Real Power Loss Reduction by Neural Network Method

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A R T I C L E I N F O

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A B S T R A C T

In this paper to solve the power loss diminishing problem, Neural Network (NN) method is used. NN is fabricated independently for every representative, to epitomize the examining location. The neural accomplishments are defined with reference to action dissemination between neurons and exterior response. Neural network ordered model poised of numerous tasks of Gaussian possibility concentration, which relate to the groups. Rendering to the last location of neuron and present position, the passage of the representative is defined. Training populace with N statistics and it situated at the center locations of trellises. In the direction of designate the objective possibility map convincingly, the formed statistics necessity be in accord with the objective possibility map, so the quantity of statistics facts positioned at a trellis ought to be relational to its committed objective possibility. Certain energetic adaptive approaches, such as the abolition, combine or putrefaction of Gaussian representations can be acquainting with into the iterative stage in order to improve the accurateness. Consequently the quantity of prototypes is stretchy in accord with the situation. Proposed Neural Network (NN) method is validated in IEEE test systems.

1. INTRODUCTION

Power loss diminishing problem is important problem in power system. Many techniques interior point technique [1], quadratic programming [2], N-R [3], successive programming [4, 5]. Marine [6], improved programming [7, 8] are applied. Then these years improved algorithms [9-26] applied. Numerous mathematical based techniques [28- 40] also applied. Teslyuk et al [41] did Optimal Artificial Neural Network applications. Monteiro da Silva et al [42] used Feed forward Morphological Neural Networks to solve the problem. Marhon et al [43] did Recurrent Neural Networks. Graves [44] used Recurrent Neural Networks to solve the problem [45-47]. In this paper Neural Network (NN) method is used to solve the problem. NN is fabricated independently for every representative, to epitomize the examining location. The neural accomplishments are defined with reference to action dissemination between neurons and exterior response. Neural network ordered model poised of numerous tasks of Gaussian possibility concentration, which relate to the groups. Training populace with N statistics facts $(N \geq H)$, which are situated at the center locations of trellises. In the direction of designate the objective possibility map convincingly, the formed statistics necessity be in accord with the objective possibility map, so the quantity of statistics facts positioned at a trellis ought to be relational to its committed objective possibility. In order to attain the noble guesstimate the factors of each Gaussian constituent requisite to be assessed. The K-means technique is principally utilized to engender K preliminary groups with great resemblance unevenly, and on this foundation the probability of intensification method is espoused to guesstimate the factors by compelling the probability stage and the intensification stage iteratively up until attaining the convergence situation. Certain energetic adaptive approaches, such as the abolition, combine or putrefaction of Gaussian representations can be acquainting with into the iterative stage in order to improve the accurateness. Consequently the quantity of prototypes is stretchy in accord with the situation.

2. PROBLEM FORMULATION

Power loss minimization is defined by

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

$where$ min $is\ minimization\ of\ power\ loss$

Subject to the constraints

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

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

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$$d = \left[VLG_1,..,VLG_{Ng}; QC_1,..,QC_{Nc}; T_1,..,T_{N_T}\right] \quad (4)$$

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

$$F_1 = P_{Minimize} = Minimize\left[\sum_m^{NTL} G_m\left[V_i^2 + V_j^2 - 2 * V_i V_j cos\emptyset_{ij}\right]\right] \quad (6)$$

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

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

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

and

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

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

Parity constraints

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

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

Disparity constraints

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

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

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

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

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

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

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

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

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

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

3. NEURAL NETWORK

Neural Network (NN) method is fabricated independently for every representative, to epitomize the examining location. The neural accomplishments are defined with reference to action dissemination between neurons and exterior response.

The location of the representatives in the zone is defined as,

$$z_i = [a_i, b_i, \emptyset_i]^T \quad (24)$$

$where\ a_i, b_i\ define\ the\ position\ of\ the$ representatives $\emptyset_i\ specify\ the$ angle of direction

$$v_i = \vartheta_i \quad (25)$$

$where\ v_i and\ \vartheta_i\ control\ inputs\ i \in \{1,2,3,..,N_v\}$.

