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Research Article

Hybridization of Whale Optimization with Hill Climbing Technique for Solving Optimal Reactive Power Problem

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ABSTRACT

In this work Hybridization of Whale Optimization Algorithm with Hill Climbing Technique (HWOHC) has been applied for solving optimal reactive power problem. Hybridization of whale optimization with Hill climbing technique (HWOHC) enriches the exploration and also enhances the arbitrary switching between two exploration points. In HWOHC two operators successively act upon each whale to found find new regions around the whale by exploration and exploitation. Then from the two rival agents it will retain the best downhill afterwards the superior will be retained and remaining will be eliminated in subsequent stages. Proposed HWOHC has been tested in standard IEEE 30, bus test system and results show the projected HWOHC algorithm reduced the power loss comprehensively. Mainly projected HWOHC algorithm solved the multi-objective formulation of the problem and with reference to reduction of power loss, voltage deviation minimization, voltage stability enhancement results has been analyzed.

Keywords: Optimal reactive power; Transmission loss; Whale optimization; Hill climbing technique

INTRODUCTION

Reactive power problem plays an important role in secure and economic operations of power system. Numerous types of methods [1-6] have been utilized to solve the optimal reactive power problem. However many scientific difficulties are found while solving problem due to an assortment of constraints. Evolutionary techniques [7-18] are applied to solve the reactive power problem. This paper proposes Hybridization of Whale Optimization Algorithm with Hill Climbing Technique (HWOHC) for solving optimal reactive power dispatch problem. Hunting behavior of whales has been imitated to formulate as Whale optimization algorithm. In bubble-net form recoiling, surrounding and spiral revised position will be there. Recoil, surrounding method; control parameter "*a*" value will be decreased then the recoiling, surrounding will be obtained is $\vec{A}$ is capricious value in the interval of [−a, a]. For better local search Hill climbing technique performs well and during the process the search continues until most excellent local optimal solution has been reached. Whale optimization algorithm's exploration and exploitation has been enhanced by hybridization with Hill climbing technique. Mainly to avoid the early convergence and local optimal solution hybridization has been done. At first based on the Gaussian distribution on each interval from the modernized whale's boundaries in the search space has been found. Hybridization of whale optimization algorithm with Hill climbing technique (HWOHC) enriches the exploration and also enhances the arbitrary switching between two exploration points. In HWOHC two operators successively act upon each whale to find new-fangled regions around the whale by exploration and exploitation. Then from the two rival agents it will retain the best downhill afterwards the superior will be retained and remaining will be eliminated in subsequent stages. Proposed Hybridization of whale optimization with Hill climbing technique (HWOHC) has been tested in standard IEEE 30, bus test system and results show the projected HWOHC algorithm reduced the power loss comprehensively. Mainly projected HWOHC algorithm solved the multi-objective formulation of the problem and with reference to reduction of power loss, voltage deviation minimization, voltage stability enhancement results has been analyzed.

METHODOLOGY

Problem formulation

Objective function of the problem is mathematically defined in general mode by,

$$Minimization\ \tilde{F}(\overline{x},\overline{y})$$

Subject to

$$E(\overline{x},\overline{y})=0 \quad (2)$$

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$$l(\bar{x},\bar{y})=0 \quad (3)$$

$$x=\left[VG_1,..,VG_{Ng};QC_1,..,QC_{Nc};T_1,..,T_{N_T}\right] \quad (4)$$

$$y=\left[PG_{slack};VL_1,..,VL_{N_{Load}};QG_1,..,QG_{Ng};SL_1,..,SL_{N_T}\right] \quad (5)$$

Then the single objective problem formulation is defined as follows.

The fitness function (OF_1) is defined to reduce the power loss (MW) in the system is written as,

$$OF_1=P_{Min}=Min\left[\sum_m^{NTL}G_m\left[V_i^2+V_j^2-2*V_iV_j cos\emptyset_{ij}\right]\right] \quad (6)$$

Minimization of Voltage deviation fitness function (OF_2) is given by,

$$OF_2=Min\left[\sum_{i=1}^{N_{LB}}\left|V_{Lk}-V_{Lk}^{desired}\right|^2+\sum_{i=1}^{Ng}\left|Q_{GK}-Q_{KG}^{Lim}\right|^2\right] \quad (7)$$

