Quantum based Polyphylla Fullo Search Optimization Algorithm for True Power Loss Reduction and Voltage Constancy Augmentation

Lenin Kanagasabai[1,*]

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ABSTRACT

This paper proposes Quantum based Polyphylla fullo search (QPS) optimization algorithm for actual power loss lessening Polyphylla fullo search (PS) optimization algorithm lures stimulation from Polyphylla fullo with double enlarged antennal. These antlers support them to passage everywhere in exploration of nutrition, and equally the antlers record the whiff of nutrition. Grounded on the concentration of whiff on every antennal, the Polyphylla fullo engenders a passage. If the whiff on the left antennal is concentrated, the Polyphylla fullo will passageway on left side. Otherwise, it will passage on right direction. The fitness rate is calculated between both directions and it is positive then the Polyphylla fullo passages in the right otherwise the movement of the Polyphylla fullo will be in left direction. Quantum mechanics has been integrated with the Polyphylla fullo search (PS) optimization algorithm and it entitled as Quantum based Polyphylla fullo search (QPS) optimization algorithm. In quantum procedure, quantum elements imitate the similar performance with the bound state as they passage in a probable ground of midpoint. Proposed Quantum based Polyphylla fullo search (QPS) optimization algorithm validated in standard systems.

1. INTRODUCTION

Power administration organization processes [1-20] the fresh statistics to deliver consistent figures base for the examination of the control system [21-44]. This paper proposes Quantum based Polyphylla fullo search (QPS) optimization algorithm for actual power loss lessening. Key objectives of the paper are Key objectives of the paper are Voltage constancy augmentation, voltage deviance minimization and Actual power loss lessening. Polyphylla fullo search (PS) optimization algorithm lures stimulation from Polyphylla fullo with double enlarged antennal. These antlers support them to passage everywhere in exploration of nutrition, and equally the antlers record the whiff of nutrition. Grounded on the concentration of whiff on every antennal, the Polyphylla fullo engenders a passage. If the whiff on the left antennal is concentrated, the Polyphylla fullo will passageway on left side. Or else, it will passage on right direction. That is the way the Polyphylla fullo creeps arbitrarily and discovers the space up until it grasps the nutrition. The whiff on both the antennal and creates a transitional passage in both directions. The fitness rate is calculated between both directions and it is positive then the Polyphylla fullo passages in the right direction or else the movement of the Polyphylla fullo will be in left direction. Grounded on the transitional fitness standards, PS calculates the new-fangled location for the Polyphylla fullo. Quantum mechanics has been integrated with the Polyphylla fullo search (PS) optimization algorithm and it entitled as Quantum based Polyphylla fullo search (QPS) optimization algorithm. In quantum procedure, quantum elements imitate the similar performance with the bound state as they passage in a probable ground of midpoint.Proposed Quantum based Polyphylla fullo search (QPS) optimization algorithm validated in standard test systems.

2. PROBLEM FORMULATION

Power loss minimization is defined by

$$Min\ \tilde{F}(\bar{d},\bar{e}) \tag{1}$$

Subject to the limits

$$A(\bar{d},\bar{e}) = 0 \tag{2}$$

$$B(\bar{d},\bar{e}) = 0 \tag{3}$$

$$d = [VLG_1,..,VLG_{Ng}; QC_1,..,QC_{Nc}; T_1,..,T_{N_T}] \tag{4}$$

$$e = [PG_{slack}; VL_1,..,VL_{N_{Load}}; QG_1,..,QG_{Ng}; SL_1,..,SL_{N_T}] \tag{5}$$

$$F_1 = P_{Minimize} = Minimize \left[\sum_m^{NTL} G_m \left[V_i^2 + V_j^2 - 2 *\right.\right.$$

[1]Prasad V.Potluri Siddhartha Institute of Technology, Kanuru, Vijayawada, Andhra Pradesh -520007.
*Corresponding author: Lenin Kanagasabai; E-mail: gklenin@gmail.com.

