Reduction of real power loss by using Kudu Herd Algorithm

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Citation

Abstract
In this paper, a new Bio-inspired algorithm, namely kudu herd algorithm (KHA) is proposed for solving reactive power dispatch problem. A population of candidate solution approach as a herd of kudus carries out a succession of jumps through the search space in order to find the most excellent solution. The logic of this algorithm is quite different from that of most population based algorithms, as the individual solutions are moved collectively in a herd-like approach. The proposed (KHA) algorithm has been tested in standard IEEE 57 bus test system and simulation results show clearly about the good performance of the proposed algorithm in reducing the real power loss.

1. Introduction

Optimal reactive power dispatch (ORPD) problem is a multi-objective optimization problem that minimizes 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 a new bio-inspired optimization algorithm called kudu herd algorithm to solve the optimal reactive power dispatch problem. KHA imitate the behaviour of a herd [21] of kudus that jump their way through a solution space to find the optimal point. The kudu is a species of antelope present in sub-Saharan Africa, which mostly lives in herds and is known for its ability to jump high and far [22]. This algorithm tries to find an optimal point by iteratively changing a population of candidate solutions. However it does not rely on evolutionary principles or swarm intelligence, but rather on herd-like behaviour with centralized decisions. The proposed algorithm KHA has been evaluated in standard IEEE 57 bus test system & the simulation results shows that our proposed approach outperforms all reported algorithms in minimization of real power loss.

2. Problem Formulation

The OPF problem is measured as a general minimization problem with constraints, and can be mathematically written in the following form:

Minimize  
\[ f(x, u) \]  
Subject to  
\[ g(x,u)=0 \]  
and  
\[ h(x,u) \leq 0 \]  

Where \( f(x,u) \) is the objective function, \( g(x,u) \) and \( h(x,u) \) are respectively the set of equality and inequality constraints. \( x \) is the vector of state variables, and \( u \) is the vector of control variables.

The state variables are the load buses (PQ buses) voltages, angles, the generator reactive powers and the slack active generator power:

\[ x = (P_{g1}, \theta_{2}, \ldots, \theta_{N}, V_{L1}, \ldots, V_{LNL}, Q_{g1}, \ldots, Q_{gng})^{T} \]  

3. Objective Function

3.1. Active Power Loss

The objective of the reactive power dispatch is to minimize the active power loss in the transmission network, which can be described as follows:

\[ F = PL = \sum_{k \in Nbr} g_k (V_i^2 + V_j^2 - 2V_iV_j \cos \theta_{ij}) \]  

or  
\[ F = PL = \sum_{i \in Ng} p_{gi} - P_d = P_{gsack} + \sum_{i \in Ng} p_{gi} - P_d \]  

Where \( g_k \): is the conductance of branch between nodes \( i \) and \( j \), Nbr: is the total number of transmission lines in power systems. \( P_d \): is the total active power demand, \( P_{gi} \): is the generator active power of unit \( i \), and \( P_{gsack} \): is the generator active power of slack bus.

3.2. Voltage Profile Improvement

For minimizing the voltage deviation in PQ buses, the objective function becomes:

\[ F = PL + \omega_v \times VD \]  

or  
\[ VD = \sum_{i=1}^{Npq} |V_i - 1| \]  

3.3. Equality Constraint

The equality constraint \( g(x,u) \) of the ORPD problem is represented by the power balance equation, where the total power generation must cover the total power demand and the power losses:

\[ p_g = p_g + p_L \]  

This equation is solved by running Newton Raphson load flow method, by calculating the active power of slack bus to determine active power loss.

3.4. Inequality Constraints

The inequality constraints \( h(x,u) \) reflect the limits on components in the power system as well as the limits created to ensure system security. Upper and lower bounds on the active power of slack bus, and reactive power of generators:

\[ p_{g_{min}} \leq p_{g_{slack}} \leq p_{g_{max}} \]  

\[ Q_{g_{min}} \leq Q_{gi} \leq Q_{g_{max}}, i \in N_{g} \]  

Upper and lower bounds on the bus voltage magnitudes:

\[ V_{i_{min}} \leq V_i \leq V_{i_{max}}, i \in N \]  

Upper and lower bounds on the transformers tap ratios:

\[ T_{i_{min}} \leq T_i \leq T_{i_{max}}, i \in N_{T} \]
Upper and lower bounds on the compensators reactive powers:

\[ Q_c^{\min} \leq Q_c \leq Q_c^{\max}, \; i \in N_c \]  (16)

Where \( N \) is the total number of buses, \( N_T \) is the total number of Transformers; \( N_c \) is the total number of shunt reactive compensators.

