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REAL POWER LOSS MINIMIZATION BY MUTUAL MAMMAL BEHAVIOR ALGORITHM

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Abstract

This paper presents a Mutual Mammal Behavior (MM) algorithm for solving Reactive power problem in power system. Modal analysis of the system is used for static voltage stability assessment. Loss minimization is taken is taken as main objective. 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 Mutual Mammal Behavior (MM) is introduced. Mammal groups like Carnivores, African lion, Cheetah, Dingo Fennec Fox, Moose, Polar Bear, Sea Otter, Blue Whale, Bottlenose Dolphin 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 Mutual 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 Mammals which interact with each other based on the biological laws of Mutual motion. MM powerful stochastic optimization technique has been utilized to solve the reactive power optimization problem. In order to evaluate up the performance of the proposed algorithm, it has been tested on Standard IEEE 57,118 bus systems. Proposed MM algorithm out performs other reported standard algorithm's in reducing real power loss.

Keywords: Reactive Power; Transmission Loss; Mutual Mammal Behavior; Optimization.

1. Introduction

Main objective is to operate the system in secure mode and also to improve the economy of the system. The sources of the reactive power are the generators, synchronous condensers, capacitors, static compensators and tap changing transformers. Various mathematical techniques

have been utilized to solve this optimal reactive power problem like the gradient method [1, 2], Newton method [3] and linear programming [4-7]. The gradient and Newton methods failed to handle inequality constraints. In last few years several biological and natural processes have been utilized in the methodologies of science and technology in an increasing manner. Among the most popular nature inspired approaches are Particle Swarm Optimization [8], the artificial immune systems [9], the Ant Colony Optimization [10], etc. Also, a number of swarm intelligence algorithms, based on the behaviour of the bees have been presented [11]. Just recently, the concept of individual-organization has been widely referenced to understand Mutual behavior of Mammals. The central principle of individual organization is that simple repeating interactions between individuals can produce complex behavioral patterns at group level [12-33]. Such inspiration comes from behavioral patterns previously seen in several Mammal groups. On the other hand, new studies have also shown the existence of Mutual memory in Mammal groups. The presence of such memory establishes that the previous history of the group structure influences the Mutual behavior exhibited in future stages. According to such principle, it is possible to model complex Mutual behaviors by using simple individual rules and configuring a general memory. In this paper, a new optimization algorithm inspired by the Mutual Mammal Behavior (MM) is proposed. In this algorithm, the searcher agents emulate a group of Mammals 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 performance of MM algorithm has been evaluated in standard IEEE 57,118 Bus test systems and the results analysis shows that our proposed approach performs well when compared to other reported algorithms.

2. Problem Formulation

The objectives of the reactive power problem is to minimize the real power loss.

2.1. Active Power Loss

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

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

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

2.2. Voltage Profile Improvement

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

$$F = P_L + \omega_v \times VD \qquad (2)$$

Where VD - voltage deviation, ω_v - is a weighting factor of voltage deviation.

And the Voltage deviation given by:

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

Where Npq- number of load buses

2.3. Equality Constraint

The equality constraint of the problem is indicated by the power balance equation as follows:

$$P_G = P_D + P_L \tag{4}$$

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

2.4. Inequality Constraints

The inequality constraint implies the limits on components in the power system in addition to the limits created to make sure system security. Upper and lower bounds on the active power of slack bus (P_g), and reactive power of generators (Q_g) are written as follows:

$$P_{gslack}^{min} \leq P_{gslack} \leq P_{gslack}^{max} \tag{5}$$

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max} , i \in N_g \tag{6}$$

Upper and lower bounds on the bus voltage magnitudes (V_i) is given by:

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

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

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

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

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

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

3. Mutual Mammal Behavior Algorithm (MM)

The MM algorithm assumes the existence of a set of operations that resembles the interaction rules that model the Mutual Mammal behavior. In the approach, each solution within the search space represents a Mammal position. The "fitness value" refers to the Mammal dominance with respect to the group. The complete process mimics the Mutual Mammal behavior. The approach

in this paper implements a memory for storing best solutions (Mammal positions) mimicking the aforementioned biologic process. Such memory is divided into two different elements, one for maintaining the best locations at each generation ($\mathbf{M}_g$) and the other for storing the best historical positions during the complete evolutionary process ($\mathbf{M}_h$).

Description of the MM Algorithm

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

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).

Initialization of Population

The algorithm begins by initializing a set **A** of *Np* Mammal positions (**A** ={**a**1, **a**2, . . . , **a**N_p}). Each Mammal position **a***i* is a *D*-dimensional vector containing parameter values to be optimized. Such values are randomly and uniformly distributed between the pre specified lower initial parameter bound a_j^{low} and the upper initial parameter bound a_j^{high}.

$$a_{j,i} \;=\; a_j^{low} \;+\; \text{rand}\,(0,1) \,.\, (a_j^{high} - a_j^{low})\,; \quad j = 1,2,.....,D\,;\, i = 1,2,....,N_p\,. \tag{10}$$

With j and *i* being the parameter and individual indexes, respectively. Hence, *aj,i* 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, . . . , **x**N_p}, so that we can choose the best *B* positions and store them in the memory $\mathbf{M}_g$ and $\mathbf{M}_h$. The fact that both memories share the same information is only allowed at this initial stage.