$V_i V_j cos\emptyset_{ij}\big]\Big]$ (6)

$F_2 = Minimize\left[\sum_{i=1}^{N_{LB}}\left|V_{Lk} - V_{Lk}^{desired}\right|^2 + \sum_{i=1}^{Ng}\left|Q_{GK} - Q_{KG}^{Lim}\right|^2\right]$ (7)

$$F_3 = Minimize\ L_{MaxImum} \quad (8)$$

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

and

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

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

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

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

$$\mathrm{P_{gslack}^{minimum}} \le \mathrm{P_{gslack}} \le \mathrm{P_{gslack}^{maximum}} \quad (14)$$

$$\mathrm{Q_{gi}^{minimum}} \le \mathrm{Q_{gi}} \le \mathrm{Q_{gi}^{maximum}}, \mathrm{i} \in \mathrm{N_g} \quad (15)$$

$$\mathrm{VL_i^{minimum}} \le \mathrm{VL_i} \le \mathrm{VL_i^{maximum}}, \mathrm{i} \in \mathrm{NL} \quad (16)$$

$$\mathrm{T_i^{minimum}} \le \mathrm{T_i} \le \mathrm{T_i^{maximum}}, \mathrm{i} \in \mathrm{N_T} \quad (17)$$

$$\mathrm{Q_c^{minimum}} \le \mathrm{Q_c} \le \mathrm{Q_C^{maximum}}, \mathrm{i} \in \mathrm{N_C} \quad (18)$$

$$|SL_i| \le S_{L_i}^{maximum}, \mathrm{i} \in \mathrm{N_{TL}} \quad (19)$$

$$\mathrm{VG_i^{minimum}} \le \mathrm{VG_i} \le \mathrm{VG_i^{maximum}}, \mathrm{i} \in \mathrm{N_g} \quad (20)$$

$$Multi\ objective\ fitness\ (MOF) = F_1 + r_iF_2 + uF_3 = F_1 + \left[\sum_{i=1}^{NL} x_v\left[VL_i - VL_i^{min}\right]^2 + \sum_{i=1}^{NG} r_g\left[QG_i - QG_i^{min}\right]^2\right] + r_fF_3 \quad (21)$$

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

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

3. QUANTUM BASED POLYPHYLLA FULLO SEARCH OPTIMIZATION ALGORITHM

Polyphylla fullo search (PS) optimization algorithm lures stimulation from Polyphylla fullo with double enlarged antennal. These antlers support them to passage everywhere in exploration of nutrition, and equally the antlers record the whiff of nutrition. Grounded on the concentration of whiff on every antennal, the Polyphylla fullo engenders a passage. If the whiff on the left antennal is concentrated, the Polyphylla fullo will passageway on left side. Or else, it will passage on right direction. That is the way the Polyphylla fullo creeps arbitrarily and discovers the space up until it grasps the nutrition.

Location of the Polyphylla fullo at “N” iteration is defined as,

$$P^N; N = 1,2,3,..,N \quad (24)$$

The cause of the whiff’s fitness function described as,

$$f(P) \quad (25)$$

Polyphylla fullo whiffs by both antennal and hence the location vectors is defined as,

$$P_{right}\ and\ P_{left} \quad (26)$$

Then the arbitrary direction vector is demarcated as “d”, The step controlling vector is symbolized as s^N

The whiff on both the antennal and creates an transitional passage in both directions and it described as,

$$P_{right} = P^N + d * s^N \quad (27)$$

$$P_{left} = P^N - d * s^N \quad (28)$$

The fitness rate is calculated between both directions and it is positive then the Polyphylla fullo passages in the right direction or else the movement of the Polyphylla fullo will be in left direction as follows,

$$\Delta\, Fitness = f\left(P_{right}\right) - f\left(P_{left}\right) \quad (29)$$

Grounded on the transitional fitness standards, PS calculates the new-fangled location for the Polyphylla fullo and it defined mathematically as follows,

$$P^N = P^{N-1} + d * s^N * \Delta\, Fitness \quad (30)$$

Then the fitness function for the new-fangled location P^N is calculated and subsequently $\Delta\, Fitness$ is added to the preceding location.

When $P^N\ is\ excellent\ than\ P^{N-1}$ then sequentially assign it as new-fangled finest location P_{best} or else abandon it.

