Collective Animal Behavior (CAB) Algorithm for Solving Optimal Reactive Power Dispatch Problem

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Abstract- This paper presents a collective animal behavior (CAB) algorithm for solving the multi-objective reactive power dispatch problem in power system. Modal analysis of the system is used for static voltage stability assessment. Loss minimization and maximization of voltage stability margin are taken as the objectives. Generator terminal voltages, reactive power generation of the capacitor banks and tap changing transformer setting are taken as the optimization variables. A meta heuristic algorithm for global optimization called the collective animal behavior (CAB) is introduced. Animal groups, such as schools of fish, flocks of birds, swarms of locusts, and herds of wildebeest, exhibit a variety of behaviors including swarming about a food source, milling around a central location, or migrating over large distances in aligned groups. These collective behaviors are often advantageous to groups, allowing them to increase their harvesting efficiency, to follow better migration routes, to improve their aerodynamic, and to avoid predation. In the proposed algorithm, the searcher agents emulate a group of animals which interact with each other based on the biological laws of collective motion. CAB powerful stochastic optimization technique has been utilized to solve the reactive power optimization problem.

Key words —Modal analysis, optimal reactive power, Transmission loss, a collective animal behavior, Optimization.

I. INTRODUCTION

Optimal reactive power dispatch problem is one of the difficult optimization problems in power systems. The sources of the reactive power are the generators, synchronous condensers, capacitors, static compensators and tap changing transformers. The problem that has to be solved in a reactive power optimization is to determine the required reactive generation at various locations so as to optimize the objective function. Here the reactive power dispatch problem involves best utilization of the existing generator bus voltage magnitudes, transformer tap setting and the output of reactive power sources so as to minimize the loss and to enhance the voltage stability of the system. It involves a non linear optimization problem. Various mathematical techniques have been adopted to solve this optimal reactive power dispatch problem. These include the gradient method [42-43], Newton method [44] and linear programming [45-48]. The gradient and Newton methods suffer from the difficulty in handling inequality constraints. To apply linear programming, the input-output function is to be expressed as a set of linear functions which may lead to loss of accuracy. Recently global optimization techniques such as genetic algorithms have been proposed to solve the reactive power flow problem [49, 50].

Global optimization (GO) is a field with applications in many areas of science, engineering, economics, and others, where mathematical modeling is used [1]. In general, the goal is to find a global optimum of an objective function defined in a given search space. Global optimization algorithms are usually broadly divided into deterministic and meta heuristic [2]. Since deterministic methods only provide a theoretical guarantee of locating a local minimum of the objective function, they often face great difficulties in solving global optimization problems [3]. On the other hand, meta heuristic methods are usually faster in locating a global optimum than deterministic ones [4]. Moreover, meta heuristic methods adapt better to black-box formulations and extremely ill-behaved functions whereas deterministic methods usually rest on at least some theoretical assumptions about the problem formulation and its analytical properties (such as Lipschitz continuity) [5].
Several Meta heuristic algorithms have been developed by a combination of rules and randomness mimicking several phenomena. Such phenomena include evolutionary processes, for example, the evolutionary algorithm proposed by Fogel et al. [6], De Jong [7], and Koza [8], the genetic algorithm (GA) proposed by Holland [9] and Goldberg [10] and the artificial immune systems proposed by de Castro and Von Zuben [11]. On the other hand, physical processes consider the simulated annealing proposed by Kirkpatrick et al. [12], the electromagnetism-like algorithm proposed by ‘Ilker et al. [13], the gravitational search algorithm proposed by Rashedi et al. [14], and the musical process of searching for a perfect state of harmony, which has been proposed by Geem et al. [15], Lee and Geem [16], and Geem [17].

Many studies have been inspired by animal behavior phenomena for developing optimization techniques. For instance, the particle swarm optimization (PSO) algorithm which models the social behavior of bird flocking or fish schooling [18]. PSO consists of a swarm of particles which move towards best positions, seen so far, within a searchable space of possible solutions. Another behavior-inspired approach is the ant colony optimization (ACO) algorithm proposed by Dorigo et al. [19], which simulates the behavior of real ant colonies. Main features of the ACO algorithm are the distributed computation, the positive feedback, and the constructive greedy search. Recently, a new meta heuristic approach which is based on the animal behavior while hunting has been proposed in [20]. Such algorithm considers hunters as search positions and preys as potential solutions.

