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Modified Monkey Optimization Algorithm for Solving Optimal Reactive Power Dispatch Problem

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Abstract

In this paper, a novel approach Modified Monkey optimization (MMO) algorithm for solving optimal reactive power dispatch problem has been presented. MMO is a population based stochastic meta-heuristic algorithm and it is inspired by intelligent foraging behaviour of monkeys. This paper improves both local leader and global leader phases. The proposed (MMO) algorithm has been tested in standard IEEE 30 bus test system and simulation results show the worthy performance of the proposed algorithm in reducing the real power loss.

Keywords: *optimal reactive power, transmission loss, modified monkey optimization, bio-inspired algorithm*

1. Introduction

Reactive power optimization plays a key role in optimal operation of power systems. Many numerical methods [1-7] have been applied to solve the optimal reactive power dispatch problem. The problem of voltage stability plays a strategic role in power system planning and operation [8]. So many Evolutionary algorithms have been already proposed to solve the reactive power flow problem [9-11]. In [12, 13], Hybrid differential evolution algorithm and Biogeography Based algorithm has been projected to solve the reactive power dispatch problem. In [14, 15], a fuzzy based technique and improved evolutionary programming has been applied to solve the optimal reactive power dispatch problem. In [16, 17] nonlinear interior point method and pattern based algorithm has been used to solve the reactive power problem. In [18-20], various types of probabilistic algorithms utilized to solve optimal reactive power problem. This paper introduces a novel Modified Monkey optimization for solving optimal reactive power dispatch power problem. Monkey Optimization algorithm [21] is fresh entry in class of swarm intelligence. This Monkey Optimization algorithm is enthused by fission fusion social structure based on foraging behaviour of monkeys when searching for quality food source and for mating. Alike to any other population based optimization techniques, artificial bee colony (ABC) consists of a population of intrinsic solutions. The intrinsic solutions are food sources of honey bees. The fitness is decided in terms of the quality of the food source that is nectar amount. Artificial bee colony is comparatively a direct, quick and population based stochastic exploration technique in the field of nature inspired algorithms. Monkey Optimization algorithm is also alike to ABC in nature. There are two fundamental processes which drive the swarm to modernize in ABC: the deviation process, which empowers exploring different fields of the exploration space, and the selection process, which guarantees the exploitation of the preceding experience. However, it has been shown that the ABC may infrequently stop moving toward the global optimum even though the population has not meeting to a local optimum [22]. It can be observed that the solution search equation of ABC algorithm is good at exploration but poor at exploitation [23]. Therefore, to uphold the good equilibrium between exploration and exploitation behaviour of ABC, it is extremely expected to develop a local exploration method in the basic ABC to strengthen the exploration region. The proposed MMO algorithm has been evaluated in standard IEEE 30 bus test system & the simulation results show that our proposed approach outperforms all reported algorithms in minimization of real power loss.

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2. Problem Formulation
2.1. 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:

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

Or,

$$F = PL = \sum_{i\in Ng} P_{gi} - P_d = P_{gslack} + \sum_{i\neq slack}^{Ng} P_{gi} - P_d \tag{2}$$

Where g_k : is the conductance of branch between nodes i and j, N_{br}: 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_{gsalck}: is the generator active power of slack bus.

2.2. Voltage Profile Improvement
For minimizing the voltage deviation in PQ buses, the objective function becomes:

$$F = PL + \omega_v \times VD \tag{3}$$

Where ωv: is a weighting factor of voltage deviation.

VD is the voltage deviation given by:

$$VD = \sum_{i=1}^{Npq} |V_i - 1| \tag{4}$$

2.3. Equality Constraint
The equality constraint of the optimal reactive power dispatch power (ORPD) problem is represented by the power balance equation, where the total power generation must cover the total power demand and the power losses:

$$P_G = P_D + P_L \tag{5}$$

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

2.4. Inequality Constraints
The inequality constraints 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:

$$P_{gslack}^{min} \le P_{gslack} \le P_{gslack}^{max} \tag{6}$$

$$Q_{gi}^{min} \le Q_{gi} \le Q_{gi}^{max}, i \in N_g \tag{7}$$

Upper and lower bounds on the bus voltage magnitudes:

$$V_i^{min} \le V_i \le V_i^{max}, i \in N \tag{8}$$

Upper and lower bounds on the transformers tap ratios:

$$T_i^{min} \le T_i \le T_i^{max}, i \in N_T \tag{9}$$

Upper and lower bounds on the compensators reactive powers:

$$Q_c^{min} \le Q_c \le Q_C^{max}, i \in N_C \tag{10}$$

Where N is the total number of buses, NT is the total number of Transformers; Nc is the total number of shunt reactive compensators.