Then in the procedure of the Polyphylla fullo search (PS) optimization algorithm there will be transformation from exploration to exploitation. Sequentially s^N value will be reduced in iterations gradually and it defined as,

$$s^N = 0.9\ \cdot s^{N-1} + 0.01 \quad (31)$$

Fig 1 shows the Flow chart of Polyphylla fullo search (PS) optimization algorithm.

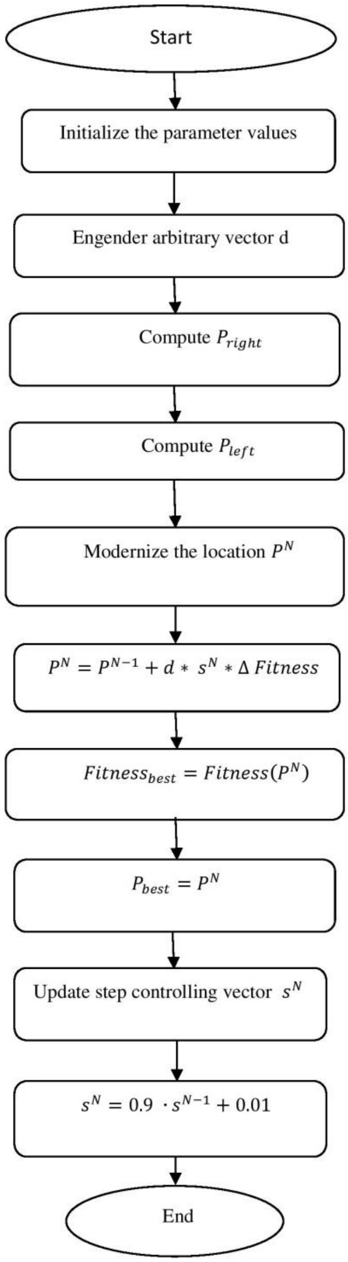

Fig 1. Flow chart of Polyphylla fullo search (PS) optimization algorithm.

a. Start
b. Initialize the parameter values
c. $while\{N, k\}$
d. Engender arbitrary vector d
e. Compute P_{right}
f. $P_{right} = P^N + d * s^N$
g. Compute P_{left}
h. $P_{left} = P^N - d * s^N$
i. Modernize the location P^N
j. $P^N = P^{N-1} + d * s^N * \Delta\, Fitness$
k. $if\ (Fitness(P^N) > Fitness_{best}), then$
l. $Fitness_{best} = Fitness(P^N)$
m. $P_{best} = P^N$
n. End if
o. Modernize the step controlling vector s^N
p. $s^N = 0.9 \cdot s^{N-1} + 0.01$
q. End while
r. End

Quantum mechanics [29-33] has been integrated with the Polyphylla fullo search (PS) optimization algorithm and it entitled as Quantum based Polyphylla fullo search (QPS) optimization algorithm. In quantum procedure, quantum elements imitate the similar performance with the bound state as they passage in a probable ground of midpoint. The wave function in the Quantum mechanics [29-33] is defined as,

$$|\Psi|^2 \cdot dx \cdot dy \cdot dz = Quantum \cdot dx \cdot dy \cdot dz$$

$where\ \Psi\ specify\ the\ probability\ density\ functional\ value$

The time reliant Schrodinger equation [29-33] is applied to assess the wave function is defined as,

$$ih \cdot \partial/\partial t \cdot \Psi(x,t) = HO \cdot \Psi(x,t) \quad (32)$$

$where\ HO\ specify\ the$ Hamiltonian operator$[29-33]$

$$HO = -h^2/2m \cdot \Delta^2 + V(x) \quad (33)$$

In the quantum scheme $\Delta Fitness$ sequentially perform as particle and it sequentially moves in delta prospective towards center.

$$SF\left(f(P_{right}) - f(P_{left})\right) = SF \cdot \Delta Fitness \rightarrow 0 \quad (34)$$

$where\ SF\ is\ scaling\ factor$

Then the delta prospective is defined as,

$$V(x) = -\gamma\delta\left(SF\left(f(P_{right}) - f(P_{left})\right)\right) \quad (35)$$

$$V(x) = -\gamma\delta(SF \cdot \Delta Fitness) = -\gamma\delta(z) \quad (36)$$

$$z = SF\left(f(P_{right}) - f(P_{left})\right) = SF \cdot \Delta Fitness \quad (37)$$