Just recently, the concept of individual-organization [21, 22] has been widely referenced to understand collective behavior of animals. The central principle of individual organization is that simple repeating interactions between individuals can produce complex behavioral patterns at group level [21, 23, 24]. Such inspiration comes from behavioral patterns previously seen in several animal groups. Examples include ant pheromone trail networks, aggregation of cockroaches, and the migration of fish schools, all of which can be accurately described in terms of individuals following simple sets of rules [25]. Some examples of these rules [24, 26] are keeping the current position or location for best individuals, local attraction or repulsion, random movements, and competition for the space within a determined distance.

On the other hand, new studies [27–29] have also shown the existence of collective memory in animal groups. The presence of such memory establishes that the previous history of the group structure influences the collective behavior exhibited in future stages. According to such principle, it is possible to model complex collective behaviors by using simple individual rules and configuring a general memory.

In this paper, a new optimization algorithm inspired by the collective animal behavior is proposed. In this algorithm, the searcher agents emulate a group of animals that interact with each other based on simple behavioral rules which are modeled as mathematical operators. Such operations are applied to each agent considering that the complete group has a memory storing their own best positions seen so far, by using a competition principle. The proposed approach has been compared to other well-known optimization methods. The results confirm a high performance of the proposed method for solving Reactive power dispatch problem. The effectiveness of the proposed approach is demonstrated through IEEE-30 bus system. The test results show the proposed algorithm gives better results with less computational burden and is fairly consistent in reaching the near optimal solution.

In recent years, the problem of voltage stability and voltage collapse has become a major concern in power system planning and operation. To enhance the voltage stability, voltage magnitudes alone will not be a reliable indicator of how far an operating point is from the collapse point [11]. The reactive power support and voltage problems are intrinsically related. Hence, this paper formulates the reactive power dispatch as a multi-objective optimization problem with loss minimization and maximization of static voltage stability margin (SVSM) as the objectives. Voltage stability evaluation using modal analysis [12] is used as the indicator of voltage stability.

II. VOLTAGE STABILITY EVALUATION

A. Modal analysis for voltage stability evaluation

Modal analysis is one of the methods for voltage stability enhancement in power systems. In this method, voltage stability analysis is done by computing eigen values and right and left eigen vectors of a jacobian matrix. It identifies the critical areas of voltage stability.
and provides information about the best actions to be taken for the improvement of system stability enhancements. The linearized steady state system power flow equations are given by:

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = \begin{bmatrix} J_{p\theta} & J_{pV} \\ J_{q\theta} & J_{qV} \end{bmatrix} \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix}$$

Where

\[ \Delta P = \text{Incremental change in bus real power}. \]
\[ \Delta Q = \text{Incremental change in bus reactive power injection}. \]
\[ \Delta \theta = \text{Incremental change in bus voltage angle}. \]
\[ \Delta V = \text{Incremental change in bus voltage}. \]

Magnitude

\[ J_{p0}, J_{pV}, J_{q0}, J_{qV} \] are sub-matrixes of the system voltage stability affected by both P and Q. However at each operating point we keep P constant and evaluate voltage stability by considering incremental relationship between Q and V.

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

\[ \Delta Q = [J_{qV} - J_{q\theta} J_{p\theta}^{-1} J_{pV}] \Delta V = J_R \Delta V \]

Where

\[ J_R = (J_{qV} - J_{q\theta} J_{p\theta}^{-1} J_{pV}) \]

\( J_R \) is called the reduced Jacobian matrix of the system.

