



Science

ENHANCED SEEKER OPTIMIZATION ALGORITHM FOR REDUCTION OF ACTIVE POWER LOSS

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Abstract

This paper projects Enhanced Seeker Optimization (ESO) algorithm for solving optimal reactive power problem. Seeker optimization algorithm (SOA) models the deeds of human search population based on their memory, experience, uncertainty reasoning and communication with each other. In Artificial Bee Colony (ABC) algorithm the colony consists of three groups of bees: employed bees, onlookers and scouts. All bees that are presently exploiting a food source are known as employed bees. The number of the employed bees is equal to the number of food sources and an employed bee is allocated to one of the sources. In this paper hybridization of the seeker optimization algorithm with artificial bee colony (ABC) algorithm has been done to solve the optimal reactive power problem. Enhanced Seeker Optimization (ESO) algorithm combines two different solution exploration equations of the ABC algorithm and solution exploration equation of the SOA in order to progress the performance of SOA and ABC algorithms. At certain period's seeker's location are modified by search principles obtained from the ABC algorithm, also it adjust the inter-subpopulation learning phase by using the binomial crossover operator. In order to evaluate the efficiency of proposed Enhanced Seeker Optimization (ESO) algorithm it has been tested in standard IEEE 57,118 bus systems and compared to other specified algorithms. Simulation results clearly indicate the best performance of the proposed Enhanced Seeker Optimization (ESO) algorithm in reducing the real power loss and voltage profiles are within the limits.

Keywords: Reactive Power; Transmission Loss; Enhanced Seeker; Optimization.

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1. 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 maintain voltage stability of the system. It involves a nonlinear optimization problem. Various mathematical techniques have been adopted to solve this optimal reactive power dispatch problem. These include the gradient method [1, 2], Newton method [3] and linear programming [4-7]. 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 many global optimization techniques have been proposed to solve the reactive power flow problem [8-10]. This paper projects Enhanced Seeker Optimization (ESO) algorithm for solving optimal reactive power problem. Seeker optimization algorithm (SOA) models the deeds of human search population [11-16] based on their memory, experience, uncertainty reasoning and communication with each other. In Artificial Bee Colony (ABC) algorithm [17-23] the colony consists of three groups of bees: employed bees, onlookers and scouts. All bees that are presently exploiting a food source are known as employed bees. The number of the employed bees is equal to the number of food sources and an employed bee is allocated to one of the sources. In this paper hybridization of the seeker optimization algorithm with artificial bee colony (ABC) algorithm has been done to solve the optimal reactive power problem. Enhanced Seeker Optimization (ESO) algorithm combines two different solution exploration equations of the ABC algorithm and solution exploration equation of the SOA in order to progress the performance of SOA and ABC algorithms. At certain period's seeker's location are modified by search principles obtained from the ABC algorithm, also it adjust the inter-subpopulation learning phase by using the binomial crossover operator. In order to evaluate the efficiency of proposed Enhanced Seeker Optimization (ESO) algorithm it has been tested in standard IEEE 57,118 bus systems and compared to other specified algorithms. Simulation results clearly indicate the best performance of the proposed Enhanced Seeker Optimization (ESO) algorithm in reducing the real power loss and voltage profiles are within the limits.

2. Objective Function

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:

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

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:

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

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

And the Voltage deviation given by:

$$VD = \sum_{i=1}^{N_{pq}} |V_i - 1| \quad (3)$$

Where N_{pq} - number of load buses

2.3. Equality Constraint

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

$$P_G = P_D + P_L \quad (4)$$

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:

$$P_{gslack}^{\min} \leq P_{gslack} \leq P_{gslack}^{\max} \quad (5)$$

$$Q_{gi}^{\min} \leq Q_{gi} \leq Q_{gi}^{\max}, i \in N_g \quad (6)$$

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

$$V_i^{\min} \leq V_i \leq V_i^{\max}, i \in N \quad (7)$$

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

$$T_i^{\min} \leq T_i \leq T_i^{\max}, i \in N_T \quad (8)$$

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

$$Q_c^{\min} \leq Q_c \leq Q_c^{\max}, i \in N_C \quad (9)$$

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. Seeker Optimization Algorithm