Then,

$$HO = -h^2/2m \cdot \Delta^2 - \gamma\delta(z) \quad (38)$$

Then the Schrodinger equation [29-33] is written as,

Schrodinger(Time − independent) is

$$\frac{d^2\Psi}{dz^2} + \frac{2m}{h^2}[G + \gamma\delta(z)]\Psi = 0 \quad (39)$$

$$\Psi(z) = \frac{1}{\sqrt{L}} e^{-\frac{|z|}{L}} \quad (40)$$

$$Quantum(z) = |\Psi(z)|^2 = \frac{1}{\sqrt{L}} e^{-\frac{|z|}{L}} \quad (41)$$

$$z = \pm \frac{L}{2} In(1/g) \quad (42)$$

$where\ u \in [0,1]$

$$z = SF \cdot \Delta Fitness = P^N - P^{N-1} \quad (43)$$

$$P^N - P^{N-1} = \pm \frac{L}{2} In(1/g) \quad (44)$$

$$P^N = P^{N-1} \pm \frac{L}{2} In(1/g) \quad (45)$$

Then

$$L = \frac{1}{e}|\Delta z|(46)$$

$$L = \frac{1}{e}|SF \cdot \Delta Fitness| \quad (47)$$

$where\ e > In\sqrt{2}$.

Fig 2 shows the flow chart of Quantum based Polyphylla fullo search (QPS) optimization algorithm.

a. Start
b. Initialize the parameter values
c. $while\{N, k\}$
d. Engender arbitrary vector d
e. Compute P_{right}
f. $P_{right} = P^N + d * s^N$
g. Compute P_{left}
h. $P_{left} = P^N - d * s^N$
i. $CalculatethevalueofL$
j. $L = \frac{1}{e}|SF \cdot \Delta Fitness|$
k. $g = random(0,1)$
l. $if(random(0,1) > 0.5), then$
m. $P^N - P^{N-1} = \pm \frac{L}{2} In(1/g)$
n. Otherwise
o. $P^N = P^{N-1} \pm \frac{L}{2} In$
p. End if
q. $if(Fitness(P^N) > Fitness_{best}), then$
r. $Fitness_{best} = Fitness(P^N)$
s. $P_{best} = P^N$
t. End if
u. Modernize the step controlling vector s^N
v. $s^N = 0.9 \cdot s^{N-1} + 0.01$
w. End while
x. End

Computational analysis of the Quantum based Polyphylla fullo search (QPS) optimization algorithm

When iteration increases and the objective functional values are in stable mode,

$$Funtional\ value\ (P^{N1}) < Funtional\ value\ (P^{N2}) \quad (48)$$

$$N1 < N2 \quad (49)$$

In the QPS approach P^{N2} is acceptable when

$$Funtional\ value\ (P^{N2}) > Funtional\ value\ (P^{N1}) \quad (50)$$

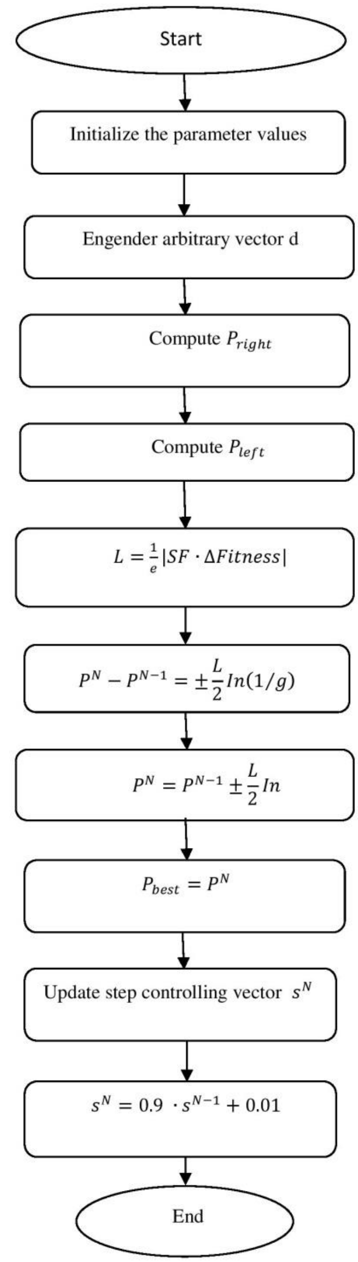

Fig 2. Flow chart of Quantum based Polyphylla fullo search (QPS) optimization algorithm.

$$N2 > N1 \quad (51)$$

If P^{N2} possess smaller value than P^{N1} then the preceding state will be retained and this reveal about the stability of the proposed algorithm.

