Amplified and quantum based brain storm optimization algorithms for real power loss reduction

Kanagasabai Lenin
Department of Electrical and Electronics Engineering, Prasad V. Potluri Siddhartha Institute of Technology, India

Article Info

Article history:
Received Jan 3, 2020
Revised Feb 19, 2020
Accepted Mar 3, 2020

Keywords:
Amplified brain storm optimization
Optimal reactive power
Quantum based brain storm optimization algorithm
Transmission loss

ABSTRACT

In this work amplified brain storm optimization (ABS) algorithm and quantum based brain storm (QBS) optimization algorithm is applied to solve the problem. A node is arbitrarily chosen from the graph as the preliminary point to form a Hamiltonian cycle. At generation \( t \) and \( t+1 \), \( L_t \) and \( L_{t+1} \) are the length of Hamiltonian cycle correspondingly. In the QBS algorithm a Quantum state of an idea is illustrated by a wave function \( \psi(G,t) \) as an alternative of the position modernized only in brain storm optimization algorithm. Monte Carlo simulation method is used, to measure the position for each idea from the quantum state to the traditional one. Proposed ABS algorithm and QBS optimization algorithm has been tested in standard IEEE 57 bus test system and real power loss reduced effectively.

This is an open access article under the CC BY-SA license.

1. INTRODUCTION

In this work minimizing true power loss is the main objective of the problem. A variety of methods [1-6] have been applied to solve the problem. Subsequently various evolutionary methods [7-16] applied to solve the problem, in that many algorithms stuck in local optimal solution In this work amplified brain storm optimization (ABS) algorithm and quantum based brain storm (QBS) optimization algorithm is used for solving optimal reactive power problem. Brain storm optimization (BSO) algorithm gets trapped into local optima when applied to different optimization problems. In the mathematical field of graph theory, a Hamiltonian path is a path in an undirected or directed graph that visits each vertex exactly once. In the proposed algorithm Hamiltonian cycle will improve the explore abilities and also stay away from local optimal solution. In QBS algorithm completely, the mechanism of quantum behavior, which causes uncertain of every idea lead to a superior capability to bounce out of the local optimal solution. Proposed ABS algorithm and QBS optimization algorithm has been tested in standard IEEE 57 bus test system.

2. PROBLEM FORMULATION

2.1. Real power loss

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

Journal homepage: http://ijape.iaescore.com
2.2. Amplification of voltage profile

\[ F = P_L + \omega_0 \times \text{Voltage Deviation} \]  

(2)

Voltage deviation given by:

\[ \text{Voltage Deviation} = \sum_{i=1}^{N} |v_i - 1| \]  

(3)

2.3. Constraint (equality)

\[ P_G = P_D + P_L \]  

(4)

2.4. Constraints (inequality)

\[ p_{\text{min}} g_{\text{slack}} \leq P_{g_{\text{slack}}} \leq p_{\text{max}} g_{\text{slack}} \]  

(5)

\[ Q_{g_{\text{min}}} \leq Q_{g_{i}} \leq Q_{g_{\text{max}}}, i \in N_{g} \]  

(6)

\[ v_{i_{\text{min}}} \leq v_{i} \leq v_{i_{\text{max}}}, i \in N \]  

(7)

\[ T_{i_{\text{min}}} \leq T_{i} \leq T_{i_{\text{max}}}, i \in N_{T} \]  

(8)

\[ Q_{c_{\text{min}}} \leq Q_{c_{i}} \leq Q_{c_{\text{max}}}, i \in N_{C} \]  

(9)

3. AMPLIFIED BRAIN STORM OPTIMIZATION ALGORITHM

BSO [17] gets trapped into local optima when applied to different optimization problems. In the projected amplified brain storm optimization algorithm Hamiltonian cycle has been applied to improve the search abilities and also to avoid of trap in local optimal solution. A node is arbitrarily chosen from the graph as the preliminary point to form a Hamiltonian cycle. At generation t and t+1, L_t and L_{t+1} are the length of Hamiltonian cycle correspondingly. Their ratio r at generation (t) can be described as:

\[ r_t = \frac{L_{t+1}}{L_t} \]  