3. Monkey Optimization Algorithm

JC Bansal et al. [21] used Social activities of monkeys to develop a stochastic optimization algorithm that impersonate fission-fusion social structure based intelligent foraging behaviour of spider monkeys. JC Bansal et al. [21] identified four key features.

Step 1. The group starts food foraging and evaluates their distance from the food.

Step 2. Group members update their positions based on the distance from the foods source and all over again evaluate distance from the food sources.

Step 3. Moreover, in this step, the local leader modernizes its best location within the group and if the location is not rationalized for a predefined number of times then all members of that group start searching of the food sources in different directions.

Step 4. Consequently, in the last step, the global leader keep informed its eternally best position and in case of inactivity, it divides the group into smaller size subgroups.

It is witnessed that in SMO algorithm [21] there are two most significant control parameters are Global Leader Limit (GLlimit) and Local Leader Limit (LLlimit) which provide suitable direction to global and local leaders respectively. In SMO immobility can be evaded by using LLlimit. If a local group leader does not keep informed her-self after a predefined number of times then that group is re-directed to another direction for in order to quest for food. Here, the term predefined number of times is referred as LLlimit. An additional control parameter, that is to say Global Leader Limit (GLlimit) is used for the identical intention by global leader. The global leader divides the group into smaller sub-groups if she does not modernize in a predefined number of times that is GLlimit. Similar to the other population-based algorithms, SMO is also a hit and trial based mutual iterative approach. The SMO development consists of seven major phases. The detailed description of each step of SMO achievement is delineated below:

a) Initialization of the Population

At the outset, SMO [21] produces an consistently dispersed primary population of N spider monkeys where each monkey SMi (i = 1, 2, ..., N) is a vector of dimension D. At this point D is the number of variables in the optimization problem and SMi represent the position of ith Spider Monkey (SM) in the population. Each spider monkey SM corresponds to the potential solution of the problem under consideration. Each SMi is initialized as follows:

$$\mathrm{SM}_{\mathrm{ij}} = \mathrm{SM}_{\min \mathrm{j}} + \emptyset \times \left(\mathrm{SM}_{\max \mathrm{j}} - \mathrm{SM}_{\min \mathrm{j}}\right) \tag{11}$$

b) Local Leader Phase (LLP)

The second phase in SMO is Local Leader phase. In this phase SM update its existing location based on the information from the local leader understanding as well as local group members understanding. The fitness value of so obtained new location is calculated. If the fitness value of the new location is higher than that of the previous location, subsequently the SM updates his location with the new one. The location modernizes equation for ith SM (which is a member of kth local group) in this phase is as follow:

$$\mathrm{SM}_{\mathrm{newij}} = \mathrm{SM}_{\mathrm{ij}} + \emptyset_1 \times \left(\mathrm{LL}_{\mathrm{kj}} - \mathrm{SM}_{\mathrm{ij}}\right) + \emptyset_2 \times \left(\mathrm{SM}_{\mathrm{rj}} - \mathrm{SM}_{\mathrm{ij}}\right) \tag{12}$$
$$\text{where } \emptyset_1 \in (0,1) \text{and } \emptyset_2 \in (-1,1)$$

Where SMij is the jth dimension of the ith SM, LLkj represents the jth dimension of the kth local group leader position. SMrj is the jth dimension of the rth SM which is chosen randomly within kth group such that r≠ i.

c) Global Leader Phase (GLP)

After achievement of the Local Leader phase next phase is Global Leader phase (GLP). During GLP phase, all the SM's bring up to date their location by means of understanding of Global Leader and local group member's understanding. The location modernizes equation for this phase is as follows:

$$SM_{newij} = SM_{ij} + \emptyset_1 \times (GL_j - SM_{ij}) + \emptyset_2 \times (SM_{rj} - SM_{ij}) \quad (13)$$
where $\emptyset_1 \in (0,1)$ and $\emptyset_2 \in (-1,1)$.

