dispatch (ORPD) problem is a multi-objective optimization problem that diminishes the real power loss and bus voltage deviation. Various mathematical techniques 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]. Global optimization has received extensive research awareness, and a great number of methods have been applied to solve this problem. Evolutionary algorithms such as genetic algorithm have been already proposed to solve the reactive power flow problem [9,10]. Evolutionary algorithm is a heuristic approach used for minimization problems by utilizing nonlinear and non-differentiable continuous space functions. In [11], Genetic algorithm has been used to solve optimal reactive power flow problem. 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], proposes a two-step approach to evaluate Reactive power reserves with respect to operating constraints and voltage stability. In [19], a programming based proposed approach used to solve the optimal reactive power dispatch problem. In [20], presents a probabilistic algorithm for optimal reactive power provision in hybrid electricity markets with uncertain loads. This paper proposes Antelope algorithm (AA) is used to solve the optimal reactive power dispatch problem. AA imitates the behavior of a herd [21, 22] of antelopes that jump their way through a solution space to find the optimal point. Antelope algorithm tries to find an optimal point by iteratively altering a population of candidate solutions. Yet it does not depend on swarm intelligence, but rather on herd-like behavior with innermost assessment. Projected Antelope Algorithm (AA) has been evaluated in standard IEEE 30 bus test system & the simulation results shows that the projected approach outperforms all reported standard algorithms in reducing the 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

$\Delta P$  = Incremental change in bus real power.

$\Delta Q$  = Incremental change in bus reactive Power injection

$\Delta\theta$  = incremental change in bus voltage angle.

$\Delta V$  = 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.

$$\Delta Q = [J_{qv} - J_{q\theta}J_{p\theta}^{-1}J_{pv}]\Delta V = J_R\Delta V \quad (2)$$

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

Where

$$J_R = (J_{qv} - J_{q\theta}J_{p\theta}^{-1}J_{pv}) \quad (4)$$

$J_R$  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,

$\xi$  = right eigenvector matrix of JR

$\eta$  = left eigenvector matrix of JR

$\Lambda$  = diagonal eigenvalue matrix of JR and

$$J_{R^{-1}} = \xi \Lambda^{-1} \eta \tag{6}$$

From (5) and (8), we have

$$\Delta V = \xi \Lambda^{-1} \eta \Delta Q \tag{7}$$

or

$$\Delta V = \sum_i \frac{\xi_i \eta_i}{\lambda_i} \Delta Q \tag{8}$$

Where  $\xi_i$  is the *i*th column right eigenvector and  $\eta$  the *i*th row left eigenvector of JR.

$\lambda_i$  is the *i*th Eigen value of JR.

The *i*th modal reactive power variation is,

$$\Delta Q_{mi} = K_i \xi_i \tag{9}$$

where,

$$K_i = \sum_j \xi_{ij}^2 - 1 \tag{10}$$

Where

$\xi_{ji}$  is the *j*th element of  $\xi_i$

The corresponding *i*th modal voltage variation is

$$\Delta V_{mi} = [1/\lambda_i] \Delta Q_{mi} \tag{11}$$

If  $|\lambda_i| = 0$  then the *i*th modal voltage will collapse .

In (10), let  $\Delta Q = e_k$  where  $e_k$  has all its elements zero except the *k*th one being 1. Then,

$$\Delta V = \sum_i \frac{\eta_{1k} \xi_i}{\lambda_i} \tag{12}$$

$\eta_{1k}$  *k* th element of  $\eta_1$

V-Q sensitivity at bus *k*

$$\frac{\partial V_k}{\partial Q_k} = \sum_i \frac{\eta_{1k} \xi_i}{\lambda_i} = \sum_i \frac{P_{ki}}{\lambda_i} \tag{13}$$

### 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.

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

Where *n* is the number of transmission lines,  $g_k$  is the conductance of branch *k*,  $V_i$  and  $V_j$  are voltage magnitude at bus *i* and bus *j*, and  $\theta_{ij}$  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.

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

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

### 3.3. System Constraints

Objective functions are subjected to these constraints shown below.