Preserve the Position of the Best Individuals

Analogous to the biological metaphor, this behavioral rule, typical from Mammal groups, is implemented as an evolutionary operation in our approach. In this operation, the first *B* elements ({**a**1, **a**2, . . . , **a**$_B$}), of the new Mammal position set **A**, are generated. Such positions are computed by the values contained inside the historical memory $\mathbf{M}_h$, considering a slight random perturbation around them. This operation can be modeled as follows:

$$a_l = m_h^l + v \tag{11}$$

While m_h^l represents the *l*-element of the historical memory $\mathbf{M}_h$. **v** is a random vector with a small enough length random vector with a small enough length.

Transfer to Close Neighbors

From the biological inspiration, Mammals 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 $\mathbf{M}_h$); otherwise, it is attracted/repelled to/from the nearest best location within the group for the current generation (i.e., the nearest position in $\mathbf{M}_g$). Therefore such operation can be modeled as follows:

$$a_i = \begin{cases} x_i \pm r \cdot (m_h^{nearest} - x_i) & \text{with probability } H \\ x_i \pm r \cdot (m_g^{nearest} - x_i) & \text{with probability } (1-H) \end{cases} \tag{12}$$

Where $i \in \{B+1, B+2, \ldots, N_p\}$, $m_h^{nearest}$ and $m_g^{nearest}$ represent the nearest elements of $\mathbf{M}_h$ and $\mathbf{M}_g$ to $\mathbf{x}_i$, while r is a random number between $[-1, 1]$. Therefore, if $r > 0$, the individual position $\mathbf{x}i$ is attracted to the position $m_h^{nearest}$ or $m_g^{nearest}$ otherwise such movement is considered as a repulsion.

Transfer Arbitrarily

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

$$a_i = \begin{cases} r & \text{with probability } P \\ x_i & \text{with probability } (1-P) \end{cases} \tag{13}$$

With $i \in \{B+1, B+2, \ldots, Np\}$ $\mathbf{r}$ a random vector defined in the search space.

Contend for the Space within a Resolute Distance (Update the Memory)

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 Mammal positions, generating N_p new positions, it is necessary to update the memory $\mathbf{M}_h$. In order to update memory $\mathbf{M}_h$, the concept of dominance is used. Mammals that interact within the group maintain a minimum distance among them. Such distance, which is defined as ρ in the context of the MM algorithm, depends on how aggressive the Mammal behaves. Hence, when two Mammals confront each other inside such distance, the most dominant individual prevails meanwhile other withdraw.

In the proposed algorithm, the historical memory $\mathbf{M}_h$ is updated considering the following procedure.
1) The elements of $\mathbf{M}_h$ and $\mathbf{M}_g$ are merged into $\mathbf{M}_U$ ($\mathbf{M}_U = \mathbf{M}_h \cup \mathbf{M}_g$).
2) Each element m_u^i of the memory $\mathbf{M}_U$ is compared pair wise to the remaining memory elements ($\{m_u^1, m_u^2, \ldots m_u^{2B-1}, \}$). If the distance between both elements is less than ρ, the

element getting a better performance in the fitness function prevails meanwhile the other is removed.

3) From the resulting elements of $\mathbf{M}_U$ (from Step 2), it is selected the B best value to build the new $\mathbf{M}_h$.

The use of the dominance principle in MM allows considering as memory elements those solutions that hold the best fitness value within the region which has been defined by the ρ 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 ρ depends on the size of the search space. A big value of ρ improves the exploration ability of the algorithm although it yields a lower convergence rate. In order to calculate the ρ value, an empirical model has been developed after considering several conducted experiments. Such model is defined by following equation:

$$\rho = \frac{\Pi_{j=1}^{D} \ (a_j^{high} - a_j^{low})}{10.D} \tag{14}$$

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.

Computation Process

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

Step 1. Set the parameters Np, B, H, P, and NI.

Step 2. Generate randomly the position set $\mathbf{A}$ _ {$\mathbf{a}1$, $\mathbf{a}2$, . . . , $\mathbf{a}Np$} using (24).

Step 3. Sort $\mathbf{A}$ according to the objective function (dominance) to build
$\mathbf{X} = \{\mathbf{x}1, \mathbf{x}2, \ldots \mathbf{x}N_p\}$.

Step 4. Choose the first B positions of $\mathbf{X}$ and store them into the memory $\mathbf{M}_g$.

Step 5. Update $\mathbf{M}_h$ according to Section 4.2.5 (during the first iteration: $\mathbf{M}_h = \mathbf{M}_g$).

Step 6. Generate the first B positions of the new solution set $\mathbf{A}$ ({$\mathbf{a}1$, $\mathbf{a}2$, . . . , $\mathbf{a_B}$}).Such positions correspond to the elements of $\mathbf{M}_h$ making a slight random perturbation around them.