Then $Funtional\ value$ approach in the direction of optimal solution P^* and it defined as,

$$Funtional\ value(P^N) = P^* \quad (52)$$

$$N \to \infty \quad (53)$$

The probabilities in the QPS approach is defined as,

$$Pb_{Ni} = Pb_{N1}, Pb_{N2}, .., Pb_{Ni-1} \quad (54)$$

Then the probability evaluated for P^{Ni},

$$Pb'_{Ni} = 1 - Pb_{Ni} \quad (55)$$

$$Pb'_{Ni} = 1 - Pb_{N1}, Pb_{N2}, .., Pb_{Ni-1} \quad (56)$$

Then in $N \to \infty$ *iteration*, the probability will be converged and it defined as,

$$\lim_{N\to\infty} Pb'_{Ni} = 1 - \lim_{N\to\infty} Pb_{N1}, Pb_{N2}, .., Pb_{Ni-1}$$
$$\lim_{N\to\infty} Pb'_{Ni} = 1 \quad (57)$$

Then the total space complexity of the QPS approach is

$$space\ complexity\ O(4 * N + 7) \quad (58)$$

Since the complexity of time to engender SF, g, P_{right} and P_{left}

4. SIMULATION RESULTS

Projected Polyphylla fullo search (PS) optimization algorithm and Quantum based Polyphylla fullo search (QPS) optimization algorithmis corroborated in IEEE 30 bus system [20]. Tables and Figures show the comparisons.

Table 1 Assessment of power loss

Technique	Loss (MW)
HDPSOTS [20]	4.52130
BATS [20]	4.68620
SIPSO [20]	4.68620
BAALO [21]	4.59000
HDQOTLBO [22]	4.55940
BATLBO [22]	4.56290
SIMGA [23]	4.94080
BAPSO [23]	4.92390
HDAS [23]	4.90590
BAFS [24]	4.57770
HDISFS [24]	4.51420
BAFS [26]	4.52750
PS	4.40790
QPS	4.40980

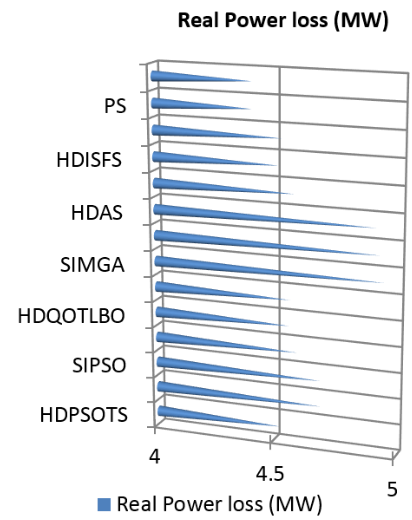

Fig 3. Assessment of loss.

Table 2. Comparison of Power aberration

Method	Power deviancy (PU)
HDPSOTVIW [25]	0.1038
HDPSOTVAC [25]	0.2064
HYPSOTV [25]	0.1354
HDPSOCF [25]	0.1287
HDPGPSO [25]	0.1202
HDSWTPSO [25]	0.1614
HDPGSWTPSO [25]	0.1539
HDMPGPSO [25]	0.0892
HDQOTLBO [22]	0.0856
BATLBO [22]	0.0913
BAFS [24]	0.1220
HDISFS [24]	0.0890
BAFS [26]	0.0877
PS	0.0831
QPS	0.0837

Then the Projected Polyphylla fullo search (PS) optimization algorithm and Quantum based Polyphylla fullo search (QPS) optimization algorithm is substantiated in IEEE 14, 30, 57, 118 and 300 bus test systems [10] deprived of Power constancy. Tables and Figures show the comparisons.