Load flow equality constraints:

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

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

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  $G_{ij}$  and  $B_{ij}$  are the mutual conductance and susceptance between bus i and bus j.

Generator bus voltage ( $V_{Gi}$ ) inequality constraint:

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

Load bus voltage ( $V_{Li}$ ) inequality constraint:

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

Switchable reactive power compensations ( $Q_{Ci}$ ) inequality constraint:

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

Reactive power generation ( $Q_{Gi}$ ) inequality constraint:

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

Transformers tap setting ( $T_i$ ) inequality constraint:

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

Transmission line flow (SLi) inequality constraint:

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

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

## 4. Antelope Algorithm

The deeds of the Antelope is jumping around their habitat in explore of the locating best food. And an Antelope finding itself in any point in space can give it a real-valued mark, indicating food quality shown in Fig .1.



Figure 1: Antelope



Figure 2: Antelope Herd Movement

The Antelope leader jumps to a given location, and all the other Antelopes jump to arbitrary positions around the leader shown in Fig 2. The Antelope’s then report their new positions and the related quality to the leader. Based on this information, the leader decides the way of its next jump. The leader’s jump distance raise smaller when two successive jumps are in conflicting directions, or else it raise larger to another level. Numerous jumps are carried out in this fashion, and the dimension of the scatter region around the leader can be condensed over time to expand information from narrower regions. The herd remembers the single best location it has been found so far. Appropriately, we try to find the point that diminishes a real valued cost function over a given bounded D-dimensional real valued investigate space:

$$\arg \min_x \text{cost}(x), x \in S \tag{24}$$

Where  $S = [lb_1, ub_1] \times \dots \times [lb_D, ub_D]$

For this reason we use a population of P antelopes (D- dimensional vectors representing candidate solutions), of which one is the head or leader.

Let we define,

$\overrightarrow{leader}$  be an D-dimensional vector containing the leader's position,

A be a P×D matrix whose first row is  $\overrightarrow{leader}$  and whose remaining rows contain the other Antelope's positions,

$\overrightarrow{rank}$  be a P-dimensional vector containing the cost-ranking of each of the Antelope's,

$\overrightarrow{jump}$  be an D-dimensional vector giving the direction of the leader's jump,

j length be a scalar value representing the leader's jump's length,

scatter be a scalar value controlling how close to the leader the Antelope's will be scattered,

$\eta^+$  and  $\eta^-$  be scalar values used to automatically lengthen or shorten the jumps,

m length be a scalar value representing the minimal allowed jump length.

Antelope Algorithm (AA) for solving optimal reactive power dispatch problem

a) Initialization of parameters

i) Initialize the leader to a random point in the search space.

ii) Initialize the (P -1) other Antelope's to an arbitrary points in a region around the leader, with parameter scatter controlling the size of this region.

iii) Appraise the cost function at each of the P points.

iv) Rank the costs and store the result in  $\overrightarrow{rank}$

v) Store the lowest cost and the associated position.

vi) Compute the jump direction according to the following formula:

$$\forall i \in [1, D], \overrightarrow{jump}_i = cov(\overrightarrow{rank}, A_i) \quad (25)$$

$\overrightarrow{jump}_i$  denotes the i-th element of the jump vector and A.i denotes the i-th column of matrix A.

vii) Initialize jump-length variable j length to the maximal distance between the leader and the other Antelope's.

b) Loop (until stopping criterion is met)

i) Update the leader's position according to the following formula:

$$\overrightarrow{leader}^{t+1} = \overrightarrow{leader}^t - \frac{jlength^t}{\|\overrightarrow{jump}^t\|} \overrightarrow{jump}^t \quad (26)$$

ii) Update the other Antelope's positions by randomly placing them in a region around the leader, the size of which is controlled by parameter scatter.

iii) Evaluate the cost function at each of the P points.

iv) Rank the costs and store the result in  $\overrightarrow{rank}$ .

v) Store the lowest cost and the associated position if it is lower than the stored best.

vi) Compute the jump direction according to formula (25).

vii) Update the jump-length variable: if the new jump is made a direction opposite to that of the last jump (if  $\overrightarrow{jump}^{t+1}, \overrightarrow{jump}^t < 0$ ) then multiply j length by  $\eta^-$ , else multiply it by  $\eta^+$ . If this makes j length smaller than m length, set it to m length.

viii) Update the scatter parameter.