Then the voltage stability index (L-index) fitness function (OF_3)is given by,

$$OF_3 = Min\ L_{Max} \quad (8)$$

$$L_{Max} = Max\ [L_j];j = 1;N_{LB} \quad (9)$$

And
$$\begin{cases} L_j=1-\sum_{i=1}^{NPV}F_{ji}\dfrac{V_i}{V_j} \\ F_{ji}=-[Y_1]^1[Y_2] \end{cases} \quad (10)$$

Such that

$$L_{Max}=Max\left[1-[Y_1]^{-1}[Y_2]\times\frac{V_i}{V_j}\right] \quad (11)$$

Then the equality constraints are

$$0=PG_i-PD_i-V_i\sum_{j\in N_B}V_j\left[G_{ij}cos\left[\emptyset_i-\emptyset_j\right]+B_{ij}sin\left[\emptyset_i-\emptyset_j\right]\right] \quad (12)$$

$$0=QG_i-QD_i-V_i\sum_{j\in N_B}V_j\left[G_{ij}sin\left[\emptyset_i-\emptyset_j\right]+B_{ij}cos\left[\emptyset_i-\emptyset_j\right]\right] \quad (13)$$

Inequality constraints

$$P_{gslack}^{min}\le P_{gslack}\le P_{gslack}^{max} \quad (14)$$

$$Q_{gi}^{min}\le Q_{gi}\le Q_{gi}^{max},\ i\in N_g \quad (15)$$

$$VL_i^{min}\le VL_i\le VL_i^{max},\ i\in NL \quad (16)$$

$$T_i^{min}\le T_i\le T_i^{max}, i\in N_T \quad (17)$$

$$Q_c^{min}\le Q_c\le Q_C^{max}, i\in N_C \quad (18)$$

$$\left|SL_i\right|\le S_{L_i}^{max}, i\in N_{TL} \quad (19)$$

$$VG_i^{min}\le VG_i\le VG_i^{max},\ i\in N_g \quad (20)$$

Then the multi objective fitness (MOF) function has been defined by,

$$MOF=OF_1+x_iOF_2+yOF_3=OF_1+\left[\sum_{i=1}^{NL}x_v\left[VL_i-VL_i^{min}\right]^2+\sum_{i=1}^{NG}x_g\left[QG_i-QG_i^{min}\right]^2\right]+x_fOF_3 \quad (21)$$

$$VL_i^{min}=\begin{cases}VL_i^{max}, VL_i>VL_i^{max}\\ VL_i^{min}, VL_i<VL_i^{min}\end{cases} \quad (22)$$

$$QG_i^{min}=\begin{cases}QG_i>QG_i^{max}\\ QG_i^{min}, QG_i<QG_i^{min}\end{cases} \quad (23)$$

Whale optimization algorithm

Hunting behaviour of whales has been imitated to formulate as Whale optimization algorithm [19]. In bubble-net form recoiling, surrounding and spiral revised position will be there.

Surrounding the prey; whale wrap up the prey then weigh up its position in the direction of the optimum solution over the progression of engorgement number of iteration form to a highest number of iteration.

$$\vec{Y}(t+1)=\vec{Y}_P(t)-\vec{A}\bullet D \quad (24)$$

$$\vec{D}=\left|B.\vec{Y}_P(t)-Y(t)\right| \quad (25)$$

$$\vec{A}=2a\,\vec{r}-\vec{a} \quad (26)$$

$$\vec{B}=2\vec{r} \quad (27)$$

$$a=2-2\frac{t}{t_{max}} \quad (28)$$

Bubble-Net Attacking technique-Exploitation Phase; it possess the recoiling, surrounding, and spiral revised position [19]. Recoil, surrounding method; control parameter "a" value will be decreased then the recoiling, surrounding will be obtained is a $\vec{A}$ is capricious value in the interval of [−a, a].