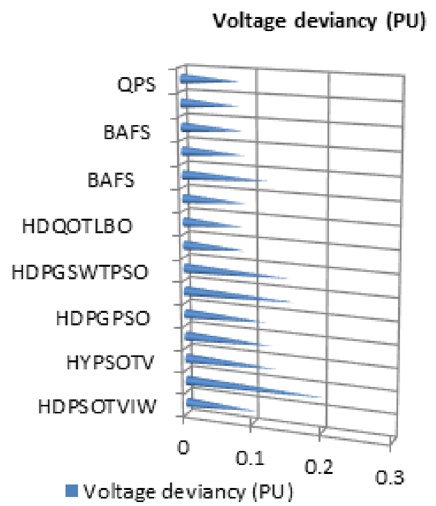

Fig 4. Assessment of Power aberration.

Table 3. Assessment of Power reliability

Method	Power reliability (PU)
HDPSOTVIW [25]	0.1258
HDPSOTVAC [25]	0.1499
HDPSOTVAC [25]	0.1271
HDPSOCF [25]	0.1261
HDPGPSO [25]	0.1264
HDSWTPSO [25]	0.1488
HDPGSWTPSO [25]	0.1394
HDMPGPSO [25]	0.1241
HDQOTLBO [22]	0.1191
BATLBO [22]	0.1180
BAALO [21]	0.1161
BAABC [21]	0.1161
BAGWO [21]	0.1242
BABA [21]	0.1252
BAFS [24]	0.1252
HDISFS [24]	0.1245
BAFS [26]	0.1007
PS	0.1002
QPS	0.1001

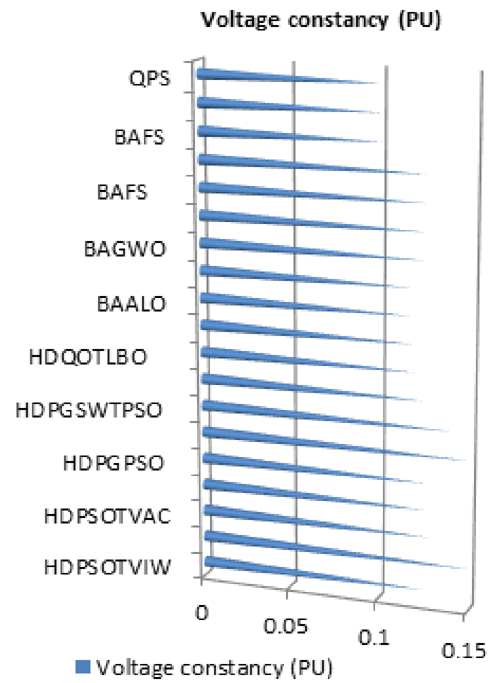

Fig 5. Assessment of Power reliability.

Table 4. Assessment of results (IEEE 14 Bus)

Method	Loss (MW)	Proportion of loss shrinking
B- value [24]	13.550	0.000
IEDPSO [24]	12.293	9.2000
BASPSO [23]	12.315	9.1000
BASEP [23]	13.346	1.500
HDSARGA [22]	13.216	2.500
PS	10.069	25.6900
QPS	10.012	26.1107

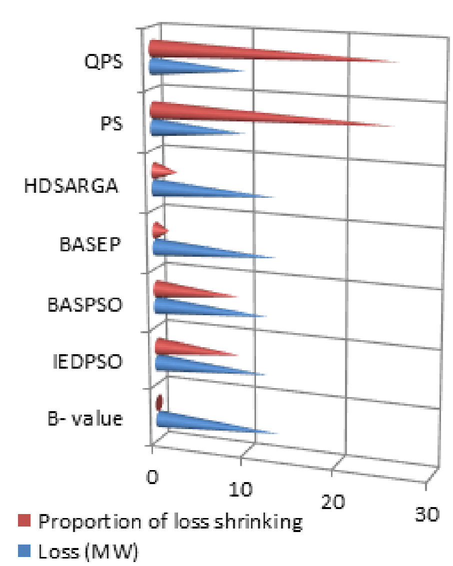

Fig 6. Power Loss assessment (IEEE 14 bus system).