A. Modes of Voltage instability:

Voltage Stability characteristics of the system can be identified by computing the eigenvalues and eigenvectors. Let

\[ J_R = \xi \Lambda \eta \]

Where,

\[ \xi = \text{right eigenvector matrix of } J_R \]
\[ \eta = \text{left eigenvector matrix of } J_R \]
\[ \Lambda = \text{diagonal eigenvalue matrix of } J_R \]

\[ J_R^{-1} = \xi \Lambda^{-1} \eta \]

From (3) and (6), we have

\[ \Delta V = \xi \Lambda^{-1} \eta \Delta Q \]

or

\[ \Delta V = \sum_k \frac{\xi_k \eta_k}{\lambda_k} \Delta Q \] (8)

Where \( \xi_k \) is the ith column right eigenvector and \( \eta \) the ith row left eigenvector of \( J_R \).
\[ \lambda_k \] is the ith eigenvalue of \( J_R \).

The ith modal reactive power variation is,

\[ \Delta Q_{mi} = K_i \xi_i \] (9)

where,

\[ K_i = \sum_k \xi_k \eta_k^2 - 1 \] (10)

Where

\( \xi_{ji} \) is the jth element of \( \xi_i \)

The corresponding ith modal voltage variation is

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

It is seen that, when the reactive power variation is along the direction of \( \xi_i \), the corresponding voltage variation is also along the same direction and magnitude is amplified by a factor which is equal to the magnitude of the inverse of the ith eigenvalue. In this sense, the magnitude of each eigenvalue \( \lambda_i \) determines the weakness of the corresponding modal voltage. The smaller the magnitude of \( \lambda_i \), the weaker will be the corresponding modal voltage. If \( |\lambda_i| = 0 \) the ith modal voltage will collapse because any change in that modal reactive power will cause infinite modal voltage variation.

In (8), let \( \Delta Q = e_k \) where \( e_k \) has all its elements zero except the kth one being 1. Then,

\[ \Delta V = \sum_i \frac{\xi_{ik} \eta_i}{\lambda_i} \]

or

\[ \eta_{ik} \] k th element of \( \eta_k \)
\[ V - Q \text{ sensitivity at bus } k \]

\[ \frac{\partial V_k}{\partial Q_k} = \sum_i \frac{\eta_{ik} \xi_i}{\lambda_i} = \sum_i \frac{P_{ki}}{\lambda_i} \] (13)

III. Problem Formulation

The optimal reactive power dispatch problem is formulated as an optimization problem in which a specific objective function is minimized while satisfying a number of equality and inequality constraints. The objectives of the reactive power dispatch problem considered here is to minimize the system real power loss and maximize the
static voltage stability margins (SVSM). This objective is achieved by proper adjustment of reactive power variables like generator voltage magnitude \( g_i \) \( V \), reactive power generation of capacitor bank \( Q_{ci} \), and transformer tap setting \( t_k \). Power flow equations are the equality constraints of the problems, while the inequality constraints include the limits on real and reactive power generation, bus voltage magnitudes, transformer tap positions and line flows. This objective function is subjected to the following constraints:

**A. Minimization of Real Power Loss**

It is aimed in this objective that minimizing of the real power loss \( P_{loss} \) in transmission lines of a power system. This is mathematically stated as follows.

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

(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 \( j \).

**B. Minimization of Voltage Deviation**

It is aimed in this objective that minimizing of the Deviations in voltage magnitudes \( VD \) at load buses. This 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 \( V_k \) is the voltage magnitude at bus \( k \).

**C. System Constraints**

In the minimization process of objective functions, some problem constraints which one is equality and others are inequality had to be met. Objective functions are subjected to these constraints shown below.