Where GLj stands for the jth dimension of the global leader location and j ∈{1, 2, ...,D} is the haphazardly preferred index.

In GLP phase, the locations of spider monkeys (SMi) are modernized based on probabilities pi's which are considered using their fitness. In this way a better candidate will have more chance to make itself better. The probability pi may be calculated using following expression:

$$p_i = 0.9 \times \frac{fitness_i}{fitness_{max}} + 0.1 \quad (14)$$

Here fitnessi is the fitness value of the ith SM and fitnessmax is the maximum fitness in the group. Further, the fitness of the newly produced position of the SM's is calculated and compared with the old one and adopted the better position.

d) Global Leader Learning (GLL) phase

In GLL phase, the location of the global leader is restructured by applying the rapacious selection approach in the population i.e., the location of the SM having most outstanding fitness in the population is selected as the modernized location of the global leader. Further, it is checked that the location of global leader is modernizing or not and if not then the Global Limit Count is incremented by 1.

e) Local Leader Learning (LLL) phase

In LLL phase, the position of the local leader is modernized by applying the greedy selection in that group i.e., the location of the SM having unmatched fitness in that group is preferred as the updated location of the local leader. Next, the updated location of the local leader is compared with the older one and if the local leader is not updated then the Local Limit Count is incremented by 1.

f) Local Leader Decision (LLD) phase

If any Local Leader position is not modernized up to a predefined threshold called Local Leader Limit (LLLimit), then all the members of that group update their locations either by arbitrary initialization or by using mutual information from Global Leader and Local Leader through equation (15), based on the pr (perturbation rate).

$$SM_{newij} = SM_{ij} + \emptyset \times (GL_j - SM_{ij}) + \emptyset \times (SM_{ij} - LL_{kj}) \quad (15)$$
where $\emptyset \in (0,1)$

It is comprehensible from the equation (15) that the modernized measurement of this SM is attracted towards global leader and fends off from the local leader.

g) Global Leader Decision (GLD) phase

In GLD phase, the position of global leader is observed and if it is not updated up to a predefined number of iterations is known as Global Leader Limit (GLlimit), then the global leader divides the population into smaller groups. Firstly, the population is divided into two groups and then three groups and so on till the maximum number of groups (MNG) are formed. Each time in GLD phase, LLL procedure is began to decide on the local leader in the recently fashioned groups. The case in which maximum number of groups is formed and even then the position of global leader is not modernized then the global leader pools all the groups to form a single group. As a consequence the predicted algorithm mimics fusion-fission structure of SMs. The complete pseudo-code of the SMO algorithm is outlined as follow [21]:

Spider Monkey Optimization (SMO) Algorithm:

Step 1. Set Population, Local Leader Limit (LLlimit), Global Leader Limit (GLlimit) and Perturbation rate (pr).

Step 2. Calculate fitness (The distance of each individual from corresponding food sources).

Step 3. Select leaders (global and local both) by smearing greedy selection.

Step 4. while (Annihilation criteria is not fulfilled) do

Step 5. Produce the new locations for all the group members by using self-experience, local leader experience and group member's experience. Using Equation (12)

Step 6. Apply the gluttonous selection process between existing location and newly generated location, based on fitness and select the enhanced one.

Step 7. Calculate the probability pi for all the group members using Equation (14).

Step 8. Produce new locations for the all the group members, selected by pi, by using self-experience, global leader experience and group members experiences Using Equation (13)

Step 9. Modernize the position of local and global leaders, by applying the greedy selection process on all the groups.

Step 10. If any Local group leader is not updating her position after a specified number of times (LLLimit) then re-direct all members of that particular group for foraging by algorithm using Equation (15).

