Enhanced wormhole optimizer algorithm for solving optimal reactive power problem

Kanagasabai Lenin
Department of EEE, Prasad V. Potluri Siddhartha Institute of Technology, India

ABSTRACT
In this paper Enhanced Wormhole Optimizer (EWO) algorithm is used to solve optimal reactive power problem. Proposed algorithm based on the Wormholes which exploits the exploration space. Between different universes objects are exchanged through white or black hole tunnels. Regardless of the inflation rate, through wormholes objects in all universes which possess high probability will shift to the most excellent universe. In the projected Enhanced Wormhole Optimizer (EWO) algorithm in order to avoid the solution to be get trapped into the local optimal solution Levy flight has been applied. Projected Enhanced Wormhole Optimizer (EWO) algorithm has been tested in standard IEEE 14, 30, 57,118,300 bus test systems and simulation results show that the EWO algorithm reduced the real power loss efficiently.

Keywords:
Enhanced wormhole optimizer
Optimal reactive power
Transmission loss

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1. INTRODUCTION
For secure and economic operations of power system optimal reactive power problem plays vital role. Several types of techniques [1-6] have been utilized to solve the problem previously. Conversely many difficulties are found while solving problem due to inequality constraints. Evolutionary techniques [7-15] are applied to solve the reactive power problem. This paper proposes Enhanced Wormhole Optimizer (EWO) algorithm for solving optimal reactive power problem. Wormhole Optimizer Algorithm is based on the Wormholes which exploit the exploration space. Wormhole tunnel are built for local change in each universe m through most excellent universe then probability of refinement the inflation rate is done through wormholes. Objects are exchanged through tunnels and wormholes objects which possess high probability will shift to the most excellent universe. In the projected Enhanced Wormhole Optimizer (EWO) algorithm in order to avoid the solution to be get trapped into the local optimal solution Levy flight has been applied. Projected Enhanced Wormhole Optimizer (EWO) algorithm has been tested in standard IEEE 14, 30, 57,118,300 bus test systems and simulation results show that the projected algorithm reduced the real power loss effectively.

2. PROBLEM FORMULATION
Objective of the problem is to reduce the true power loss:

\[ F = P_L = \sum_{k \in \text{Nbr}} g_k \left(V_i^2 + V_j^2 - 2V_iV_j\cos\theta_{ij}\right) \]  

(1)
Voltage deviation given as follows:

\[ F = P_L + o_v \times Voltage\ Deviation \]  
\[ Voltage\ Deviation = \sum_{i=1}^{Npq} |V_i - 1| \]  

Constraint (Equality)

\[ P_c = P_D + P_L \]  

Constraints (Inequality)

\[ p_{g_{\text{slack}}}^{\min} \leq p_{g_{\text{slack}}} \leq p_{g_{\text{slack}}}^{\max} \]  
\[ q_{\text{gi}}^{\min} \leq q_{\text{gi}} \leq q_{\text{gi}}^{\max}, i \in N_g \]  
\[ v_i^{\min} \leq v_i \leq v_i^{\max}, i \in N \]  
\[ t_i^{\min} \leq t_i \leq t_i^{\max}, i \in N_T \]  
\[ q_c^{\min} \leq q_c \leq q_c^{\max}, i \in N_c \]  

3. Enhanced Wormhole Optimizer Algorithm

Wormhole Optimizer Algorithm is based on the Wormholes which exploit the exploration space. Through wormholes objects which has high probability will shift to the most excellent universe and it modeled by using roulette wheel selection methodology as follows,

\[ U = \begin{bmatrix} y_{11} & \cdots & y_{1d} \\ \vdots & \ddots & \vdots \\ y_{n1} & \cdots & y_{nd} \end{bmatrix} \]  

Number of the variables is indicated by “d” and number of universe which is considered as candidate solution is indicated by “n”.

\[ y_{ij} = \begin{cases} y_{kj} \text{ random}_1 < NI(U_i) \\ y_{ij} \text{ random}_1 < NI(U_i) \end{cases} \]  

Through roulette wheel selection \( y_{ij} \)'s “j”th parameter of the “k”th universe will be chosen, in the “i”th universe “j”th parameter is expressed by \( y_{kj} \), ith universe inflation rate indicated by \( NI(U_i) \), ith universe indicated by \( U_i, \text{ random}_1 \in [0,1] \).