Load flow equality constraints:

\[
P_{Gi} - P_{Di} - V_i \sum_{j=1}^{nb} v_j^* \left[ \frac{G_{ij}}{v_i^*} \cos \theta_{ij} + \frac{B_{ij}}{v_i^*} \sin \theta_{ij} \right] = 0, i = 1, 2, ..., nb
\]

(16)

\[
Q_{Gi} - Q_{Di} V_i \sum_{j=1}^{nb} v_j^* \left[ \frac{G_{ij}}{v_i^*} \cos \theta_{ij} + \frac{B_{ij}}{v_i^*} \sin \theta_{ij} \right] = 0, i = 1, 2, ..., nb
\]

(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 \( Gi \) and \( Bi \) are the mutual conductance and susceptance between bus \( i \) and bus \( j \). Generator bus voltage \( (VGi) \) inequality constraint:

\[
V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{max}, i \in ng
\]

Load bus voltage \( (VLi) \) inequality constraint:

\[
V_{Li}^{min} \leq V_{Li} \leq V_{Li}^{max}, i \in nl
\]

Switchable reactive power compensations \( (QCi) \) inequality constraint:

\[
Q_{Ci}^{min} \leq Q_{Ci} \leq Q_{Ci}^{max}, i \in nc
\]

Reactive power generation \( (QGi) \) inequality constraint:

\[
Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max}, i \in ng
\]

Transformers tap setting \( (T_i) \) inequality constraint:

\[
T_{i}^{min} \leq T_{i} \leq T_{i}^{max}, i \in nt
\]

Transmission line flow \( (SLi) \) inequality constraint:

\[
S_{Li}^{min} \leq S_{Li} \leq S_{Li}^{max}, i \in nl
\]

(23)

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

The load flow equality constraints are satisfied by Power flow algorithm. The generator bus voltage \( (VGi) \), the transformer tap setting \( (T_i) \) and the Switchable reactive power Compensations \( (QCi) \) are optimization variables and they are self-restricted between the minimum and maximum value by the GSA algorithm. The limits on active power generation at the slack bus \( (PG_s) \), load bus voltages \( (VLi) \) and reactive power generation \( (QGi) \), transmission line flow \( (SLi) \) are state variables. They are restricted by adding a penalty function to the objective functions.

**Where**

\( NB \) number of buses in the system
\( Ng \) number of generating units in the system
\( t_k \) tap setting of transformer branch \( k \)
\( P_d \) real power generation at slack bus
\( V_i \) voltage magnitude at bus \( i \)
\( P_{d,i} \) real and reactive powers injected at bus \( i \)
\( P_{d,i}, Q_{d,i} \) real and reactive power generations at bus \( i \)
\( G_{ij}, B_{ij} \) mutual conductance and susceptance between bus \( i \) and \( j \)
\( G_{ij} \) self conductance and susceptance of bus \( i \)
\( \theta_{ij} \) voltage angle difference between bus \( i \) and \( j \)

**IV. BIOLOGIC FUNDAMENTALS**
The remarkable collective behavior of organisms such as swarming ants, schooling fish, and flocking birds has long captivated the attention of naturalists and scientists. Despite a long history of scientific research, the relationship between individuals and group-level properties has just recently begun to be deciphered [30].

Grouping individuals often have to make rapid decisions about where to move or what behavior to perform in uncertain and dangerous environments. However, each individual typically has only a relatively local sensing ability [31]. Groups are, therefore, often composed of individuals that differ with respect to their informational status and individuals are usually not aware of the informational state of others [32], such as whether they are knowledgeable about a pertinent resource or about a threat.

Animal groups are based on a hierarchic structure [33] which considers different individuals according to a fitness principle called dominance [34] which is the domain of some individuals within a group that occurs when competition for resources leads to confrontation. Several studies [35, 36] have found that such animal behavior lead to more stable groups with better cohesion properties among individuals.

Recent studies have begun to elucidate how repeated interactions among grouping animals scale to collective behavior. They have remarkably revealed that collective decision making mechanisms across a wide range of animal group types; from insects to birds (and even among humans in certain circumstances) seem to share similar functional characteristics [21, 25, 37]. Furthermore, at a certain level of description, collective decision making by organisms shares essential common features such as a general memory. Although some differences may arise, there are good reasons to increase communication between researchers working in collective animal behavior and those involved in cognitive science [24].

Despite the variety of behaviors and motions of animal groups, it is possible that many of the different collective behavioral patterns are generated by simple rules followed by individual group members. Some authors have developed different models, one of them, known as the self-propelled particle (SPP) model, attempts to capture the collective behavior of animal groups in terms of interactions between group members which follow a diffusion process [38–41].