The algorithm fundamentally takes three parameters: the population size P, the scatter-range scatter, and the minimal jump-length m length. P is the number of cost-function evaluations in each iteration and the concentration of exploitation of each visited area. The scatter range controls "how local" the search is at each iteration: a lower scatter value will let the random evaluations occur in a narrower region around the leader. The minimum jump-length is used to avoid convergence to local optima. Parameters  $\eta^+$  and  $\eta^-$  are directly inspired by those of Riedmiller and Braun's RPROP algorithm [23] for the training of feed forward neural networks. The idea, interpret the original article, is that two successive jumps in conflicting directions

designate that the last jump was too long and the algorithm has jumped over a local minimum; jump-length is then decreased by factor  $\eta^-$ . Otherwise, jump-length is slightly increased by factor  $\eta^+$  in order to increase speed of convergence in shallow regions. Although our setting is quite different, we used the original values of both parameters,  $\eta^+ = 0.49$  and  $\eta^- = 1.1$ . We chose to use the rank of costs instead of costs to compute the jump direction. This makes the algorithm invariant to any increasing transformation of the cost function. Antelope's were uniformly distributed inside a hyper parallel piped centred on the leader, according to the following formula:

$$\forall (i, j) \in [2, P] \times [1, D], a_{ij} = \overrightarrow{leader_j} + (r_{ij} - 0.5) \times scatter \times (ub_j - lb_j) \quad (27)$$

Where  $a_{ij}$  denotes element (i, j) of matrix A,  $\overrightarrow{leader_j}$  is the leader-vector's j-th element, scatter is a scalar value chosen in [0,1],  $ub_j$  and  $lb_j$  are respectively the upper and lower bounds of dimension j, and  $r_{ij}$  is a random value uniformly drawn from [0,1]. A better choice might be to generate normal deviates from  $\overrightarrow{leader}$ .

## 5. Simulation Results

The efficiency of the proposed Antelope Algorithm (AA) for solving the multi-objective reactive power dispatch problem 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 AA – ORPD optimal control variables

Control variables	Variable setting
V1	1.042
V2	1.045
V5	1.046
V8	1.034
V11	1.001
V13	1.038
T11	1.00
T12	1.00
T15	1.01
T36	1.01
Qc10	2
Qc12	2
Qc15	3
Qc17	0
Qc20	2
Qc23	3

Qc24	3
Qc29	2
Real power loss	4.2958
SVSM	0.2478

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 0.2478 to 0.2489, 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 AA -Voltage Stability Control Reactive Power Dispatch Optimal Control Variables

Control Variables	Variable Setting
V1	1.049
V2	1.047
V5	1.048
V8	1.037
V11	1.003
V13	1.030
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	4.9879
SVSM	0.2489

Table 3: Voltage Stability under Contingency State

Sl.No	Contingency	ORPD Setting	VSCRPD Setting
1	28-27	0.1409	0.1424
2	4-12	0.1649	0.1652
3	1-3	0.1769	0.1779
4	2-4	0.2029	0.2041



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 (MW)
Evolutionary programming [24]	5.0159
Genetic algorithm [25]	4.665
Real coded GA with Lindex as SVSM [26]	4.568
Real coded genetic algorithm [27]	4.5015
Proposed AA method	4.2958

## 6. Conclusion

Antelope Algorithm (AA) has been effectively applied for solving Optimal Reactive Power Dispatch problem. The Antelope Algorithm (AA) based Optimal Reactive Power Dispatch has been successfully tested in standard IEEE 30 bus system. Performance comparisons with well-known population-based algorithms give advance results. Antelope Algorithm (AA) succeeded in plummeting real power loss, when compare to other reported standard algorithms. The simulation results presented in preceding section prove the capability of Antelope Algorithm (AA) approach to arrive at near global optimal solution.

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