Renewal of the Spiral position; in a helix-shaped form Whale and prey will be positioned and defined by,

$$\vec{Y}(t+1)=\vec{D}^{'*}\ e^{bt*}\cos(2\pi l)+\vec{Y}_P(t) \quad (29)$$

$$\vec{D}^{'}=\left|\vec{Y}_P(t)-\vec{Y}(t)\right| \quad (30)$$

Enclosing path will be reduced during the course of the optimization with reasonable property and it defined by,

$$\vec{Y}(t+1)=\begin{cases}\vec{Y}_P(t)-\vec{A}\bullet D & if\ p<0.50\\ \vec{D}^{'*}\ e^{bt*}\cos(2\pi l)+\vec{Y}_P(t) & if\ p\ge 0.50\end{cases} \quad (31)$$

Exploration for prey (Exploration Phase)

Individual whale position are restructured with reference to capriciously chosen entity,

$$\vec{D}=\left|\vec{B}.\vec{Y}_{random}-\vec{Y}\right| \quad (32)$$

$$\vec{Y}(t+1)=\vec{Y}_{random}-\vec{A}\bullet D \quad (33)$$

a. Initialization of parameters

b. Whale population is initialized

c. Best individual is selected as the optimal position by $i\ge n\,j\left(if\left(i_{rank}<j_{rank}\right)\right)$.

d. By $\vec{Y}(t+1)=\begin{cases}\vec{Y}_P(t)-\vec{A}\bullet D & if\ p<0.50\\ \vec{D}^{'*}\ e^{bt*}\cos(2\pi l)+\vec{Y}_P(t) & if\ p\ge 0.50\end{cases}$ current position of individual whales are modernized when p<0.5 and |A| <1; when |A| ≥ 1, an capricious entity whale $\vec{Y}_{arbitrary}$ is chosen, and current positions of entity whales rationalized by $\vec{D}=\left|\vec{B}.\vec{Y}_{random}-\vec{Y}\right|;\ \vec{Y}(t+1)=\vec{Y}_{random}-\vec{A}\bullet D$

e. Current positions of entity whales are rationalized When p ≥ 0.5, by $\vec{Y}(t+1)=\begin{cases}\vec{Y}_P(t)-\vec{A}\bullet D & if\ p<0.50\\ \vec{D}^{'*}\ e^{bt*}\cos(2\pi l)+\vec{Y}_P(t) & if\ p\ge 0.50\end{cases}$

f. Rationalized locations of the whales are verified

g. When maximum number of iterations has been reached, stop;

otherwise go to step c.

Hill climbing technique

For better local search Hill climbing technique [20] performs well and in this process the search continues until most excellent local optimal solution.

The exploitation begins with arbitrary points $y = (y_1, y_2, \ldots y_N)$. Two operators N,β has been utilized for direction-finding and to engender fresh solution $y' = (y_1', y_2', \ldots, y_N')$.

Then in the operator "n" arbitrarily chosen neighbouring Point of "y" is given by,

$$y_i' = y_i \pm U(0,1) \times bandwidth, i \in [1,2.,,N] \quad (34)$$

Elements of the new-fangled position are renewed with reference to its present values in the "β" operator phase and it defined by,

$$y_i' \leftarrow \begin{cases} y_r & z < \beta \\ y_i & otherwise \end{cases} \quad (35)$$

Then Hill climbing technique compare the y_i' with y_i then enhanced downhill values will be stored,

$$y_i \leftarrow \begin{cases} y_i' & f(y_i') \le f(y_i) \\ y_i & otherwise \end{cases} \quad (36)$$

In this technique exploration phase is controlled "β" operator and exploitation phase is controlled by the operator "N". Mainly with the help of "β" operator escaping from the local solution will be attained.

a. N, β, Bandwidth and maximum number of iterations are fixed

b. By $y_i = Lower\,bound_i + (Lower\,bound_i - Upper\,bound_i) \times U(0,1)$ population are initialized

c. $f(y)$is calculated

d. While (t<T) do

e. Apply $y_i' = y_i \pm U(0,1) \times bandwidth, i \in [1,2.,,N]$

f. For i=1,2,... N do

g. Fix an arbitrary value within (0, 1) to z

h. *If* $z \le \beta$ then

i. $y_i' = Lower\,bound_i + (Lower\,bound_i - Upper\,bound_i) \times U(0,1)$

j. End if

k. End for

l. *If* $f(y') \le f(y)$ then

m. $y = y'$

n. End if

o. t=t+1

p. End while

q. Revisit the most excellent solution

Hybridization of whale optimization algorithm with hill climbing technique

Whale optimization algorithm's exploration and exploitation has been enhanced by hybridization with Hill climbing technique. Mainly to avoid the early convergence and local optimal solution hybridization has been done. At first based on the Gaussian distribution on each interval from the modernized whale's boundaries in the search space has been found.