In between two universes wormhole tunnel [16, 17] are built then the local change for each universe is done by most excellent universe and the elevated probability of refinement the inflation rate through wormholes is done by,

\[ y_{ij} = \begin{cases} Y_j + \text{Tr.distance rate} \times \left( (u_b - l_b) \times \text{rand}_4 + l_b \right) \text{ rand}_4 < 0.5 \\ Y_j - \text{Tr.distance rate} \times \left( (u_b - l_b) \times \text{rand}_4 + l_b \right) \text{ rand}_4 \geq 0.5 \text{ rand}_2 < w \text{ e p} \\ y_{ij} \text{ rand}_2 \geq w \text{ e p} \end{cases} \]  

Wormhole existence probability indicated by “w e p”, “tr.” Indicates the travelling and random denoted by “ rand”.

During the optimization procedure exploitation has been enhanced as follows,

\[ \text{Wormhole existence probability} = w_{\text{minimum}} + \text{current iteration} \left( \frac{w_{\text{maximum}} - w_{\text{minimum}}}{\text{maximum iteration}} \right) \]
In order to improve the local search precisely travelling distance rate will be increased over the iterations as follows,

\[
Travelling \ distance \ rate = 1 - \frac{\text{current iteration}^{1/p}}{\text{maximum iteration}^{1/p}} \tag{14}
\]

In the projected Enhanced Wormhole Optimizer (EWO) algorithm in order to avoid the solution to be get trapped into the local optimal solution Levy flight has been applied. Levy flight is a rank of non-Gaussian random procedure whose capricious walks are haggard from Levy stable distribution. Allocation by \( L(s) \sim |s|^{-\beta} \) where \( 0 < \beta < 2 \) is an index. Scientifically defined as,

\[
L(s,\gamma,\mu) = \begin{cases} \frac{\Gamma(\gamma)}{\sqrt{2\pi s^{\gamma}}} & \text{if } s \leq 0 \\ \exp\left[-\frac{\gamma}{\sin(\gamma\pi/2)} \frac{1}{(s-\mu)^{\gamma/2}} \right] & \text{if } 0 < \mu < s < \infty \end{cases} \tag{15}
\]

In terms of Fourier transform Levy distribution defined as

\[
F(k) = \exp[-\alpha|k|^\beta], 0 < \beta \leq 2, \tag{16}
\]

Fresh state is calculated as,

\[
Y_{t+1} = Y_t + \alpha \oplus \text{Levy} (\beta) \tag{17}
\]

\[
Y_{t+1} = y_t + \text{random} \times \text{Levy}(\beta) \tag{18}
\]

In the projected Enhanced Wormhole Optimizer (EWO) algorithm while generation of new solutions \( U_{i+1} \) Levy flight \( y \) will be applied,

\[
U_{i+1} = U_i + K(lb + (ub - lb) \times \text{levy}(y)) \times U_i \tag{19}
\]

Levy flight will be applied in the adaptive mode to balance the exploration and exploitation by applying large levy weight initially and final course the weight of the levy will be decreased,

\[
K = \left(\frac{\text{maximum iteration} - \text{current iteration}}{\text{maximum iteration}}\right) \tag{20}
\]

By using Mantegna's algorithm Non-trivial scheme of engendering step size by,

\[
s = \frac{u}{|v|^\beta} \tag{21}
\]

\[
Y_{t+1} = Y_t + \text{random} \times \text{Levy}(\beta) \sim 0.01 \frac{u}{|v|^{1/\beta}} (y_j^t - gb) \tag{22}
\]

\[
u \sim N(0, \sigma_u^2) \quad v \sim N(0, \sigma_v^2) \tag{23}
\]

with

\[
\sigma_u = \left\{ \frac{\Gamma(1+\beta)\sin(\pi\beta/2)}{\Gamma((1+\beta)/2)\beta^{1/2}\Gamma(1+1/\beta)} \right\}^{1/\beta}, \quad \sigma_v = 1 \tag{24}
\]

then,

\[
\text{Levy}(y) = 0.01 \times \frac{u \times \sigma_u}{|v|^{1/\beta}} \tag{25}
\]

Start

In put ; “d” & “n” ; Lower bound = \([Lb_1, Lb_2, \ldots, Lbd]\) ; Upper bound = \([Ub_1, Ub_2, \ldots, Ubd]\) ; Maximum number of iterations