Then the network model defined as,

$$\dot{z_i} = f(\dot{z_i}, \dot{v_i}) \quad (26)$$

$$\dot{a_i} = s_i cos\emptyset_i \quad (27)$$

$$\dot{b_i} = s_i sin\emptyset_i \quad (28)$$

$$\dot{\emptyset_i} = \vartheta_i \quad (29)$$

$where\ s_i\ indicate\ the\ swiftness$

$$z_i^{t+1} = z_i^t + f(z_i^t, v_i^t, \Delta t) \quad (30)$$

$$a_i^{t+1} = a_i^t + s_i^t cos(\emptyset_i^t + \vartheta_i^t \cdot \Delta t) \quad (31)$$

$$b_i^{t+1} = b_i^t + s_i^t sin(\emptyset_i^t + \vartheta_i^t \cdot \Delta t) \quad (32)$$

$$\emptyset_i^{t+1} = \emptyset_i^t + s_i^t \cdot \Delta t \quad (33)$$

$where\ t\ and\ \Delta t\ specify\ the\ present\ and\ interval\ time$

It is presumed that the representatives are moving form present location to neighbour and the drive angle is defined as,

$$\emptyset_i^t \in \{0^\circ, \dots, 315^\circ\} \quad (34)$$

$$\vartheta_i^t \in \{-90^\circ, -45^\circ, 0^\circ, 45^\circ, 90^\circ\} \quad (35)$$

The zone is alienated into identical trellises

$$H = H_a \times H_b \quad (36)$$

Trellises are allocated to,

$$Q(a_h) \in [0,1] \quad (37)$$

$where\ a_h\ specify\ the$ Trellises poistion

The total value of the allied trellises is,

$$\sum_{h=1}^h Q(a_h) = 1 \quad (38)$$

With reference to the Bernoulli distribution the surveillance factor is defined as,

$$c_h^{1:t} = \{c_m^1, \dots, c_m^t\} \quad (39)$$

Then the probability and modernize the time rendering to thee Bayesian rule is as follows,

$$Q(a_h|c_h^{1:t}) = \partial \cdot Q(a_h|c_h^{1:t-1}) * \left(1 - d(c_m^t|a_h)\right) \quad (40)$$

$$where\ \partial = \frac{1}{\sum_{h=1}^{h} Q(a_h|c_h^{1:t-1}) * \left(1 - d(c_m^t|a_h)\right)} \quad (41)$$

$$d(c_m^t|a_h) = \begin{cases} d_{area}, & c_m^t = 1 \\ 0, & c_m^t = 0 \end{cases} \quad (42)$$

Trellises are allocated with flags,

$$Flag = O(a_h) \quad (43)$$

Rendering to with and without hindrances,

$$O(a_h) = 1 \quad (44)$$

$$O(a_h) = 0 \quad (45)$$

$$Complex\ zone = \{a_h \in Radius^2 | O(a_h) = 1\} \quad (46)$$

Then the search with the provisional probability is defined as,

$$\overline{P^t} = \sum_{h=1}^{h} Q(a_h|c_h^{1:t-1}) * \left(1 - d(c_m^t|a_h)\right) \quad (47)$$

$$\overline{P^{1:t}} = \prod_{i=1}^{t} \overline{P^{\iota}} \quad (48)$$

$$P^{1:t} = 1 - \overline{P^{1:t}} \quad (49)$$

$$P^i = \overline{P^{1:\iota-1}} * (1 - \overline{P^{\iota}}) \quad (50)$$

Cluster of examine tracks are defined as,

$$e = \left\{e_1^{1:T}, \dots, e_{N_v}^{1:T}\right\} \quad (51)$$

$$e^* = arg \max_{e \in E} P^{1:T}(E) \quad (52)$$

$$E \cap Complex\ zone = \varphi, p_{min} < p < p_{max} \quad (53)$$

The association weight (AW) between the neurons h and k is described as,

$$AW_{hk} = \begin{cases} e^{-\gamma|a_h - a_k|}, & |a_h - a_k| \le Radius \\ 0, & |a_h - a_k| > Radius \end{cases} \quad (54)$$