Then throughout the learning step whale's new-fangled location has been obtained by,

$$y_i(t+1) = y_i(t) + 0.001G\,(y_i(t) - \text{lower bound, upper bound} - y_i(t)) + CS_1R_1(y_r(t)) - y_i(t)) + CS_2R_2(y_p(t)) - y_i(t)) \quad (37)$$

Where CS_1,CS_2 cognitive and social factors are then R_1, R_2 are random numbers

$$CS_1 = (1 - t/T) \quad (38)$$

$$CS_2 = 2(t/T) \quad (39)$$

Hybridization of Whale Optimization Algorithm with Hill Climbing Technique (HWOHC) enriches the exploration and also enhances the arbitrary switching between two exploration points.

In HWOHC two operators successively act upon each whale to found find new regions around the whale by exploration and exploitation. Then from the two rival agents it will retain the best downhill afterwards the superior will be retained and remaining will be eliminated in subsequent stages. Then the position of the whales are renewed in the "N" operator phase by,

$$y_i' = y_i \pm U(0,1) \times bandwidth \times (2r - 1), i \in [1,2.,,N] \quad (40)$$

r-Random value within (0,1)

For all whales the "β" operator has been applied by $y_i' \leftarrow \begin{cases} y_r & z < \beta \\ y_i & otherwise \end{cases}$

and $y_i \leftarrow \begin{cases} y_i' & f(y_i') \le f(y_i) \\ y_i & otherwise \end{cases}$

Initialize the parameters β, Bandwidth, N and maximum number iterations

a. Initialize the parameters β, Bandwidth, N and maximum number iterations

b. Position of whales y_i are initialized arbitrarily

c. Fitness of exploration agents are calculated

d. Fix y_p as the most excellent or best solution

e. While (t<T) do

f. Renew the parameters

g. For each whale do

h. If p<0.5 then

i. If |A| >1 then

j. If q<0.5 then

k. Find out an arbitrary leader y_{random}

l. Modernize the position by $\vec{Y}(t+1) = \vec{Y}_{random} - \vec{A} \cdot D$

m. Otherwise if q>0.5 then

n. Renew the positions by $y_i(t+1) = y_i(t) + 0.001G(y_i(t)$- *lower bound, upper bound* $- y_i(t) + CS_1R_1(y_r(t)\,y_i(t) + CS_2R_2(y_p(t) - y_i(t))$

o. End if

p. Otherwise if |A| <1 then

q. If r<0.5 then

r. Modernize the positions by $\vec{Y}(t+1) = \vec{Y}_p(t) - \vec{A} \cdot D$

s. Otherwise if r>0.5 then

t. Execute the N-operator by $y_i' = y_i \pm U(0,1) \times bandwidth \times (2r - 1),\ i \in [1,2.,,N]$

u. Execute the β-operator by $y_i' \leftarrow \begin{cases} y_r & z < \beta \\ y_i & otherwise \end{cases}$

v. Execute the S-operator by $y_i \leftarrow \begin{cases} y_i' & f(y_i') \le f(y_i) \\ y_i & otherwise \end{cases}$

w. End if

x. Otherwise if p>0.5 then

y. Renew the positions by $\vec{Y}(t+1) = \vec{D}^{*} e^{bt^{*}} \cos(2\pi l) + \vec{Y}_p(t)$

z. End if

aa. End for

ab. Test the space restrictions

ac. Renew the leader y_p if there is a new-fangled superior solution

ad. t=t+1

ae. End while

af. Revisit the leader y_p

SIMULATION RESULTS

Projected Hybridization of whale optimization algorithm with Hill climbing technique (HWOHC) has been tested in standard IEEE 30 bus system Tables 1 and 2 show the system parameters [21-24]. Then Tables 3-6 shows the comparison. Figures 1-4 shows the comparison of parameters.

Table 1: Control variables.

System	Variables	Minimum (PU)	Maximum (PU)
IEEE 30 Bus	Generator voltage	0.95	1.1
	Transformer tap	0.9	1.1
	VAR source	0	5 (MVAR)

Table 2: Parameters.

Description	IEEE 30 bus
NB-number of buses	30
NG-Number of generators	6
NT-number of transformers	4
NQ-number of shunt	9
NE-Number of branches	41
PLoss (base case) MW	5.66
Base care for VD (PU)	0.58217

Table 3: Comparison of real power loss.