(10)

Hamilton cycle algorithm as follows:

\begin{enumerate}
  \item Commence
  \item Step 1: node v1 chosen as initial point,.
  \item Step 2: is chosen and is picked with least weight linkingv1, then the v_p,v_{p+1} is obtained.
  \item Step 3: when i<1n, subsequently i+1 is used to substitute i, and revisit to Step 2;
  \item Step 4: v_{i+1},v_{i+2} is chosen and w(v_{i+1}) + w(v_{i+2})<w(v_{i+1}) + w(v_{i+2})
  \item Then C_{i} = (C - \{v_{i+1},v_{i+2}\}) U \{v_{i+1},v_{i+2}\}
  \item End if
  \item Step 5: C is substituted by C, and revisit Step 4.
  \item Step 6: compute the extent of the Hamiltonian cycle C.
  \item End for
\end{enumerate}

In the proposed amplified brain storm optimization (ABSO) algorithm Hamiltonian cycle will improve the explore abilities and also stay away from local optimal solution.

\begin{enumerate}
  \item Commence
  \item Step 1: “n” potential solutions are arbitrarily engendered
  \item Step 2: “n” individuals are clustered into “m” clusters
  \item Step 3: “n” individuals will be appraised
  \item Step 4: In every cluster rank the individuals then the most excellent individual’s are recorded as cluster center
  \item Step 5: Between 0 and 1 arbitrarily a value will be engendered; If the value is smaller than a probability; then i. a cluster center has been Arbitrarily chosen; ii. To swap the certain cluster center arbitrarily engender an individual
\end{enumerate}
Step 6: new-fangled individuals are engendered

Calculate the Hamiltonian cycle C and its extent L, by Hamilton algorithm
{
Commence
Step 1: node v1 chosen as initial point,
Step 2: v1,v2,...,vi is chosen and vi+1 is picked with least weight linking vi, then the 
v1,v2,...,vi+1 obtained.
Step 3: when i+1<n, subsequently i+1 is used to substitute i, and revisit to Step 2
Step 4: for all i and j in cycle Ci, if l<i+j<n, then 
i ≠ j ; vi,vj ∈ E(G) 

vi+1,vj+1 ∈ E(G), w(vi,vj) + w(vi+1,vj+1) < w(vi,vj+1) + w(vi+1,vj) 

Then Ci = (C – [vi,vj+1,vj+1]) ∪ [vi,vj+1,vj+1] 

End if

End for

Step 5: C is substituted by C1, and revisit Step 4.
Step 6: compute the extent of the Hamiltonian cycle C.
End for "i"
}

When t>1 then calculate value of the \( r_t \) by \( r_t = \frac{t_{\text{max}}}{t} \)
End if

Execute decision optimization procedure
{
Commence
\( r_{\text{minimum}} < r_t < r_{\text{maximum}} \) or \( r_t = r_{\text{maximum}} \)
Arbitrarily engender \( n_r \) individuals;
End if

End

} 

Calculate the population according to the recently modernized positions;
t = t+1.

Step 7: when "n" new-fangled individuals are engendered, then go to Step 8; or else go to
Step 6.
Step 8: end conditions met ; or else go to Step 2.
End

4. QUANTUM BASED BRAIN STORM OPTIMIZATION ALGORITHM

In BSO algorithm population is indicated as swarm moreover every individual is described as an idea. Originally, every idea is arbitrarily initialized inside the exploration space. Subsequently most excellent one in every cluster is selected as the cluster centre. Sporadically, an arbitrarily chosen centre is swapped by a recently engendered idea, by that the swarm has been kept away from the local optimum.

\[
x_{\text{new}}^{ij} = x_{\text{old}}^{ij} + \xi N(\mu, \sigma)
\]

\[
x_{\text{new}}^{ij} = \omega_1^* x_{\text{old1}}^{ij} + \omega_2^* x_{\text{old2}}^{ij}
\]

\( \xi \) is a factor used in the evolution process and can be articulated as,

\[
\xi(t) = \log \sigma g \left( \frac{N_{\text{max}}/2-N_r}{t}, \right)^\kappa \text{ random}
\]