Table 5 Assessment of loss (IEEE 30 bus system)

Method	Loss in MW	Quantity of Shrinking Loss
B- value [14]	17.5500	0.0000
IEDPSO[14]	16.0700	8.40000
BASPSO [13]	16.2500	7.4000
BASEP [11]	16.3800	6.60000
BASGA [12]	16.0900	8.30000
SIPSO [15]	17.5246	0.14472
IEDDEPSO [15]	17.52	0.17094
BASJAYA [15]	17.536	0.07977
PS	14.089	19.7207
QPS	14.064	19.8632

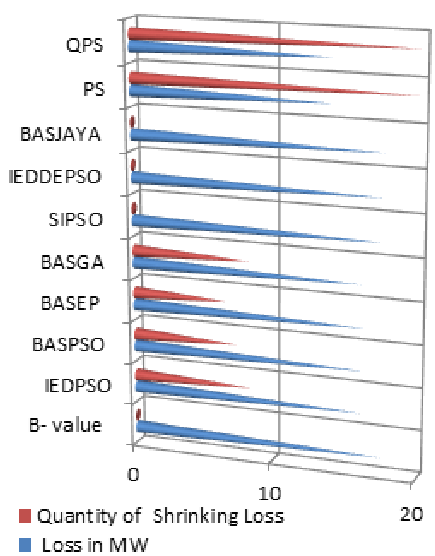

Fig 7. Appraisal of Power Loss (IEEE 30 bus system).

Table 6. Assessment of parameters (IEEE 57 Bus system)

Parameter	Loss (MW)	Quantity of Shrinking Loss
B-value [14]	27.8	0.00
IEDPSO [14]	23.51	15.400
BASPSO [13]	23.86	14.100
CALGA[12]	25.24	9.200
ADEGA [12]	24.56	11.600
PS	21.092	24.1294
QPS	21.081	24.1690

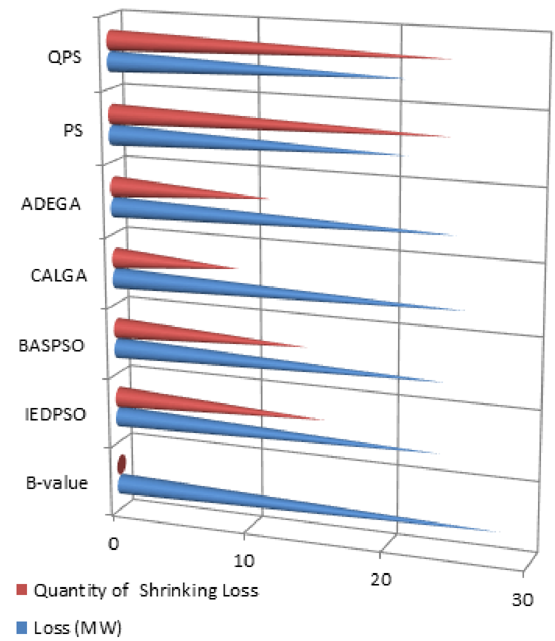

Fig 8. Loss assessment (IEEE 57 bus system).

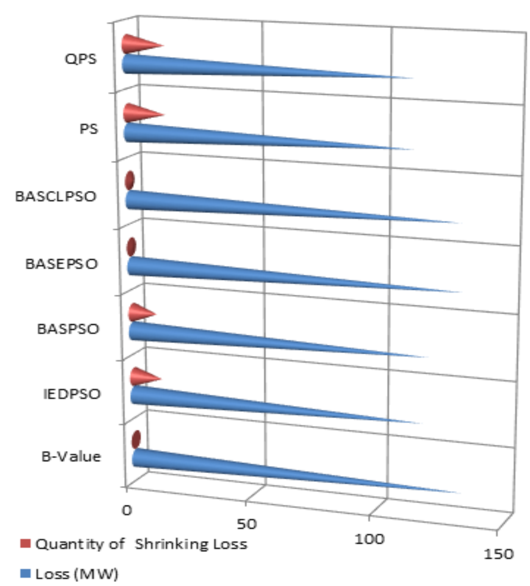

Fig 9. Loss assessment (IEEE 118 bus system)

Table 7 Assessment of results (IEEE 118 Bus system)