On the other hand, following a biological approach, Couzin and krauze [24, 25] have proposed a model in which individual animals follow simple rules of thumb: 1. keep the current position (or location) for best individuals, 2. Move from or to nearby neighbors (local attraction or repulsion), 3. Move randomly, and 4. Compete for the space within of a determined distance. Each individual thus admits three different movements: attraction, repulsion, or random and holds two kinds of states: preserve the position or compete for a determined position. In the model, the movement, which is executed by each individual, is decided randomly (according to an internal motivation). On the other hand, the states follow a fixed criteria set.

The dynamical spatial structure of an animal group can be explained in terms of its history [36]. Despite such a fact, the majority of studies have failed in considering the existence of memory in behavioral models. However, recent research [27, 42] have also shown the existence of collective memory in animal groups. The presence of such memory establishes that the previous history of the group structure influences the collective behavior which is exhibited in future stages. Such memory can contain the location of special group members (the dominant individuals) or the averaged movements produced by the group.

According to these new developments, it is possible to model complex collective behaviors by using simple individual rules and setting a general memory. In this work, the behavioral model of animal groups inspires the definition of novel evolutionary operators which outline the CAB algorithm. A memory is incorporated to store best animal positions (best solutions) considering a competition-dominance mechanism.

A. Collective Animal Behavior Algorithm (CAB)

The CAB algorithm assumes the existence of a set of operations that resembles the interaction rules that model the collective animal behavior. In the approach, each solution within the search space represents an animal position. The “fitness value” refers to the animal dominance with respect to the group. The complete process mimics the collective animal behavior. The approach in this paper implements a memory for storing
best solutions (animal positions) mimicking the aforementioned biologic process. Such memory is divided into two different elements, one for maintaining the best locations at each generation \((M_h)\) and the other for storing the best historical positions during the complete evolutionary process \((M_b)\).

**B. Description of the CAB Algorithm**

Following other Meta heuristic approaches, the CAB algorithm is an iterative process that starts by initializing the population randomly (generated random solutions or animal positions). Then, the following four operations are applied until a termination criterion is met (i.e., the iteration number \(N_I\)).

1. Keep the position of the best individuals.
2. Move from or to nearby neighbors (local attraction and repulsion).
3. Move randomly.
4. Compete for the space within a determined distance (update the memory).

**C. Initializing the Population**

The algorithm begins by initializing a set \(A\) of \(N_p\) animal positions \((A = \{a_1, a_2, \ldots, a_{N_p}\})\). Each animal position \(a_i\) is a \(D\)-dimensional vector containing parameter values to be optimized. Such values are randomly and uniformly distributed between the lower initial parameter bound \(a_j^{\text{low}}\) and the upper initial parameter bound \(a_j^{\text{high}}\).

\[
a_{ji} = a_{ji}^{\text{low}} + \text{rand}(0,1) \cdot (a_{ji}^{\text{high}} - a_{ji}^{\text{low}}); \quad j = 1,2,\ldots,D; \quad i = 1,2,\ldots,N_p,
\]

(24)

\(a_j\) and \(i\) being the parameter and individual indexes, respectively. Hence, \(a_{ji}\) is the \(j\)th parameter of the \(i\)th individual. All the initial positions \(A\) are sorted according to the fitness function (dominance) to form a new individual set \(X = \{x_1, x_2, \ldots, x_{N_p}\}\), so that we can choose the best \(B\) positions and store them in the memory \(M_x\) and \(M_h\). The fact that both memories share the same information is only allowed at this initial stage.

**D. Keep the Position of the Best Individuals**

Analogous to the biological metaphor, this behavioral rule, typical from animal groups, is implemented as an evolutionary operation in our approach. In this operation, the first \(B\) elements \((\{a_1, a_2, \ldots, a_B\})\), of the new animal position set \(A\), are generated. Such positions are computed by the values contained inside the historical memory \(M_h\), considering a slight random perturbation around them. This operation can be modeled as follows:

\[
a_i = m_i^h + v
\]

(25)

While \(m_i^h\) represents the \(l\)-element of the historical memory \(M_h\), \(v\) is a random vector with a small enough length random vector with a small enough length.