Quantum state of an idea is illustrated by a wave function \( \Psi(x, t) \) as an alternative of the position modernized only in Brain storm optimization algorithm. By using Schrödinger equation probability density function of the position is identified such that each idea is located. Monte Carlo simulation method is used, to measure the position for each idea from the quantum state to the traditional one.

\[
x_{\text{new}}^{ij} = \begin{cases} 
q_{ij} + (1/2)^i \ln(1/\alpha) \text{ (random} < 0.5) \\
q_{ij} - (1/2)^i \ln(1/\alpha) \text{ (random} \geq 0.5) 
\end{cases}
\]

\[
q_{ij} = \text{random} \cdot x_{g.\text{best}}^{ij} + (1 - \text{random}) \cdot x_{c.\text{best}}^{ij}
\]

\[
l_{ij} = 2b |m_{\text{best}}| - x_{\text{old}}^{ij}
\]

\[
b = 1 - 0.5 \cdot \frac{N_r}{N_{\text{max}}}
\]

\[
m_{\text{best}} = \sum_{i=1}^{k} x_{c.\text{best}}^{ij}/k
\]
\[ x_{\text{new}}^{(l)} = \begin{cases} \text{random} \times x_{\text{best}}^{(l)} + (1 - \text{random}) \times x_{\text{best}}^{(l)} + \left( \beta \left| \frac{x_{\text{best}}^{(l)} - x_{\text{new}}^{(l)}}{k - x_{\text{best}}^{(l)}} \right| \right) \times \ln(1/\alpha) + \xi \cdot N(\mu, \sigma) & (\text{random} < 0.5) \\ \text{random} \times x_{\text{best}}^{(l)} + (1 - \text{random}) \times x_{\text{best}}^{(l)} + \left( \beta \left| \frac{x_{\text{best}}^{(l)} - x_{\text{new}}^{(l)}}{k - x_{\text{best}}^{(l)}} \right| \right) \times \ln(1/\alpha) + \xi \cdot N(\mu, \sigma) & (\text{random} \geq 0.5) \end{cases} \] (19)

Step a: Initialize the parameters.
Step b: Arbitrarily produce "n" ideas
Step c: By k-means algorithm cluster "n" ideas.
Step d: With a predetermined probability modernize the centre of a capriciously chosen cluster.
Step e: Individual generation created.
Step f: Quantum mechanism is exploited based on the chosen idea
Step g: Crossover operator is implemented
Step h: evaluate the new-fangled idea with the older one,
Step i: If "n" ideas have been engender, then go to Step 9. Or else go to Step 5.
Step j: Stop whether the present number of iterations N* attain the N_max. or else, go to

5. SIMULATION STUDY

Proposed ABS optimization algorithm and QBS optimization algorithm has been tested, in IEEE 57 Bus system [18]. Table 1 shows the comparison results.