Seeker optimization algorithm (SOA) models the deeds of human search population based on their memory, experience, uncertainty reasoning and communication with each other. Therefore the individual of this population is called seeker or searcher. In the SOA, the total population is equally categorized into three subpopulations according to the directories of the seekers. All the seekers in the same subpopulation constitute a neighborhood which symbolizes the social component for the social sharing of information. Seeker i has the following attributes: the current Position $x_i = (x_{i1}, x_{i2}, \dots, x_{iD})$, the dimension of the problem D , the iteration number t , the personal best position $p_{i,best}$ so far, and the neighborhood best position g_{best} so far. The algorithm uses exploration direction and step length to update the positions of seekers. In the SOA, the search direction is determined by seeker's egotistic behaviour, altruistic behaviour and pro-

activeness behaviour, while step length is given by ambiguity reasoning behaviour. Search direction α_{ij} and step length d_{ij} are separately computed for each individual i on each dimension j at each iteration t , where $\alpha_{ij} \geq 0$ and $d_{ij} \in \{-1; 0; 1\}$. At each iteration the position of each seeker is modernized by:

$$x_{ij}(t + 1) = x_{ij}(t) + \alpha_{ij}(t).d_{ij} \quad (10)$$

Where $i = 1, 2, \dots, SN$; $j = 1, 2, \dots, D$ (SN is the number of seekers). Also, at each iteration, the current positions of the poorest two individuals of each subpopulation are swapped with the best ones in each of the other two subpopulations, which are called inter-subpopulation learning.

Algorithm of Seeker optimization

Create SN positions uniformly and arbitrarily in the exploration space;

$t = 0$;

Appraise all the seekers and save the historical best position;

Repeat

Calculate search direction and step length for each

Seeker;

Modernize each seeker's position

Estimate all the seekers and save the historical best position;

Implement the inter-subpopulation learning operation;

$t = t + 1$;

Until $t = T_{\max}$

3.1. Design of the Search Direction

Seeker supportive behaviour types that are modeled are: egoistic, altruistic and pro-active behaviour. Seeker's behaviour is considered egoistic if he believes that he should go toward his personal best position $p_{i,best}$ through intellectual learning. For reaching the desired goal, by altruistic behaviour, seekers want to communicate with each other and adjust their behaviors in response to other seekers in the same neighborhood region. If a seeker wants to alter his exploration direction and exhibit goal-directed behaviour according to his previous behaviour, then it is considered that his behaviour is pro-active. The expression for exploration direction d_i , which models these types of behaviour, for the i^{th} seeker is:

$$d_i = \omega \cdot \text{sign}(p_{i,best} - x_i) + r_1 \cdot (g_{best} - x_i) + r_2 \cdot (x_i(t_1)) - x_i(t_2) \quad (11)$$

Where the function $\text{sign}()$ is a signum function on each dimension of the input vector, ω is the inertia weight, $t_1, t_2 \in \{t, t - 1, t - 2\}$, $x(t_1)$ and $x(t_2)$ are the best and the worst positions in the set $x(t)$, $x(t - 1)$, $x(t - 2)$ respectively, and r_1 and r_2 are real numbers chosen consistently and arbitrarily in the range $[0, 1]$. The balance between global and local exploration and exploitation is provided by reducing the value of inertia weight. Here, inertia weight is linearly decreased from 0.9 to 0.1 during a run.

3.2. Design of the Step Size

Fuzzy reasoning is used to produce the step length because the uncertain reasoning of human searching. The ambiguity rule of intelligent search is described as “If {function value is small}, then {search radius is small}”. The linear membership function was used for “step length”. The vector μ_i which is the grade of membership from cloud model and fuzzy set theory needs to be planned in order to compute the step length. It is inverse proportional to the objective function value of x_i . Hence, the best position so far has the maximum $\mu_{max} = 1.0$, while other positions have a $\mu < 1.0$, and the worst position so far has the minimum μ_{min} . The expression is presented as:

$$\mu_i = \mu_{max} - \frac{S-I_i}{S-1} \cdot (\mu_{max} - \mu_{min}) \quad (12)$$

Where S denotes the size of the subpopulation to which the seekers belong, I_i is the sequence number of x_i after sorting the objective function values in ascending order. Besides the vector μ_i we need to calculate vector δ_i by:

$$\delta_i = \omega \cdot abs(x_{max} - x_{min}) \quad (13)$$

Where the absolute value of the input vector as the corresponding output vector is represented by the symbol $abs()$, x_{max} and x_{min} are the positions of the best and the worst seeker in the subpopulation to which the i^{th} seeker belongs, respectively. In order to introduce the arbitrariness in each variable and to progress the local search capability, the following equation is introduced to convert μ_i into a vector with elements as given by:

$$\mu_{ij} = rand(\mu_i, 1), j = 1, 2, \dots, D \quad (14)$$

The equation used for creating the step length α_i for i^{th} seeker is:

$$\alpha_i = \delta_i \cdot \sqrt{-1n(\mu_i)} \quad (15)$$

4. Artificial Bee Colony Algorithm

In Artificial Bee Colony (ABC) algorithm the colony of artificial bees consists of three groups of bees: employed bees, onlookers and scouts. All bees that are presently exploiting a food source are known as employed bees. The number of the employed bees is equal to the number of food sources and an employed bee is allocated to one of the sources. Each food source is a possible solution for the problem and the nectar amount of a food source signifies the quality of the solution represented by the fitness value. Onlookers are those bees that are waiting in the hive for the employed bees to share information about the food sources presently being exploited by them, while scouts are those bees that are penetrating for new food sources arbitrarily. The number of onlooker and employed bees is the same. Onlookers are assigned to a food source based on probability. Like the employed bees, onlookers compute a new solution from its food source. After certain number of cycles, if food source cannot be further developed, it is abandoned and swapped by arbitrarily generated food source. This is called exploration procedure and it is performed by the scout bees. Hence, employed and onlooker bees carry out exploitation procedure, while scout bees perform exploration. Short pseudo code of the ABC algorithm is given below:

Initialize the population of solutions
 Calculate the population
 $t = 0$;
 Repeat
 Employed bee phase
 Compute probabilities for onlookers
 Onlooker bee phase
 Scout bee phase
 Remember the best solution achieved so far
 $t = t + 1$;
 Until $t = T_{max}$

In employed bee phase an update procedure is performed for each solution in order to produce a new-fangled solution:

$$v_{ij} = x_{ij} + rand. (x_{ij} - x_{kj}) \quad (16)$$

Where $k = 1, 2, \dots, SN$, $j = 1, 2, \dots, D$ are arbitrarily chosen indexes, $k \neq i$, and $rand$ is a random number between $[-1, 1]$ (SN is the number of solutions, D is the dimension of the problem). Then, a grasping selection is done between x_i and v_i , which completes the modernize process. The main dissimilarity between the employed bee phase and the onlooker bee phase is that every solution in the employed bee phase involves the update procedure, while only the selected solutions have the opportunity to update in the onlooker bee phase. An inactive solution refers to a solution that does not change over a certain number of generations. In scout bee phase one of the most sluggish solutions is selected and swapped by a new arbitrarily created solution.

5. Enhanced Seeker Optimization Algorithm

Enhanced Seeker Optimization (ESO) algorithm combines two different solution exploration equations of the Artificial Bee Colony (ABC) algorithm and solution exploration equation of the Seeker optimization algorithm (SOA) in order to progress the performance of SOA and ABC algorithms. Also, algorithm implements the modified inter-subpopulation learning using the binomial crossover operator. Therefore, Enhanced Seeker Optimization (ESO) algorithm has changed the phase of updating seeker's positions and inter-subpopulation learning phase. The initialization phase remained the same as in SOA. Excluding common control parameters (solution number and maximum number of iterations), the Enhanced Seeker Optimization (ESO) algorithm keeps control parameter *Subpop N* (subpopulation number) from SOA, while it does not include any other control parameter from the ABC algorithm. The introduced modifications are described as follows.

5.1. Adjustment of Updating Seeker's Positions

In the first 55% of iterations the Enhanced Seeker Optimization (ESO) algorithm is searching for candidate solutions using exploration formula of ABC which is given by Eq. (16). After each candidate solution is formed and then appraised, its performance is compared with the old solution and a greedy selection mechanism is engaged as the selection operation between the old and the new candidate. If the new solution has better function value than the old candidate

solution, it swaps the old one in the memory. In the continuing iterations, ESO chooses between search equation Eq. (10) which is used in SOA and the variant of ABC search equation which can be described as:

$$v_{ij} = \begin{cases} x_{ij} + rand_i \cdot (x_{ij} - x_{kj}), & \text{if } R_j < 0.5 \\ x_{ij} & , \text{otherwise} \end{cases} \quad (17)$$

Where R_j is a random number within $[0, 1)$, k is randomly chosen index from the whole population and has to be different from i , and $rand_i$ is a random number between $[-1, 1]$ and $j = 1, 2, \dots, D$. The similar search equation is used in the ABC algorithm extended for constrained optimization problems, but the main difference is that in the Eq. (17) the value $rand_i$ is kept fixed for every $j = 1, 2, \dots, D$. Also this modification is used in order to improve the ABC algorithm for the engineering optimization problems. The distinction between the Eq. (16) and the Eq. (17) is in the number of the optimization parameters which will be changed. In the basic ABC, while producing a new solution, v_i , changing only one parameter of the parent solution x_i results in a slow convergence rate. In order to overcome this disadvantage, we set the probability of changing the optimization parameter to 0.5. Also, in these iterations, the greedy selection mechanism is not used between the old and the new candidate solution. Hence, the diversity in the population is increased.