4. Kudu Herd Algorithm

The behaviour of the kudu is jumping around their habitat in search of the location containing the best food. And a kudu finding itself in any point in space can give it a real-valued mark, indicating food quality shown in Fig. 1.

![Fig. 1. Kudu Herd](image)

The kudu leader jumps to a given location, and all the other kudus jump to arbitrary positions around the leader shown in Fig 2. The kudus then report their fresh 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 if two successive jumps are in conflicting directions, or else it raise larger. Several jumps are executed in this fashion, and the dimension of the disperse region around the leader can be reduced over time to develop information from narrower regions. The herd remembers the single best location it has been found so far. Properly, we try to find the point that reduces a real valued cost function over a given bounded D-dimensional real valued explore space:

\[ \arg \min_x \text{cost}(x), \; x \in S \]  (17)

Where \( S = [lb_1, ub_1] \times \ldots \times [lb_D, ub_D] \)

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

Let we define \( \text{leader} \) be an D-dimensional vector containing the leader’s position,

\[ \text{leader} = [vZ_1, \ldots, vZ_D] \]

\( A \) be a \( P \times D \) matrix whose first row is \( \text{leader} \) and whose remaining rows contain the other kudus’ positions,

\[ \text{rank} = [r1, \ldots, rP] \]  a P-dimensional vector containing the cost-ranking of each of the kudus,

\( \text{jump} \) 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,

\( \eta^+ \) 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.

KHA for solving optimal reactive power dispatch problem

a) Initialization

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

ii) Initialize the \( (P-1) \) other kudus to random points in a region around the leader, with parameter scatter controlling the size of this region.

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

iv) Rank the costs and store the result in \( \text{rank} \)

v) Store the lowest cost and the associated position.

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

\[ \forall i \in [1, D], \text{jump}_i = \text{cov} (\text{rank}, A_i) \]  (18)

\( \text{jump}_i \) denotes the \( i \)-th element of the jump vector and \( A.i \) denotes the \( i \)-th column of matrix \( A \).

b) Loop (until stopping criterion is met)

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

\[ \text{leader}^{t+1} = \text{leader}^t - \frac{\text{length}^t \cdot \text{jump}^t}{\|\text{jump}^t\|} \]  (19)

ii) Update the other kudus’ 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 \( \text{rank} \).

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 (18).

vii) Update the jump-length variable: if the new jump is made a direction opposite to that of the last jump (if \( \text{jump}^{t+1} = \text{jump}^t < 0 \)) 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 \( \text{scatter} \), and the minimal jump-length \( m \). \( P \) 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 increasing transformation of the cost function. Kudus were

\[ \text{leader} = \frac{\text{leader}_j + (r_j \cdot 0.5) \times \text{scatter} \times (ub_j - lb_j)}{2} \]  

(20)

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

### 5. Simulation Results

The proposed KHA algorithm for solving ORPD problem is tested for standard IEEE-57 bus power system. The IEEE 57-bus system consists of 80 branches, seven generator-buses and 17 branches under load tap setting transformer branches. The possible 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. In this case, the search space has 27 dimensions, i.e., the seven generator voltages, 17 transformer taps, and three capacitor banks. The system variable limits are given in Table 1. The initial conditions for the IEEE-57 bus power system are given as follows:

\[ P_{\text{load}} = 12.412 \text{ p.u.} \quad Q_{\text{load}} = 3.345 \text{ p.u.} \]

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

\[ \sum P_G = 12.7894 \text{ p.u.} \quad \sum Q_G = 3.4678 \text{ p.u.} \]

\[ P_{\text{loss}} = 0.28381 \text{ p.u.} \quad Q_{\text{loss}} = -1.2399 \text{ p.u.} \]

Table 2 shows the various system control variables i.e. generator bus voltages, shunt capacitances and transformer tap settings obtained after KHA based optimization which are within their acceptable limits. In Table 3, a comparison of optimum results obtained from proposed KHA with other optimization techniques for ORPD mentioned in literature for IEEE-57 bus power system is given. These results indicate the robustness of proposed KHA approach for providing better optimal solution in case of IEEE-57 bus system.