| Control variables | Base case | MPSO [19] | PSO [19] | CGA [19] | AGA [19] | ABS | QBS |
|-------------------|-----------|-----------|----------|----------|----------|-----|-----|
| VG 1              | 1.040     | 1.093     | 1.083    | 0.968    | 1.027    | 1.019| 1.020|
| VG 2              | 1.010     | 1.086     | 1.071    | 1.049    | 1.014    | 1.025| 1.022|
| VG 3              | 0.985     | 1.056     | 1.055    | 1.056    | 1.033    | 1.027| 1.019|
| VG 6              | 0.980     | 1.038     | 1.036    | 0.987    | 1.001    | 1.021| 1.012|
| VG 8              | 1.005     | 1.066     | 1.059    | 1.022    | 1.051    | 1.027| 1.037|
| VG 9              | 0.980     | 1.054     | 1.048    | 0.991    | 1.051    | 1.035| 1.028|
| VG 12             | 1.015     | 1.054     | 1.046    | 1.004    | 1.057    | 1.049| 1.046|
| Tap 19            | 0.970     | 0.975     | 0.987    | 0.920    | 1.030    | 0.908| 0.900|
| Tap 20            | 0.978     | 0.982     | 0.983    | 0.920    | 1.020    | 0.906| 0.911|
| Tap 31            | 1.043     | 0.975     | 0.981    | 0.970    | 1.060    | 0.909| 0.916|
| Tap 35            | 1.000     | 1.025     | 1.003    | NR*  | NR*  | 1.013| 1.014|
| Tap 36            | 1.000     | 1.002     | 0.985    | NR*  | NR*  | 1.015| 1.012|
| Tap 37            | 1.043     | 1.007     | 1.009    | 0.900    | 0.990    | 1.006| 1.017|
| Tap 41            | 0.967     | 0.994     | 1.007    | 0.910    | 1.100    | 0.947| 0.936|
| Tap 46            | 0.975     | 1.013     | 1.018    | 1.100    | 0.980    | 1.019| 1.014|
| Tap 54            | 0.955     | 0.988     | 0.986    | 0.940    | 1.010    | 0.921| 0.920|
| Tap 58            | 0.955     | 0.979     | 0.992    | 0.950    | 1.080    | 0.937| 0.932|
| Tap 59            | 0.900     | 0.983     | 0.990    | 1.030    | 0.940    | 0.926| 0.921|
| Tap 65            | 0.930     | 1.015     | 0.997    | 1.090    | 0.950    | 1.006| 1.013|
| Tap 66            | 0.895     | 0.975     | 0.984    | 0.900    | 1.050    | 0.934| 0.926|
| Tap 67            | 0.958     | 1.020     | 0.990    | 0.900    | 0.950    | 1.006| 1.052|
| Tap 73            | 0.958     | 1.001     | 0.988    | 1.000    | 1.010    | 1.013| 1.007|
| Tap 76            | 0.980     | 0.979     | 0.980    | 0.960    | 0.940    | 0.947| 0.923|
| Tap 80            | 0.940     | 1.002     | 1.017    | 1.000    | 1.000    | 1.009| 1.037|
| QC 18             | 0.1       | 0.179     | 0.131    | 0.084    | 0.016    | 0.150| 0.147|
| QC 25             | 0.059     | 0.176     | 0.144    | 0.008    | 0.015    | 0.142| 0.138|
| QC 53             | 0.063     | 0.141     | 0.162    | 0.053    | 0.038    | 0.127| 0.121|
| PG (MW)           | 1278.6    | 1274.4    | 1274.8   | 1276    | 1275    | 1272.99| 1272.04|
| QG (Mvar)         | 321.08    | 272.27    | 276.58   | 309.1   | 304.4   | 272.57| 272.12|
| Reduction in PLoss (%) | 0     | 15.4     | 14.1    | 9.2     | 11.6    | 25.32| 27.88|
| Total PLoss (Mw)  | 27.8      | 23.51     | 23.86    | 25.24   | 24.56   | 20.760| 20.049|

NR* - Not reported.

6. CONCLUSION

In this paper ABS optimization algorithm and QBS optimization algorithm successfully solved the optimal reactive power problem. In projected ABS algorithm to escape BSO from local optima and to maintain the optimization process Hamiltonian cycle has been utilized. In the mathematical field of graph theory, a Hamiltonian path is a path in an undirected or directed graph that visits each vertex exactly once. In QBS approach by using Schrödinger equation probability density function of the position is identified such that each idea is located. Monte Carlo simulation method is used, to measure the position for each idea from the quantum state to the traditional one. Proposed ABS algorithm and QBS optimization algorithm has been tested in standard IEEE 57 bus test system and simulation results show the projected algorithms reduced the real power loss efficiently.
REFERENCES