Output: Optimal solution

Step a: Initialization of parameters

\textit{Enhanced wormhole optimizer algorithm for solving optimal reactive ... (Kanagasabai Lenin)}
Engender arbitrary universes “U” by $U^P = \{ U_1, U_2, ..., U_n \}$

Initialize Wormhole existence probability, travelling distance rate, objective function

$t = 0$

Step b: categorization and reorganize; arrange the universes; universe inflation rate (UI) will be reorganized

Step c: Iteration; while $t < \text{Maximum iteration}$

Compute universe inflation rate; UI ($U^P_i$ : $i = 1, 2, ..., n$)

For every universe “$U_i$”; modernize Wormhole existence probability, travelling distance rate by

Wormhole existence probability = $w_{\text{minimum}} + \text{current iteration} \times \left( \frac{w_{\text{maximum}} - w_{\text{minimum}}}{\text{maximum iteration}} \right)$

Travelling distance rate = $1 - \left( \frac{\text{current iteration}}{\text{maximum iteration}} \right)^{1/3}$; Black hole index value = $i$

Modernize the value “$U$” by $U_{i+1} = U_i + K (l_b + (u_b - l_b) * \text{levy}(y)) \times U_i$

For every object $y_{ij}$: random $= \text{random} (0, 1)$;

If $\text{random}_1 < \text{UI}(U_i)$; white hole index = roulette wheel selection (-UI);

End if

End for

$t = t + 1$

End while

Step d: End; output the optimal solution

4. SIMULATION RESULTS

At first in standard IEEE 14 bus system [18] the validity of the proposed Enhanced Wormhole Optimizer (EWO) algorithm has been tested. Table 1 shows the constraints of control variables Table 2 shows the limits of reactive power generators and comparison results are presented in Table 3.

Table 1. Constraints of control variables

| System   | Variables | Minimum (PU) | Maximum (PU) |
|----------|-----------|--------------|--------------|
| IEEE 14  | Generator | 0.95         | 1.1          |
|          | Voltage   | 0.9          | 1.1          |
|          | Transformer | 0.9      | 1.1          |
|          | Tap       | 0            | 0.2          |
|          | VAR Source | 0           | 0.2          |

Table 2. Constrains of reactive power generators

| System   | Variables | Q Minimum (PU) | Q Maximum (PU) |
|----------|-----------|----------------|----------------|
| IEEE 14  | Generator | 1              | 10             |
|          | Tap       | 3              | 40             |
|          | VAR Source | 6             | 24             |

Table 3. Simulation results of IEEE -14 system

| Control variables | Base case | MPSO [19] | PSO [19] | EP [19] | SARGA [19] | EWO  |
|-------------------|-----------|-----------|-----------|---------|------------|------|
| $V_G$ -1          | 1.060     | 1.100     | 1.100     | NR*     | NR*        | 1.013|
| $V_G$ -2          | 1.045     | 1.085     | 1.086     | 1.029   | 1.060      | 1.014|
| $V_G$ -3          | 1.010     | 1.055     | 1.056     | 1.016   | 1.036      | 1.002|
| $V_G$ -8          | 1.090     | 1.074     | 1.060     | 1.053   | 1.078      | 1.021|
| $Q_C$ -9          | 0.19      | 14.64     | 0.185     | 0.18    | 0.06       | 0.120|
| $P_C$             | 272.39    | 271.32    | 271.32    | NR*     | NR*        | 271.78|
| $Q_G$ (Mvar)      | 82.44     | 75.79     | 76.79     | NR*     | NR*        | 75.79|
| Reduction in $P_Loss$ (%) | 0         | 9.2       | 9.1       | 1.5     | 2.5        | 25.85|
| Total $P_Loss$ (Mw) | 13.550    | 12.293    | 13.346    | 13.216  | 10.047     |      |

NR* - Not reported.
Then Enhanced Wormhole Optimizer (EWO) algorithm has been tested, in IEEE 30 Bus system. Table 4 shows the constraints of control variables, Table 5 shows the limits of reactive power generators and comparison results are presented in Table 6.