**E. Move from or to Nearby Neighbors**

From the biological inspiration, animals experiment a random local attraction or repulsion according to an internal motivation. Therefore, we have implemented new evolutionary operators that mimic such biological pattern. For this operation, a uniform random number \(r_m\) is generated within the range \([0, 1]\). If \(r_m\) is less than a threshold \(H\), a determined individual position is attracted/repelled considering the nearest best historical position within the group (i.e., the nearest position in \(M_h\)); otherwise, it is attracted/repelled to/from the nearest best location within the group for the current generation (i.e., the nearest position in \(M_x\)). Therefore such operation can be modeled as follows:

\[
\begin{align*}
    a_i &= m_i^h + v, \\
    x_i &= x_i^\text{nearest} + r \cdot (m_i^h - x_i) \quad \text{with probability } H, \\
    x_i &= x_i^\text{nearest} + r \cdot (m_i^p - x_i) \quad \text{with probability } (1 - H)
\end{align*}
\]

(26)

Where \(i \in \{B+1, B+2, \ldots, N_p\}\), \(m_i^\text{nearest}\) and \(m_i^\text{nearest}\) represent the nearest elements of \(M_h\) and \(M_x\) to \(x_i\), while \(r\) is a random number between \([-1, 1]\). Therefore, if \(r > 0\), the individual position \(x_i\) is attracted to the position \(m_i^\text{nearest}\) or \(m_i^\text{nearest}\) otherwise such movement is considered as a repulsion.

**F. Move Randomly**

...
Following the biological model, under some probability \( P \), one animal randomly changes its position. Such behavioral rule is implemented considering the next expression:

\[
a_i = \begin{cases} 
    r & \text{with probability } P \\
    x_i & \text{with probability } (1 - P)
\end{cases}
\]  

(27)

With \( i \in \{ B+1, B+2, \ldots, Np \} \) \( r \) a random vector defined in the search space. This operator is similar to reinitializing the particle in a random position, as it is done by (24).

Once the operations to keep the position of the best individuals, such as moving from or to nearby neighbors and moving randomly, have been applied to all \( N_p \) animal positions, generating \( N_p \) new positions, it is necessary to update the memory \( M_h \). In order to update memory \( M_h \), the concept of dominance is used. Animals that interact within the group maintain a minimum distance among them. Such distance, which is defined as \( \rho \) in the context of the CAB algorithm, depends on how aggressive the animal behaves \([34, 42]\). Hence, when two animals confront each other inside such distance, the most dominant individual prevails meanwhile other withdraw. Figure 1 depicts the process.

In the proposed algorithm, the historical memory \( M_h \) is updated considering the following procedure.

1. The elements of \( M_h \) and \( M_g \) are merged into \( M_U \) (\( M_U = M_h \cup M_g \)).
2. Each element \( m^i_u \) of the memory \( M_U \) is compared pairwise to the remaining memory elements \( (m^1_u, m^2_u, \ldots, m^{N_p-1}_u) \). If the distance between both elements is less than \( \rho \), the element getting a better performance in the fitness function prevails meanwhile the other is removed.
3. From the resulting elements of \( M_U \) (from Step 2), it is selected the \( B \) best value to build the new \( M_h \).

The use of the dominance principle in CAB allows considering as memory elements those solutions that hold the best fitness value within the region which has been defined by the \( \rho \) distance. The procedure improves the exploration ability by incorporating information regarding previously found potential solutions during the algorithm’s evolution. In general, the value of \( \rho \) depends on the size of the search space. A big value of \( \rho \) improves the exploration ability of the algorithm although it yields a lower convergence rate. In order to calculate the \( \rho \) value, an empirical model has been developed after considering several conducted experiments. Such model is defined by following equation:

\[
\rho = \frac{\sum_{j=1}^{N_h} (\zeta_j - \zeta_{low})}{10D}
\]  

(28)
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Where $a_j^{low}$ and $a_j^{high}$ represent the pre specified lower and upper bound of the $j$-parameter respectively, within a $D$-dimensional space.