[1] K. Y. Lee, Y. M. Park and J. L. Ortiz, "Fuel-cost minimisation for both real-and reactive-power dispatches," in IEEE Proceedings C - Generation, Transmission and Distribution, vol. 131, no. 3, pp. 85-93, May 1984.
[2] N. I. Deeb and S. M. Shahidehpour, "An efficient technique for reactive power dispatch using a revised linear programming approach," Electric Power System Research, vol 15, no. 2, pp. 121-134, 1988.
[3] M. Bjelogrlic, M. S. Calovic, P. Ristanovic and B. S. Babic, "Application of Newton's optimal power flow in voltage/reactive power control," in IEEE Transactions on Power Systems, vol. 5, no. 4, pp. 1447-1454, 1990.
[4] S. Granville, "Optimal reactive dispatch through interior point methods," in IEEE Transactions on Power Systems, vol. 9, no. 1, pp. 136-146, 1994.
[5] N. Grudinin, "Reactive power optimization using successive quadratic programming method," in IEEE Transactions on Power Systems, vol. 13, no. 4, pp. 1219-1225, 1998.
[6] R. N. S. Mei, M. H. Sulaiman, Z. Mustaffa and H. Daniyal, "Optimal reactive power dispatch solution by loss minimization using moth-flame optimization technique," Appl. Soft Comput., vol. 59, 210-222, 2017.
[7] Gonggui Chen, Lilian Liu, Zhizhong Zhang and Shanwai Huang, "Optimal reactive power dispatch by improved GSA-based algorithm with the novel strategies to handle constraints," Appl. Soft Comput., vol. 50, 58-70, 2017.
[8] E. Naderi, H. Narimani, M. Fathi, M. R. Narimani, "A novel fuzzy adaptive configuration of particle swarm optimization to solve large-scale optimal reactive power dispatch," Appl. Soft Comput., vol. 53, pp. 441-456, 2017.
[9] A. A. Heidari, R. A. Abbaspour, A. R. Jordeli, "Gaussian bare-bones water cycle algorithm for optimal reactive power dispatch in electrical power systems," Appl. Soft Comput., vol. 57, pp. 657-671, 2017.
[10] M. Morgan, N. R. H. Abdullah, M. H. Sulaiman, M. Mustafa, R. Samad, "Benchmark Studies on Optimal Reactive Power Dispatch (ORPD) Based Multi-objective Evolutionary Programming (MOEP) Using Mutation Based on Adaptive Mutation Adapter (AMO) and Polynomial Mutation Operator (PMO)," Journal of Electrical Systems, vol. 12, no. 1, pp. 121-132, 2016.
[11] R. N. S. Mei, M. H. Sulaiman and Z. Mustaffa, "Ant Lion Optimizer for Optimal Reactive Power Dispatch Solution," Journal of Electrical Systems, Special Issue AMPE2015, pp. 68-74, 2015.
[12] P. Anbarasan and T. Jayabarathi, "Optimal reactive power dispatch problem solved by symbiotic organism search algorithm," 2017 Innovations in Power and Advanced Computing Technologies (i-PACT), Vellore, pp. 1-8, 2017.
[13] A. Gagliano and F. Nocera, "Analysis of the performances of electric energy storage in residential applications," International Journal of Heat and Technology, vol. 35, Special Issue 1, pp. S41-S48, 2017.
[14] M. Caldera, P. Ungaro, G. Cammarata and G. Puglisi, "Survey-based analysis of the electrical energy demand in Italian households," Mathematical Modelling of Engineering Problems, vol. 5, no. 3, pp. 217-224, 2018.
[15] M. Basu, "Quasi-oppositional differential evolution for optimal reactive power dispatch," International Journal of Electrical Power & Energy Systems, vol. 78, pp. 29-40, 2016.
[16] Xin-She Yang, "Bat algorithm for multi-objective optimization," International Journal of Bio-Inspired Computation, vol. 3, no. 5, pp. 267-274, 2011.
[17] Y. Shi, "Brain storm optimization algorithm in objective space," 2015 IEEE Congress on Evolutionary Computation (CEC), Sendai, pp. 1227-1234, 2015.
[18] IEEE., "The IEEE-test systems," 1993. [Online]. Available at: https://labs.ece.uw.edu/pstca/pf57/pg_tca57bus.htm.
[19] A. N. Hussain, A. A. Abdullah and O. M. Neda, "Modified particle swarm optimization for solution of reactive power dispatch," Research J. of Applied Sciences, Engineering and Technology, vol. 15, no. 8, pp. 316-327, 2018.