Step 11. If Global Leader is not modernizing her position for a specified number of times (GLLimit) then she divides the group into smaller groups by following steps.

Step 12. End While

4. Modified Monkey Optimization (MMO) Algorithm

Exploration of the whole search space and exploitation of the best solutions found in its proximity may be balanced by maintaining the diversity in local leader and global leader phase of SMO. In order to balance exploration and exploitation of local search space the proposed algorithm alter both local leader phase and global leader phase using modified golden section search (GSS) [24]. Original GSS method does not use any gradient information of the function to finds the optima of a uni-modal continuous function. GSS processes the interval [a = −1.2, b = 1.2] and initiates two intermediate points:

$$F1 = b - (b - a) \times \psi, \tag{16}$$

$$F2 = a + (b - a) \times \psi, \tag{17}$$

Here ψ = 0.618 is the golden ratio.

The detailed GSS process [25] is described as follows:

Golden Section Search procedure
Input: Optimization function
Min f(x) s.t. a ≤ x ≤ b and termination criteria
Repeat while termination criteria fulfill
Calculate F1and F2 as follow
F1=b-(b-a)*Ψ and F2=a+(b-a)*Ψ here a = −1.2, b = 1.2 and Ψ=0.618(Golden ratio)
Compute f(F1) and f(F2)
If f(F1)< f(F2) then
b = F2 and the solution fall in range [a,b]
else
a = F1 and the solution fall in range [a,b]
end if
end while

The proposed strategy modify Equation (12) and (13) in the following manner. Here f is determined by GSS process as outlined in above algorithm. Position update in local leader phase is done using Equation (18).

$$\mathrm{SM}_{\mathrm{newij}} = \mathrm{SM}_{\mathrm{ij}} + \emptyset_1 \times (\mathrm{LL}_{\mathrm{kj}} - \mathrm{SM}_{\mathrm{ij}}) + \emptyset_2 \times (\mathrm{SM}_{\mathrm{rj}} - \mathrm{SM}_{\mathrm{ij}}) + \mathrm{f} \times (\mathrm{SM}_{\mathrm{rj}} - \mathrm{SM}_{\mathrm{ij}}) \tag{18}$$

here $\emptyset_1 \in (0,1)$ and $\emptyset_2 \in (-1,1)$ f is decided by GSS.

Position update in local leader phase is done using Equation (19).

$$\mathrm{SM}_{\mathrm{newij}} = \mathrm{SM}_{\mathrm{ij}} + \emptyset_1 \times (\mathrm{GL}_{\mathrm{j}} - \mathrm{SM}_{\mathrm{ij}}) + \emptyset_2 \times (\mathrm{SM}_{\mathrm{rj}} - \mathrm{SM}_{\mathrm{ij}}) + \mathrm{f} \times (\mathrm{SM}_{\mathrm{rj}} - \mathrm{SM}_{\mathrm{ij}}) \tag{19}$$

here $\emptyset_1 \in (0,1)$ and $\emptyset_2 \in (-1,1)$ f is decided by GSS.

MMO Algorithm:

Step 1. Initialize Population, Local Leader Limit (LLlimit), Global Leader Limit (GLlimit) and Perturbation rate (pr).

Step 2. Compute fitness (The distance of each individual from corresponding food sources).

Step 3. Select leaders (global and local both) by applying greedy selection.

Step 4. while (extermination criteria is not fulfilled) do

Step 5. For finding the objective (Food Source), generate the new locations for all the group members by using self-experience, local leader experience and group member's experience.

$$SM_{newij} = SM_{ij} + \emptyset_1 \times (LL_{kj} - SM_{ij}) + \emptyset_2 \times (SM_{rj} - SM_{ij}) + f \times (SM_{rj} - SM_{ij})$$

where $\emptyset_1 \in (0,1)$ and $\emptyset_2 \in (-1,1)$ f is decided by GSS.