Table 4. Constraints of control variables

| System       | Variables  | Minimum (PU) | Maximum (PU) |
|--------------|------------|--------------|---------------|
| IEEE 30 Bus  | Generator  | 0.95         | 1.1           |
|              | Voltage    |              |               |
|              | Transformer| 0.9          | 1.1           |
|              | Tap        |              |               |
|              | VAR Source | 0            | 0.20          |

Table 5. Constrain of reactive power generators

| System       | Variables | Q Minimum (PU) | Q Maximum (PU) |
|--------------|-----------|----------------|----------------|
| IEEE 30 Bus  | 1         | 0              | 10             |
|              | 2         | -40            | 50             |
|              | 5         | -40            | 40             |
|              | 8         | -10            | 40             |
|              | 11        | -6             | 24             |
|              | 13        | -6             | 24             |

Table 6. Simulation results of IEEE −30 system

| Control variables | Base case | MPSO [19] | PSO [19] | EP [19] | SARGA [19] | EWO |
|-------------------|-----------|-----------|-----------|---------|------------|-----|
| PG (MW)           | 300.9     | 299.54    | 299.54    | NR*     | NR*        | 297.68 |
| QG (Mvar)         | 133.9     | 130.83    | 130.94    | NR*     | NR*        | 131.41 |
| Reduction in PLoss (%) | 0        | 8.4       | 7.4       | 6.6     | 8.3        | 19.37  |
| Total PLoss (Mw)  | 17.55     | 16.07     | 16.25     | 16.38   | 16.09      | 14.149 |

Then the proposed Enhanced Wormhole Optimizer (EWO) algorithm has been tested, in IEEE 57 Bus system. Table 7 shows the constraints of control variables, Table 8 shows the limits of reactive power generators and comparison results are presented in Table 9.

Table 7. Constraints of control variables

| System       | Variables  | Minimum (PU) | Maximum (PU) |
|--------------|------------|--------------|---------------|
| IEEE 57 Bus  | Generator  | 0.95         | 1.1           |
|              | Voltage    |              |               |
|              | Transformer| 0.9          | 1.1           |
|              | VAR Source | 0            | 0.20          |

Table 8. Constrains of reactive power generators

| System       | Variables | Q Minimum (PU) | Q Maximum (PU) |
|--------------|-----------|----------------|----------------|
| IEEE 57 Bus  | 1         | -140           | 200            |
|              | 2         | -17            | 50             |
|              | 3         | -10            | 60             |
|              | 6         | -8             | 25             |
|              | 8         | -140           | 200            |
|              | 9         | -3             | 9              |
|              | 12        | -150           | 155            |
Then the proposed Enhanced Wormhole Optimizer algorithm has been tested in IEEE 118 Bus system. Table 10 shows the constraints of control variables and comparison results are presented in Table 11.