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

Step 8. If NI is completed, the process is finished; otherwise, go back to Step 3. The best value in $\mathbf{M}_h$ represents the global solution for the optimization problem

4. Simulation Results

Proposed Mutual Mammal Behavior (MM) algorithm is tested in standard IEEE-57 bus power system. The reactive power compensation buses are 18, 25 and 53. Bus 2, 3, 6, 8, 9 and 12 are PV buses and bus 1 is selected as slack-bus. The system variable limits are given in Table 1. The preliminary conditions for the IEEE-57 bus power system are given as follows:
P_{load} = 12.229 p.u. Q_{load} = 3.015 p.u.

The total initial generations and power losses are obtained as follows:
$\sum P_G$ = 12.5611 p.u. $\sum Q_G$ = 3.3312 p.u.
P_{loss} = 0.25828 p.u. Q_{loss} = -1.2039 p.u.

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

Table 1: Variable limits

Reactive Power Generation Limits							
Bus no	1	2	3	6	8	9	12
Qgmin	-1.4	-.015	-.02	-0.04	-1.3	-0.03	-0.4
Qgmax	1	0.3	0.4	0.21	1	0.04	1.50
Voltage And Tap Setting Limits							
vgmin	Vgmax	vpqmin	Vpqmax	tkmin	tkmax		
0.9	1.0	0.91	1.05	0.9	1.0		
Shunt Capacitor Limits							
Bus no	18	25	53				
Qcmin	0	0	0				
Qcmax	10	5.2	6.1				

Table 2: Control variables obtained after optimization

Control Variables	MM
V1	1.1
V2	1.049
V3	1.043
V6	1.033
V8	1.031
V9	1.018
V12	1.020
Qc18	0.0672
Qc25	0.200
Qc53	0.0472
T4-18	1.010
T21-20	1.068

T24-25	0.889
T24-26	0.884
T7-29	1.065
T34-32	0.882
T11-41	1.025
T15-45	1.040
T14-46	0.910
T10-51	1.021
T13-49	1.060
T11-43	0.910
T40-56	0.900
T39-57	0.950
T9-55	0.950

Table 3: Comparison results

S.No.	Optimization Algorithm	Finest Solution	Poorest Solution	Normal Solution
1	NLP [34]	0.25902	0.30854	0.27858
2	CGA [34]	0.25244	0.27507	0.26293
3	AGA [34]	0.24564	0.26671	0.25127
4	PSO-w [34]	0.24270	0.26152	0.24725
5	PSO-cf [34]	0.24280	0.26032	0.24698
6	CLPSO [34]	0.24515	0.24780	0.24673
7	SPSO-07 [34]	0.24430	0.25457	0.24752
8	L-DE [34]	0.27812	0.41909	0.33177
9	L-SACP-DE [34]	0.27915	0.36978	0.31032
10	L-SaDE [34]	0.24267	0.24391	0.24311
11	SOA [34]	0.24265	0.24280	0.24270
12	LM [35]	0.2484	0.2922	0.2641
13	MBEP1 [35]	0.2474	0.2848	0.2643
14	MBEP2 [35]	0.2482	0.283	0.2592
15	BES100 [35]	0.2438	0.263	0.2541
16	BES200 [35]	0.3417	0.2486	0.2443
17	Proposed MM	0.22126	0.23131	0.22189

Then Mutual Mammal Behavior (MM) has been tested in standard IEEE 118-bus test system [36] .The system has 54 generator buses, 64 load buses, 186 branches and 9 of them are with the tap setting transformers. The limits of voltage on generator buses are 0.95 -1.1 per-unit., and on load buses are 0.95 -1.05 per-unit. The limit of transformer rate is 0.9 -1.1, with the changes step of 0.025. The limitations of reactive power source are listed in Table 4, with the change in step of 0.01.

Table 4: Limitation of reactive power sources

BUS	5	34	37	44	45	46	48
QCMAX	0	14	0	10	10	10	15
QCMIN	-40	0	-25	0	0	0	0
BUS	74	79	82	83	105	107	110
QCMAX	12	20	20	10	20	6	6
QCMIN	0	0	0	0	0	0	0

The statistical comparison results of 50 trial runs have been list in Table 5 and the results clearly show the better performance of proposed MM algorithm.

Table 5: Comparison results

Active power loss (MW)	BBO [37]	ILSBBO/ strategy1 [37]	ILSBBO/ strategy1 [37]	Proposed MM
Min	128.77	126.98	124.78	116.81
Max	132.64	137.34	132.39	120.90
Average	130.21	130.37	129.22	118.65

3. Conclusion

In this paper an innovative approach MM algorithm used to solve reactive power problem. This article recommends a novel metaheuristic optimization algorithm that is called Mutual Mammal Behavior algorithm (MM). The MM algorithm presents two important characteristics: a. MM operators allow a better trade-off between exploration and exploitation of the search space; b. the use of its embedded memory incorporates information regarding previously found local minima (potential solutions) during the evolution process. The performance of the proposed algorithm has been demonstrated by testing it on standard IEEE 57,118 test bus systems. Proposed MM algorithm out performs other reported standard algorithm's in reducing real power loss.

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