The energetic output value eo_h^{t+1} is modernized with stimulus (st) at "t" by,

$$eo_h^{t+1} = f\left(st_h^t + \sum_{k \in N(h)} AW_{hk} \cdot AW_k^t\right) \quad (55)$$

$$st_h^t = 1 - \overline{P^t} = Q(a_h|c_h^{1:t-1}) * d_{area} \quad (56)$$

$$st_h^t = \begin{cases} Q(a_h|c_h^{1:t-1}) * d_{area}, \\ if\, a_h \notin Complex\ zone, p_{min} < p < p_{max} \\ -L\ otherwise \end{cases} \quad (57)$$

Rendering to the transfer function,

$$eo_h^{t+1} = \begin{cases} \frac{st_h^t + \sum_{k \in N(h)} AW_{hk} \cdot AW_k^t}{\sum_{h=1, st_h^t \ge 0}^{h} \left(st_h^t + \sum_{k \in N(h)} AW_{hk} \cdot AW_k^t\right)}, & st_h^t \ge 0 \\ 0, & st_h^t < 0 \end{cases} \quad (58)$$

Representative localizes at a position,

$$Q^t = a_h \quad (59)$$

Then the subsequent location Q^{t+1} is selected as follows,

$$Q^{t+1} = a_{k^*} \quad (60)$$

$$neuron\ k^* = arg \max_{k \in N(h)} (eo_k^{t+1}) \quad (61)$$

Rendering to the last location of neuron (a_l) and present position, the passage of the representative is defined as,

$$g_k^{t+1} = \begin{cases} cos\Delta\theta, \Delta\theta \le \frac{\pi}{2} \\ -\infty, \Delta\theta > \frac{\pi}{2} \end{cases} \quad (62)$$

$$Q^{t+1} = a_{k^*} \quad (63)$$

$$neuron\ k^* = arg \max_{k \in N(h)} (eo_k^{t+1} + \partial\, g_k^{t+1}) \quad (64)$$

Neural network ordered model poised of numerous tasks of Gaussian possibility concentration, which relate to the groups. Training populace with N statistics facts $(N \ge H)$, which are situated at the center locations of trellises. In the direction of designate the objective possibility map convincingly, the formed statistics necessity be in accord with the objective possibility map, so the quantity of statistics facts positioned at a trellis ought to be relational to its committed objective possibility.

$$N_h = [p(a_h) \cdot N] \quad (65)$$

$$\sum_{h=1}^{H} N_h = N \quad (66)$$

Gaussian constituents $GC_k(a)$ and weight δ_k is defined as,

$$GC_k(a) = \frac{1}{\sqrt{(2\pi)^2 |C_k|}}\, exp\left(-\frac{1}{2}(a - \sigma_k)\right)^T \cdot C_k^{-1}(a - \sigma_k) \quad (67)$$

$$\sum_{k=1}^{k} \delta_k = 1 \quad (68)$$

Total weights of all Gaussian constituents $GC_k(a)$ is defined as,

$$Q(a) \approx \sum_{k=1}^{k} \delta_k \cdot GC_k(a) \quad (69)$$

In order to attain the noble guesstimate the factors of each Gaussian constituent requisite to be assessed. The K-means technique is principally utilized to engender K preliminary groups with great resemblance unevenly, and on this foundation the probability of intensification method is espoused to guesstimate the factors by compelling the probability stage and the intensification stage iteratively up until attaining the convergence situation. Certain energetic adaptive approaches, such as the abolition, combine or putrefaction of Gaussian representations can be acquainting with into the iterative stage in order to improve the accurateness. Consequently the quantity of prototypes is stretchy in accord with the situation.