In the SOA search equation which is used in Enhanced Seeker Optimization (ESO) algorithm, the Eq. (13) for calculating vector δ_i is changed. It has been concluded that the vector δ is a sensitive parameter and that proposed calculation of its values was not suitable for optimization of multimodal functions. In order to overcome this obstacle, δ_i is calculated by:

$$\delta = \omega \cdot abs(x_{max} - x_{rand}) \quad (18)$$

Where x_{rand} are the positions of the seekers in the same subpopulation where the solution i belongs. Also, in order to further increase the diversity of the solutions, and the population, in the Enhanced Seeker Optimization (ESO) algorithm the inertia weight parameter w is linearly decreased from 0.9 to 0.7 during a run.

The Enhanced Seeker Optimization (ESO) algorithm included a new control parameter which is called behavior rate (BR) in order to select the exploration equation in the following way: if an arbitrary number between $[0, 1]$ is less than BR the SOA search equation is used, otherwise the Eq. (17) is performed.

5.2. Modification of Inter-Subpopulation Learning

In the modified inter-subpopulation learning the positions of seekers with the lowest objective function values of each subpopulation l are united with the positions of seekers with the highest objective function values of $(l+t) \bmod \text{Subpop } N$ subpopulations respectively, where $t = 1, 2, 3, \dots, NSC$. NSC denotes the number of the worst seekers of each population which are combined with the best seekers. The appropriate seekers are united using the following binomial crossover operator as expressed in:

$$xl_{nj_{worst}} = \begin{cases} x_{ij}, \text{best} & , \text{if } R_j < 0.5 \\ xl_{nj}, \text{worst} & , \text{otherwise} \end{cases} \quad (19)$$

In Eq. (19) R_j is random number within $[0,1]$, $x_{lnj_{worst}}$ is denoted as the j^{th} variable of the n^{th} worst position in the l^{th} sub population, $x_{i,j,best}$ is the j^{th} variable of the best position in the i^{th} subpopulation. It can be concluded that in the Enhanced Seeker Optimization (ESO) algorithm have two new control parameters in comparison with the original Seeker optimization algorithm (SOA): the behavior rate (BR) and the number of seekers of each subpopulation for combination (NSC). Behavior rate parameter controls which of the exploration equations for producing new population will be used. In the inter-subpopulation learning of SOA it has been noticed that it may not always bring the benefits for multimodal functions since it may attract all agents towards a local optimal solution. Hence, in order to provide better equilibrium between exploitation and exploration capabilities of the algorithm, the described modifications are introduced.

6. Simulation Results

Proposed Enhanced Seeker Optimization (ESO) algorithm has been 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:

$$P_{load} = 12.012 \text{ p.u. } Q_{load} = 3.016 \text{ p.u.}$$

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

$$\sum P_G = 12.5042 \text{ p.u. } \sum Q_G = 3.3214 \text{ p.u.}$$

$$P_{loss} = 0.25628 \text{ p.u. } Q_{loss} = -1.2012 \text{ p.u.}$$

Table 2 shows the various system control variables & Table 3, gives the comparison of optimum results.

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	ESO
V1	1.1
V2	1.038
V3	1.047
V6	1.036

V8	1.031
V9	1.018
V12	1.024
Qc18	0.0659
Qc25	0.201
Qc53	0.0450
T4-18	1.010
T21-20	1.058
T24-25	0.879
T24-26	0.811
T7-29	1.050
T34-32	0.882
T11-41	1.023
T15-45	1.040
T14-46	0.910
T10-51	1.020
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 [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	0.263	0.2541
16	BES200 [25]	0.3417	0.2486	0.2443
17	Proposed ESO	0.22102	0.23118	0.22134

Proposed Enhanced Seeker Optimization (ESO) algorithm has been tested in standard IEEE 118-bus test system [26]. 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 have been list in Table 5 and the results clearly show the better performance of proposed Enhanced Seeker Optimization (ESO) algorithm.

Table 5: Comparison results

Active power loss (MW)	BBO [27]	ILSBBO/strategy1 [27]	ILSBBO/strategy1 [27]	Proposed ESO
Min	128.77	126.98	124.78	116.32
Max	132.64	137.34	132.39	122.74
Average	130.21	130.37	129.22	118.46

7. Conclusion

In this paper Enhanced Seeker Optimization (ESO) algorithm successfully solved the optimal reactive power problem. Enhanced Seeker Optimization (ESO) algorithm combines two different solution exploration equations of the ABC algorithm and solution exploration equation of the Seeker optimization algorithm (SOA) in order to progress the performance of SOA & Artificial Bee Colony (ABC) algorithm. At certain period's seeker's location are modified by search principles obtained from the ABC algorithm, also it adjust the inter-subpopulation learning phase by using the binomial crossover operator. In order to evaluate the efficiency of proposed Enhanced Seeker Optimization (ESO) algorithm it has been tested in standard IEEE 57,118 bus systems and compared to other specified algorithms. Simulation results clearly indicate the best performance of the proposed Enhanced Seeker Optimization (ESO) algorithm in reducing the real power loss and voltage profiles are within the limits.

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