<table>
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<tr>
<th>Control Variables</th>
<th>KHA</th>
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<tbody>
<tr>
<td>V1</td>
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<td>V9</td>
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<td>V12</td>
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<td>T9-55</td>
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Table 1. Variables limits

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<th>reactive power generation limits</th>
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<th>1</th>
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<th>3</th>
<th>6</th>
<th>8</th>
<th>9</th>
<th>12</th>
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<tbody>
<tr>
<td>( Q_{\text{min}} )</td>
<td>-1.4</td>
<td>-0.17</td>
<td>-0.01</td>
<td>-0.08</td>
<td>-1.4</td>
<td>-0.03</td>
<td>-0.3</td>
<td></td>
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<tr>
<td>( Q_{\text{max}} )</td>
<td>2</td>
<td>0.5</td>
<td>0.6</td>
<td>0.25</td>
<td>2</td>
<td>0.09</td>
<td>1.55</td>
<td></td>
</tr>
<tr>
<td>voltage and tap setting limits</td>
<td>( V_{\text{min}} )</td>
<td>( V_{\text{max}} )</td>
<td>( V_{\text{pmin}} )</td>
<td>( V_{\text{pmax}} )</td>
<td>( V_{\text{min}} )</td>
<td>( V_{\text{max}} )</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>0.9</td>
<td>1.1</td>
<td>0.94</td>
<td>1.08</td>
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<td>1.1</td>
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<td>shunt capacitor limits</td>
<td>( q_{\text{min}} )</td>
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</tr>
<tr>
<td></td>
<td>bus no</td>
<td>18</td>
<td>25</td>
<td>53</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>( q_{\text{min}} )</td>
<td>0</td>
<td>0</td>
<td>0</td>
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</tr>
<tr>
<td></td>
<td>( q_{\text{max}} )</td>
<td>10</td>
<td>5.9</td>
<td>6.3</td>
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</table>
simulation results presented in previous section prove the give boosting results. KHA succeeded in reducing real power capability of KHA approach to arrive at near global optimal comparisons with well-known population-based algorithms tested in standard IEEE-57 bus system. Performance KHA based Optimal Reactive Power Dispatch is successfully solving Optimal Reactive Power Dispatch problem. The

S. No. | Optimization Algorithm | Best Solution | Worst Solution | Average Solution
---|-----------------------|---------------|----------------|----------------|
1  | NLP [24]             | 0.25902       | 0.30854        | 0.27858        |
2  | CGA [24]             | 0.25244       | 0.27507        | 0.26293        |
3  | AGA [24]             | 0.24564       | 0.26671        | 0.25127        |
4  | PSO-w [24]           | 0.24270       | 0.26152        | 0.24725        |
5  | PSO-cf [24]          | 0.24280       | 0.26032        | 0.24698        |
6  | CLPSO [24]           | 0.24515       | 0.24780        | 0.24673        |
7  | SPSO-07 [24]         | 0.24430       | 0.25457        | 0.24752        |
8  | L-DE [24]            | 0.27812       | 0.41909        | 0.33177        |
9  | L-SACP-DE [24]       | 0.27915       | 0.36978        | 0.31032        |
10 | L-SaDE [24]          | 0.24267       | 0.24391        | 0.24311        |
11 | SOA [24]             | 0.24265       | 0.24280        | 0.24270        |
12 | LM [25]              | 0.2484        | 0.2922         | 0.2641         |
13 | MBEP1 [25]           | 0.2474        | 0.2848         | 0.2643         |
14 | MBEP2 [25]           | 0.2482        | 0.283          | 0.2592         |
15 | BES100 [25]          | 0.2438        | 0.26            | 0.2541         |
16 | BES200 [25]          | 0.3417        | 0.2486         | 0.2443         |
17 | Proposed KHA         | 0.22445       | 0.23898        | 0.23135        |

6. Conclusion

Kudu Herd Algorithm has been successfully applied for solving Optimal Reactive Power Dispatch problem. The KHA based Optimal Reactive Power Dispatch is successfully tested in standard IEEE-57 bus system. Performance comparisons with well-known population-based algorithms give boosting results. KHA succeeded in reducing real power loss, when compare to other specified algorithms. The simulation results presented in previous section prove the capability of KHA approach to arrive at near global optimal solution.

References

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