Step 6. Apply the gluttonous selection process between existing location and newly generated location, based on fitness and select the better one;

Step 7. Calculate the probability pi for all the group members using,

$$p_i = 0.9 \times \frac{fitness_i}{fitness_{max}} + 0.1$$

Step 8. Produce new locations for the all the group members, selected by pi, by using self-experience, global leader experience and group member's experiences.

$$SM_{newij} = SM_{ij} + \emptyset_1 \times (GL_j - SM_{ij}) + \emptyset_2 \times (SM_{rj} - SM_{ij}) + f \times (SM_{rj} - SM_{ij})$$

where $\emptyset_1 \in (0,1)$ and $\emptyset_2 \in (-1,1)$ f is decided by GSS.

Step 9. Modernize the position of local and global leaders, by applying the greedy selection process on all the groups.

Step 10. If any Local group leader is not updating her position after a specified number of times (LLLimit) then re-direct all members of that particular group for foraging by algorithm.

if U(0,1) ≥ pr

$$SM_{newij} = SM_{min\,j} + \emptyset \times (SM_{max\,j} - SM_{min\,j})$$

Else

$$SM_{newij} = SM_{ij} + \emptyset \times (GL_j - SM_{ij}) + \emptyset \times (SM_{ij} - LL_{kj})$$

where $\emptyset \in (0,1)$

Step 11. If Global Leader is not updating her position for a specified number of times (GLLimit) then she divides the group into smaller groups by following steps.

if Global Limit Count > GLLimit then set Global Limit Count = 0
if Number of groups < MNG then
Divide the population into groups.
else
Pool all the groups to make a single group.
Modernize Local Leaders position.

5. Simulation Results

MMO algorithm has been tested on the IEEE 30-bus, 41 branch system. It has a total of 13 control variables as follows: 6 generator-bus voltage magnitudes, 4 transformer-tap settings, and 2 bus shunt reactive compensators. Bus 1 is the slack bus, 2, 5, 8, 11 and 13 are taken as PV generator buses and the rest are PQ load buses. The measured security constraints are the voltage magnitudes of all buses, the reactive power limits of the shunt VAR compensators and the transformers tap settings limits. The variables limits are listed in Table 1.

The transformer taps and the reactive power source installation are discrete with the changes step of 0.01. The power limits generators buses are represented in Table 2. Generators buses are: PV buses 2, 5, 8, 11, 13 and slack bus is 1. The others are PQ-buses.

Table 1. Initial Variables Limits (PU)

Control variables	Min.value	Max.value	Type
Generator: Vg	0.92	1.08	Continuous
Load Bus: VL	0.90	1.01	Continuous
T	0.90	1.40	Discrete
Qc	-0.11	0.30	Discrete

Table 2. Generators Power Limits in MW and MVAR

Bus n°	Pg	Pgmin	Pgmax	Qgmin
1	97.00	50	200	-20
2	80.00	20	80	-20
5	52.00	15	55	-13
8	20.00	10	31	-13
11	20.00	10	25	-10
13	20.00	11	40	-13

Table 3 show that the proposed approach succeeds in keeping the dependent variables within their limits. Table 4 summarizes the results of the optimal solution by different methods. It reveals the reduction of real power loss after optimization.

Table 3. Values of Control Variables after Optimization and Active Power Loss

Control Variables (p.u)	MMO
V1	1.0308
V2	1.0379
V5	1.0190
V8	1.0289
V11	1.0619
V13	1.0428
T4,12	0.00
T6,9	0.01
T6,10	0.91
T28,27	0.90
Q10	0.11
Q24	0.10
PLOSS	4.5328
VD	0.9081

Table 4. Comparison Results of Different Methods

Methods	Ploss (MW)
SGA (26)	4.98
PSO (27)	4.9262
LP (28)	5.988
EP (28)	4.963
CGA (28)	4.980
AGA (28)	4.926
CLPSO (28)	4.7208
HSA (29)	4.7624
BB-BC (30)	4.690
MMO	4.5328

6. Conclusion

In this paper, the MMO has been successfully implemented to solve Optimal Reactive Power Dispatch problem. The main advantages of the MMO are easily handling of non-linear constraints. The proposed algorithm has been tested on the IEEE 30-bus system to minimize the active power loss. The optimal setting of control variables are well within the limits. The results were compared with the other heuristic methods and proposed MMO demonstrated its effectiveness and robustness in minimizing the real power loss.

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