Parameters	Real power loss			
	DE [22]	GSA [22]	APOPSO [22]	HWOHC
VG1	1.1	1.071	1.100	1.099
VG2	1.09	1.022	1.084	1.039
VG5	1.07	1.040	1.056	1.037
VG8	1.07	1.051	1.076	1.041
VG11	1.1	0.977	1.091	1.090
VG13	5	0.968	1.100	0.980
QC 10	5	1.653	5.000	4.971
QC 12	5	4.3722	5.000	5.000
QC 15	5	0.1199	4.879	4.782
QC 17	5	2.0876	4.976	4.960
QC 20	4.41	0.357	3.821	3.700
QC 21	5	0.2602	4.541	4.661
QC 23	2.8004	0.0000	2.354	2.400
QC 24	5	1.3839	4.654	4.500
QC 29	2.5979	0.0000	2.175	2.161
T11(6-9)	1.04	1.0985	1.029	1.011
T12(6-10)	0.9097	0.9824	0.911	0.900
T15(4-12)	0.98	1.095	0.952	0.940
T36(28-27)	0.9689	1.0593	0.958	0.939
PLoss(MW)	4.555	4.5143	4.398	4.235
VD (PU)	1.9589	0.87522	1.047	1.044
L-index(PU)	0.5513	0.14109	0.1267	0.1200

Table 4: Comparison of different algorithms with reference to voltage stability improvement.

Parameters	Voltage stability improvement			
	DE [22]	GSA [22]	APOPSO [22]	HWOHC
VG1	1.01	0.983	1.011	1.022
VG2	0.99	1.044	1.001	1.013
VG5	1.02	1.020	1.014	1.014
VG8	1.02	0.999	1.009	1.013
VG11	1.01	1.077	0.954	0.942
VG13	1.03	1.044	1.000	1.000
QC 10	4.94	0	4.102	4.101
QC 12	1.0885	0.4735	2.124	2.123
QC 15	4.9985	5	4.512	4.490
QC 17	0.2393	0	0.000	0.000
QC 20	4.99	5	5.000	5.000
QC 21	4.90	0	5.000	5.000
QC 23	4.9863	4.9998	5.000	5.000
QC 24	4.9663	5	5.000	5.000
QC 29	2.2325	5	4.120	4.130
T11(6-9)	1.02	0.9	0.998	0.992
T12(6-10)	0.9038	1.1	0.822	0.810
T15(4-12)	1.01	1.051	0.954	0.939
T36(28-27)	0.9635	0.9619	0.958	0.938
PLoss (MW)	6.4755	6.9117	5.698	5.425
VD (PU)	0.0911	0.0676	0.087	0.084
L-index(PU)	0.14352	0.1349	0.1377	0.1313

Table 5: Comparison with reference to voltage deviation minimization.

Parameters	Voltage deviation minimization			
	DE [22]	GSA [22]	APOPSO [22]	HWOHC
VG1	1.09	1.1	1.043	1.031
VG2	1.09	1.1	1.061	1.052
VG5	1.09	1.1	1.061	1.040
VG8	1.04	1.1	1.057	1.041
VG11	1.09	1.1	1.048	1.043
VG13	0.95	1.1	1.091	1.072
QC 10	0.69	5	0.040	0.031
QC 12	4.7163	5	0.039	0.034
QC 15	4.4931	5	0.038	0.032
QC 17	4.51	5	0.040	0.033

QC 20	4.48	5	0.037	0.032
QC 21	4.60	5	0.009	0.011
QC 23	3.8806	5	0.019	0.013
QC 24	3.8806	5	0.011	0.012
QC 29	3.2541	5	0.001	0.000
T11(6-9)	0.90	0.9	0.919	0.912
T12(6-10)	0.9029	0.9	0.924	0.910
T15(4-12)	0.90	0.9	0.938	0.920
T36(28-27)	0.936	1.0195	0.924	0.924
PLoss (MW)	7.0733	4.9752	4.478	4.236
VD (PU)	1.419	0.21579	1.8579	1.8205
L-index (PU)	0.1246	0.13684	0.1227	0.1174

Table 6: Comparison of values with reference to multi-objective formulation.

