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

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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 $\Psi(\vec{x},t)$ 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.

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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

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

2.2. Amplification of voltage profile

$$\mathbf{F} = \mathrm{P_L} + \omega_\mathrm{v} \times \text{Voltage Deviation} \tag{2}$$

Voltage deviation given by:

$$\text{Voltage Deviation} = \sum_{i=1}^{Npq} |V_i - 1| \tag{3}$$

2.3. Constraint (equality)

$$\mathbf{P_G} = \mathbf{P_D} + \mathbf{P_L} \tag{4}$$

2.4. Constraints (inequality)

$$\mathrm{P_{gslack}^{min}} \leq \mathrm{P_{gslack}} \leq \mathrm{P_{gslack}^{max}} \tag{5}$$

$$\mathrm{Q_{gi}^{min}} \leq \mathrm{Q_{gi}} \leq \mathrm{Q_{gi}^{max}}, i \in \mathrm{N_g} \tag{6}$$

$$\mathrm{V_i^{min}} \leq \mathrm{V_i} \leq \mathrm{V_i^{max}}, i \in \mathrm{N} \tag{7}$$

$$\mathrm{T_i^{min}} \leq \mathrm{T_i} \leq \mathrm{T_i^{max}}, i \in \mathrm{N_T} \tag{8}$$

$$\mathrm{Q_c^{min}} \leq \mathrm{Q_c} \leq \mathrm{Q_C^{max}}, i \in \mathrm{N_C} \tag{9}$$

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 $t(r_t)$ can be described as:

$$r_t = \frac{L_{t+1}}{L_t} \tag{10}$$

Hamilton cycle algorithm as follows:

Commence
Step 1: node $v1$ chosen as initial point,.
Step 2: $v_1, v_2, .., v_i$ is chosen and v_{i+1} is picked with least weight linkingv_1, then the $v_1, v_2, .., v_{i+1}$ is obtained.
Step 3: when i+1<n, subsequently i+1 is used to substitute i, and revisit to Step 2; condition not occurred , then revisit to the final Hamiltonian cycle $C = v_1, v_2, .., v_n v_1$then go back to Step 4.
Step 4: $v_i v_j \in E(G)$; $v_{i+1}, v_{j+1} \in E(G), w(v_i v_j) + w(v_{i+1} v_{j+1}) < w(v_i v_{i+1}) + w(v_j v_{j+1})$
Then $C_1 = (C - \{v_i v_{i+1}, v_j v_{j+1}\}) \cup \{v_i v_j, v_{i+1} v_{j+1}\}$
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

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

Commence
Step 1: "n" potential solutions are arbitrarily engendered
Step 2: "n" individuals are clustered into "m" clusters
Step 3: "n" individuals will be appraised
Step 4: In every cluster rank the individuals then the most excellent individual's are recorded as cluster center **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

```
Step 6: new-fangled individuals are engendered
Calculate the Hamiltonian cycle C and its extent Lt 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 v1, then the v1,v2,..,vi+1 is 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 C, if 1< i+1<j<n, then
i ≠ j ; vivj ∈ E(G)
vi+1,vj+1 ∈ E(G), w(vivj) + w(vi+1vj+1) < w(vivi+1) + w(vjvj+1)
Then C1 = (C − {vivi+1, vjvj+1}) ∪ {vivj, vi+1vj+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 rt by rt = Lt+1/Lt
End if
Execute decision optimization procedure
{
Commence
rminimum < rt < rmaximum or rt = rmaximum
Arbitrarily engender nr 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.

$$x_{new}^{ij} = x_{old}^{ij} + \xi\, N(\mu,\sigma) \tag{11}$$

$$x_{new}^{ij} = \omega_1^* x_{old1}^{ij} + \omega_2^* x_{old2}^{ij} \tag{12}$$

ξ is a factor used in the evolution process and can be articulated as,

$$\xi(t) = \log sig\left(\frac{N_C max/2 - N_c}{\xi}\right)^* random \tag{13}$$

Quantum state of an idea is illustrated by a wave function $\Psi(\vec{x},t)$ 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.

$$x_{new}^{ij} = \begin{cases} q_{ij} + (1_{ij}/2)^* In(1/u)\ (random < 0.5) \\ q_{ij} - (1_{ij}/2)^* In(1/u)\ (random \geq 0.5) \end{cases} \tag{14}$$

$$q_{ij} = random^* x_{g\,best}^{j} + (1 - random)^* x_{c\,best}^{ij} \tag{15}$$

$$l_{ij} = 2b\left|mbest^{j} - x_{old}^{ij}\right| \tag{16}$$

$$b = 1 - 0.5^* \frac{N_c}{N_c max} \tag{17}$$

$$mbest^{j} = \sum_{i=1}^{k} x_{cbest}^{ij}/k \tag{18}$$

$$x_{new}^{ij} = \begin{cases} random * x_{best}^{j} + (1 - random) * x_{c\,best}^{ij} + \left(b\left|\sum_{i=1}^{k} x_{cbest}^{ij}/k - x_{old}^{ij}\right|\right) * In(1/u) + \xi\, N(\mu,\sigma)\ (random < 0.5) \\ random * x_{best}^{j} + (1 - random) * x_{c\,best}^{ij} + \left(b\left|\sum_{i=1}^{k} x_{cbest}^{ij}/k - x_{old}^{ij}\right|\right) * In(1/u) + \xi\, N(\mu,\sigma)\ (random \geq 0.5) \end{cases} \quad (19)$$

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_c attain the N_{cmax}. 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.

Table 1. Simulation results of IEEE-57 system

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	1.011	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 71	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 projetced 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.

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