Prospective Prize rendering to the weight δ_k *is defined as*,

$$PP_k = 0.95\ \delta_k \quad (70)$$

Then the zone of additional region is defined with axial stretch as follows,

$$ZAR_k = 4\pi\tau_{ak}\tau_{bk}/ZAR_{trellis} - \sum_{a_h \in k} O(a_h) \quad (71)$$

Transporting expanse is defined by,

$$Te_k = |\sigma_k - a_h|/t_{trellis} \quad (72)$$

The forthcoming recognition prize is for the trellis is defined as,

$$Frp_a^t = \frac{1}{K}\sum_{k=1}^{k}\left(\frac{1+cos\Delta\beta}{2}\cdot\frac{PP_k - P_k^{1:t}}{ZAR_k + Te_k}\right) \quad (73)$$

$$st_h^t = \begin{cases} Q(a_h|c_h^{1:t-1}) * d_{area} + \sigma Frp_a^t, \\ if\, a_h \notin Complex\ zone, p_{min} < p < p_{max} \\ -L\ otherwise \end{cases} \quad (74)$$

Then the control of feedback and forward is defined as,

$$\vartheta_i = \emptyset_i^d + k(\emptyset_i^d - \emptyset_i) \quad (76)$$

Fig 1 shows the Flow chart of Neural Network (NN) method.

a. Start
b. Initialize the parameters
c. Neuron actions are initialized; $eo_h^o = Q(a_h)$
d. $t = 0$
e. Determine the population – training rendering to Q
f. Engender Gaussian representations through K-means
g. The variables of Gaussian representations are appraised through the probability of intensification method
h. $while(t < T)$
i. $For\ every$ representative i
j. $For\ every\ neuron\ a$
k. Compute the forthcoming recognition prize
l. $PP_k = 0.95\ \delta_k$
m. $ZAR_k = 4\pi\tau_{ak}\tau_{bk}/ZAR_{trellis} - \sum_{a_h \in k} O(a_h)$
n. $Te_k = |\sigma_k - a_h|/t_{trellis}$
o. $Frp_a^t = \frac{1}{K}\sum_{k=1}^{k}\left(\frac{1+cos\Delta\beta}{2}\cdot\frac{PP_k - P_k^{1:t}}{ZAR_k + Te_k}\right)$
p. Compute st_h^t
q. $st_h^t = \begin{cases} Q(a_h|c_h^{1:t-1}) * d_{area} + \sigma Frp_a^t, if\, a_h \notin Complex\ zone, p_{min} < p < p_{max} \\ -L\ otherwise \end{cases}$
r. Define the association weight (AW) between the neurons h and k
s. $AW_{hk} = \begin{cases} e^{-\gamma|a_h - a_k|}, & |a_h - a_k| \le Radius \\ 0, & |a_h - a_k| > Radius \end{cases}$