Parameters	Multi-objective	
	APOPSO [22]	HWOHC
VG1	1.020	1.013
VG2	1.033	1.022
VG5	1.000	1.000
VG8	1.004	1.000
VG11	1.032	1.019
VG13	1.028	1.017
QC 10	0.051	0.039
QC 12	0.002	0.001
QC 15	0.044	0.036
QC 17	0.009	0.019
QC 20	0.048	0.035
QC 21	0.041	0.034
QC 23	0.033	0.018
QC 24	0.050	0.037
QC 29	0.015	0.011
T11(6-9)	1.042	1.035
T12(6-10)	0.909	0.900
T15(4-12)	1.023	1.011
T36(28-27)	0.958	0.940
PLoss (MW)	4.842	4.739
VD (PU)	1.009	1.002
L-index (PU)	0.1192	0.1183

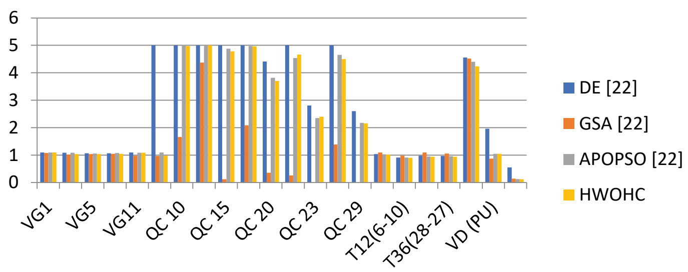

Figure 1: Comparison of parameters (Real power loss).

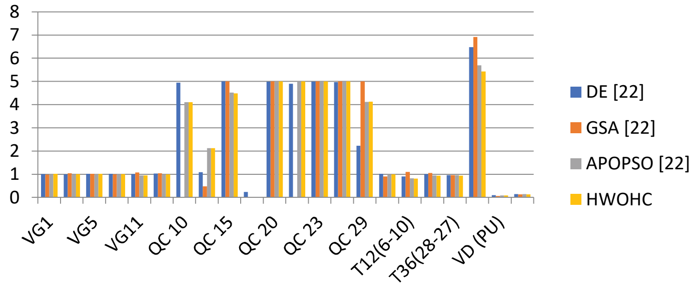

Figure 2: Comparison of parameters (Voltage stability improvement).

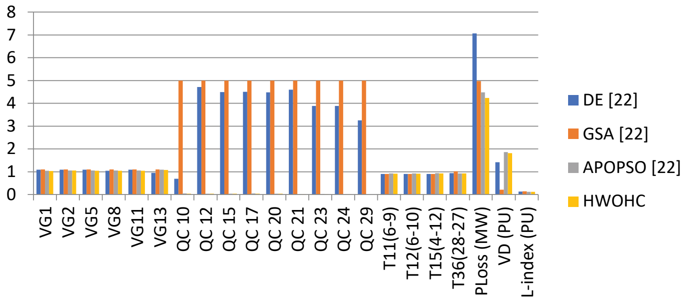

Figure 3: Comparison of parameters (Voltage deviation minimization).

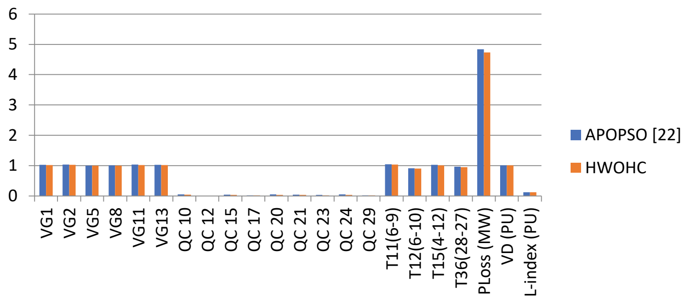

Figure 4: Comparison of parameters (Multi-objective).

DISCUSSION AND CONCLUSION

In this work optimal reactive power dispatch problem has been successfully solved by Hybridization of Whale Optimization Algorithm with Hill Climbing Technique (HWOHC). Whale optimization algorithm's exploration and exploitation has been enhanced by hybridization with Hill climbing technique. Two operators successively act upon each whale to found find new regions around the whale by exploration and exploitation. Then from the two rival agents it will retain the best downhill afterwards the superior has been retained and remaining eliminated in subsequent stages. Proposed HWOHC algorithm has been tested in standard IEEE 30, bus test system and projected HWOHC algorithm solved the multi-objective formulation of the problem and with reference to power loss, voltage deviation minimization, voltage stability enhancement results has been analyzed.

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