H. Computational Procedure

The computational procedure for the proposed algorithm can be summarized as follows:

Step 1. Set the parameters $N_p, B, H, P$, and $N_I$.

Step 2. Generate randomly the position set $A \_ \{a_1, a_2, \ldots, a_{N_p}\}$ using (24).

Step 3. Sort $A$ according to the objective function (dominance) to build $X = \{x_1, x_2, \ldots, x_{N_p}\}$.

Step 4. Choose the first $B$ positions of $X$ and store them into the memory $M_b$.

Step 5. Update $M_b$ according to Section 4.2.5 (during the first iteration: $M_b = M_g$).

Step 6. Generate the first $B$ positions of the new solution set $A \_ \{a_1, a_2, \ldots, a_{N_p}\}$). Such positions correspond to the elements of $M_b$ making a slight random perturbation around them,

$$a_i = m_i^b + \nu, \quad (29)$$

being $\nu$ a random vector of a small enough length.

Step 7. Generate the rest of the $A$ elements using the attraction, repulsion, and random movements.

Step 8. If $N_I$ is completed, the process is finished; otherwise, go back to Step 3. The best value in $M_b$ represents the global solution for the optimization problem.

V. Simulation Results

The validity of the proposed Algorithm technique is demonstrated on 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 real power settings are taken from [1]. 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.

Table 1. Voltage Stability under Contingency State

<table>
<thead>
<tr>
<th>Sl.No</th>
<th>Contigency</th>
<th>ORPD Setting</th>
<th>Vscrpd Setting</th>
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<tr>
<td>1</td>
<td>28-27</td>
<td>0.1400</td>
<td>0.1422</td>
</tr>
<tr>
<td>2</td>
<td>4-12</td>
<td>0.1658</td>
<td>0.1662</td>
</tr>
<tr>
<td>3</td>
<td>1-3</td>
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</tr>
<tr>
<td>4</td>
<td>2-4</td>
<td>0.2012</td>
<td>0.2032</td>
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Table 2. Limit Violation Checking of State Variables

<table>
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<th>State variables</th>
<th>limits</th>
<th>ORPD</th>
<th>VSCRPD</th>
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</thead>
<tbody>
<tr>
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<td>lower</td>
<td>upper</td>
<td></td>
</tr>
<tr>
<td>Q1</td>
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<td>Q11</td>
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Table 3. COMPARISON OF REAL POWER LOSS

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<td>Genetic algorithm[52]</td>
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<tr>
<td>Real coded GA with Lindex as SVSM[53]</td>
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<td>Real coded genetic algorithm[54]</td>
<td>4.5015</td>
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<tr>
<td>Proposed CAB method</td>
<td>4.2898</td>
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VI. CONCLUSION

In this paper a novel approach CAB algorithm used to solve optimal reactive power dispatch problem, considering various generator constraints, has been successfully applied. This article proposes a novel metaheuristic optimization algorithm that is called the collective animal behavior algorithm (CAB). In CAB, the searcher agents emulate a group of animals that interact with each other considering simple behavioral rules which are modeled as mathematical operators. Such operations are applied to each agent considering that the complete group has a memory storing the best positions seen so far by using a competition principle. The CAB algorithm presents two important characteristics: 1. CAB operators allow a better tradeoff between exploration and exploitation of the search space; 2. the use of its embedded memory incorporates information regarding previously found local minima (potential solutions) during the evolution process. The proposed method formulates reactive power dispatch problem as a mixed integer non-linear optimization problem and determines control strategy with continuous and discrete control variables such as generator bus voltage, reactive power generation of capacitor banks and on load tap changing transformer tap position. To handle the mixed variables a flexible representation scheme was proposed. The performance of the proposed algorithm demonstrated through its voltage stability assessment by modal analysis is effective at various instants following system contingencies. Also this method has a good performance for voltage stability Enhancement of large, complex power system networks. The effectiveness of the proposed method is demonstrated on IEEE 30-bus system.

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