| Control variables | Base case | MPSO [19] | PSO [19] | CGA [19] | AGA [19] | EWO |
|-------------------|-----------|-----------|----------|----------|----------|-----|
| VG 1              | 1.040     | 1.093     | 1.083    | 0.968    | 1.027    | 1.032 |
| VG 2              | 1.010     | 1.086     | 1.071    | 1.049    | 1.011    | 1.010 |
| VG 3              | 0.985     | 1.056     | 1.055    | 1.056    | 1.033    | 1.034 |
| VG 6              | 0.980     | 1.038     | 1.036    | 0.987    | 1.001    | 1.012 |
| VG 8              | 1.005     | 1.066     | 1.059    | 1.022    | 1.051    | 1.030 |
| VG 9              | 0.980     | 1.054     | 1.048    | 0.991    | 1.051    | 1.011 |
| VG 12             | 1.015     | 1.054     | 1.046    | 1.004    | 1.057    | 1.040 |
| Tap 19            | 0.970     | 0.975     | 0.987    | 0.920    | 1.030    | 0.952 |
| Tap 20            | 0.978     | 0.982     | 0.983    | 0.920    | 1.020    | 0.937 |
| Tap 31            | 1.043     | 0.975     | 0.981    | 0.970    | 1.060    | 0.920 |
| Tap 35            | 1.000     | 1.025     | 1.003    | NR*      | NR*      | 1.019 |
| Tap 36            | 1.000     | 1.002     | 0.985    | NR*      | NR*      | 1.007 |
| Tap 37            | 1.043     | 1.007     | 1.009    | 0.900    | 0.990    | 1.009 |
| Tap 41            | 0.967     | 0.994     | 1.007    | 0.910    | 1.100    | 0.990 |
| Tap 46            | 0.975     | 1.013     | 1.018    | 1.100    | 0.980    | 1.010 |
| Tap 54            | 0.955     | 0.988     | 0.986    | 0.940    | 1.010    | 0.971 |
| Tap 58            | 0.955     | 0.979     | 0.992    | 0.950    | 1.080    | 0.966 |
| Tap 59            | 0.900     | 0.983     | 0.990    | 1.030    | 0.940    | 0.963 |
| Tap 65            | 0.930     | 1.015     | 0.997    | 1.090    | 0.950    | 1.001 |
| Tap 66            | 0.895     | 0.975     | 0.984    | 0.900    | 1.050    | 0.950 |
| Tap 71            | 0.958     | 1.020     | 0.990    | 0.900    | 0.950    | 1.001 |
| Tap 73            | 0.958     | 1.001     | 0.988    | 1.000    | 1.010    | 1.000 |
| Tap 76            | 0.980     | 0.979     | 0.980    | 0.960    | 0.940    | 0.968 |
| Tap 80            | 0.940     | 1.002     | 1.017    | 1.000    | 1.000    | 1.002 |
| QC 18             | 0.1       | 0.179     | 0.131    | 0.084    | 0.016    | 0.174 |
| QC 25             | 0.059     | 0.176     | 0.144    | 0.008    | 0.015    | 0.168 |
| QC 53             | 0.063     | 0.141     | 0.162    | 0.053    | 0.038    | 0.140 |
| PG (MW)           | 1278.6    | 1274.4    | 1274.8   | 1276    | 1275    | 1270.13 |
| QG (Mvar)         | 321.08    | 272.27    | 276.58   | 309.1   | 304.4   | 272.34 |
| Reduction in Ploss (%) | 0      | 15.4       | 14.1     | 9.2     | 11.6     | 24.07 |
| Total Ploss (Mw)  | 27.8      | 23.51      | 23.86    | 25.24   | 24.56    | 21.108 |

| System Variables | Minimum (PU) | Maximum (PU) |
|------------------|--------------|--------------|
| IEEE 118 Bus     | 0.95          | 1.1          |
| Transformer Tap  | 0.9           | 1.1          |
| VAR Source       | 0             | 0.20         |

NR* - Not reported.

| System Variables | Minimum (PU) | Maximum (PU) |
|------------------|--------------|--------------|
| IEEE 118 Bus     | 0.95          | 1.1          |
| Transformer Tap  | 0.9           | 1.1          |
| VAR Source       | 0             | 0.20         |
Then IEEE 300 bus system [18] is used as test system to validate the performance of Enhanced Wormhole Optimizer (EWO) algorithm. Table 12 shows the comparison of real power loss obtained after optimization.

### Table 12. Comparison of Real Power Loss

| Parameter | Method CSA [20] | Method EGA [21] | Method EEO [21] | EWO |
|-----------|-----------------|-----------------|-----------------|-----|
| PLOSS (MW) | 635.8942 | 646.2998 | 650.6027 | 612.1026 |
| PQ(MVAR) | 795.6 | 604.3 | 653.5 | * NR* |
| Reduction in PLOSS (%) | 0 | 11.7 | 10.1 | 6 | 1.3 | 14.15 |
| Total PLOSS (Mw) | 132.8 | 117.19 | 119.34 | 131.99 | 130.96 | 114.005 |

NR* - Not reported.
5. CONCLUSION

In this paper proposed Enhanced Wormhole Optimizer (EWO) algorithm successfully solved the optimal reactive power problems. Between different universes objects are exchanged through white or black hole tunnels. Regardless of the inflation rate, through wormholes objects in all universes which possess high probability will shift to the most excellent universe. In between two universes wormhole tunnel are built then the local change for each universe is done by most excellent universe and the elevated probability of refinement the inflation rate through wormholes. Levy flight has been applied effectively and it leads to the improvement of the quality of solution. Proposed Enhanced Wormhole Optimizer (EWO) algorithm has been tested in standard IEEE 14, 30, 57,118,300 bus test systems and simulation results show that the EWO algorithm reduced the real power loss efficiently. Percentage of real power loss reduction has been enhanced when compared to other standard algorithms.

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