Parameter	Loss (MW)	Quantity of Shrinking Loss
B-Value [14]	132.8	0.00
IEDPSO [14]	117.19	11.700
BASPSO [13]	119.34	10.100
BASEPSO [11]	131.99	0.600
BASCLPSO [11]	130.96	1.300
PS	112.73	15.1129
QPS	112.44	15.3313

Table 8. Loss assessment (IEEE 300 Bus system)

Parameter	Loss (MW)
ADEGA [35]	646.299800
FAREA [35]	650.602700
BASCSO [34]	635.894200
PS	625.142327
QPS	625.112814

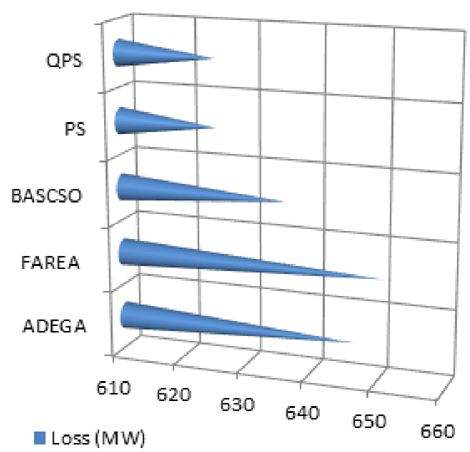

Fig 10. Loss assessment (IEEE 300 bus system).

Table 9. Convergence characteristics

Technique	PS	QPS
Loss (1)	4.4079	4.4098
Loss (2)	14.089	14.064
T(S)- (1)	29.17	27.86
T(S) -(2)	22.16	20.74
Iterations (1)	31	30
Iterations (2)	29	24

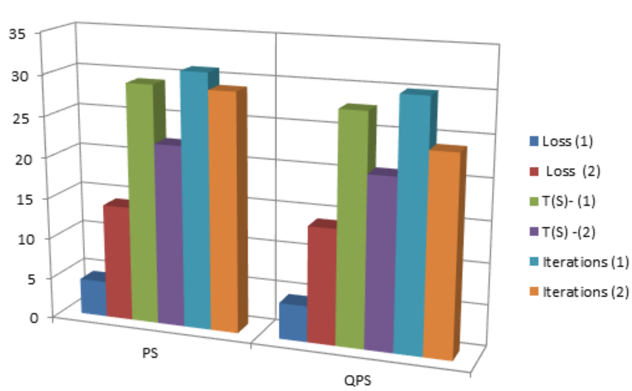

Fig 11. CC of Polyphylla fullo search (PS) optimization algorithm and Quantum based Polyphylla fullo search (QPS) optimization algorithm.

Table 9 and Fig 11 shows the convergence characteristics ofProjected Polyphylla fullo search (PS) optimization algorithm and Quantum based Polyphylla fullo search (QPS) optimization algorithm.

5. CONCLUSION

Quantum based Polyphylla fullo search (QPS) optimization algorithm condensed the loss ingeniously. The fitness rate is calculated between both directions and it is positive then the Polyphylla fullo passages in the right direction or else the movement of the Polyphylla fullo will be in left direction. Grounded on the transitional fitness standards, PS calculates the new-fangled location for the Polyphylla fullo. Then the fitness function for the new-fangled location P^N is calculated and subsequently Δ Fitness is added to the preceding location. When P^N is more excellent than P^{N-1} then sequentially assign it as new-fangled finest location P_{best} or else abandon it. Then in the procedure of the Polyphylla fullo search (PS) optimization algorithm there will be transformation from exploration to exploitation. Sequentially s^N value will be reduced in iterations gradually.Quantum mechanics has been integrated with the Polyphylla fullo search (PS) optimization algorithm and it entitled as Quantum based Polyphylla fullo search (QPS) optimization algorithm. In quantum procedure, quantum elements imitate the similar performance with the bound state as they passage in a probable ground of midpoint. In the quantum scheme ΔFitness sequentially perform as particle and it sequentially moves in delta prospective towards center. Percentage of loss drop by QPS is 19.8632 (IEEE 30 bus), 24.1690 (IEEE 57 bus), 15.3313 (IEEE 118 bus).

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