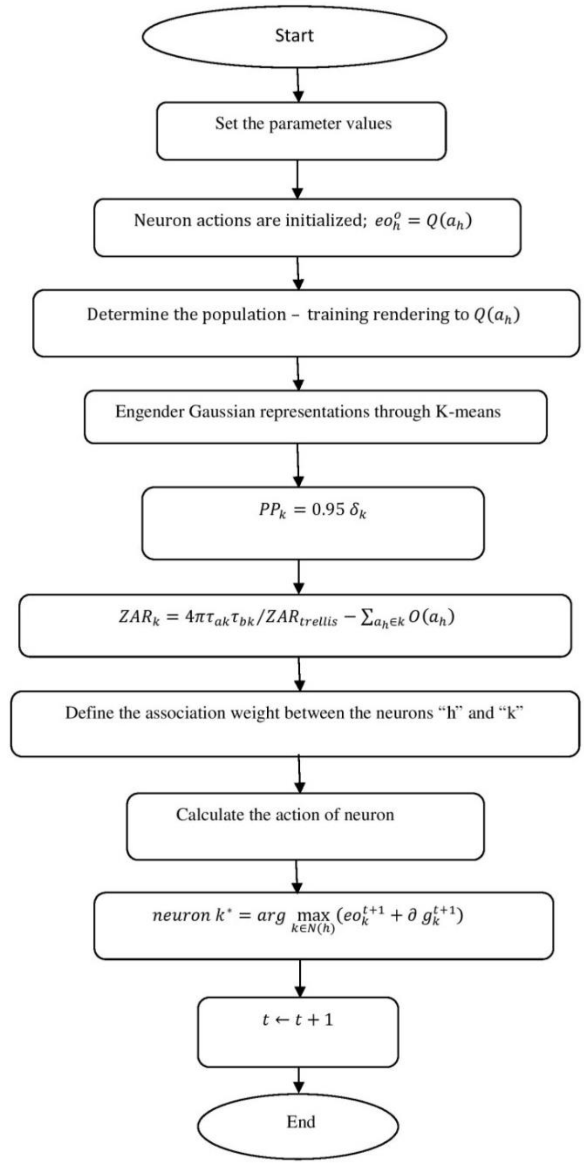

Fig 1. Flow chart of Neural Network (NN) method

a. Calculate the action of neuron
b. $eo_h^{t+1} = \begin{cases} \frac{st_h^t + \sum_{k \in N(h)} AW_{hk} \cdot AW_k^t}{\sum_{h=1, st_h^t \ge 0}^{h} (st_h^t + \sum_{k \in N(h)} AW_{hk} \cdot AW_k^t)}, & st_h^t \ge 0 \\ 0, & st_h^t < 0 \end{cases}$
c. $End\ for$
d. Select the subsequent position
e. $g_k^{t+1} = \begin{cases} cos\Delta\theta, \Delta\theta \le \frac{\pi}{2} \\ -\infty, \Delta\theta > \frac{\pi}{2} \end{cases}$
f. $Q^{t+1} = a_{k^*}$
g. $neuron\ k^* = arg \max_{k \in N(h)} (eo_k^{t+1} + \partial\, g_k^{t+1})$
h. End for
i. $t \leftarrow t + 1$

j. End while
k. End

Neural Network (NN) method Computational complication in the initialization procedure is equivalent to $O(M)$.

$$O(T \times M) + O(T \times M \times E) \tag{77}$$

Then the computation complexity of Neural Network (NN) method is,

$$O\big(N \times (T + TE)\big) \tag{78}$$

4. SIMULATION RESULTS AND DISCUSSION

Projected Neural Network (NN) method is validated in IEEE 30 bus system [20]. In Table 1 to 3 show the evaluation. Figures 2 to 4 gives review amongst the approaches.

Table 1 Assessment of loss

Technique	Power loss (MW)
HDPSOTS [30]	4.5213
BITS [30]	4.6862
SUPSO [30]	4.6862
BIALO [31]	4.5900
HDQOTLBO [32]	4.5594
BITLBO [32]	4.5629
SUGA [33]	4.9408
BIPSO [33]	4.9239
HDAS [33]	4.9059
BIFS [34]	4.5777
HDISFS [35]	4.5142
BIFS [36]	4.5275
NN	4.3928

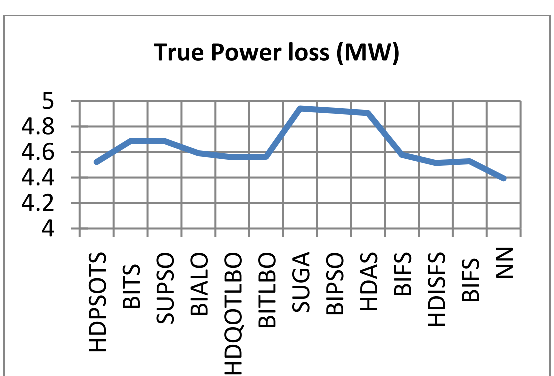

Fig 2.Valuation of real power loss.

Table 2 Comparison of electrical energy eccentricity

Technique	Electrical energy deviancy (PU)
HDPSOTS [30]	0.1038
BITS [30]	0.2064
SUPSO [30]	0.1354
BIALO [31]	0.1287
HDQOTLBO [32]	0.1202
BITLBO [32]	0.1614
SUGA [33]	0.1539
BIPSO [33]	0.0892
HDAS [33]	0.0856
BIFS [34]	0.0913
HDISFS [35]	0.1220
BIFS [36]	0.0890
NN	0.0820

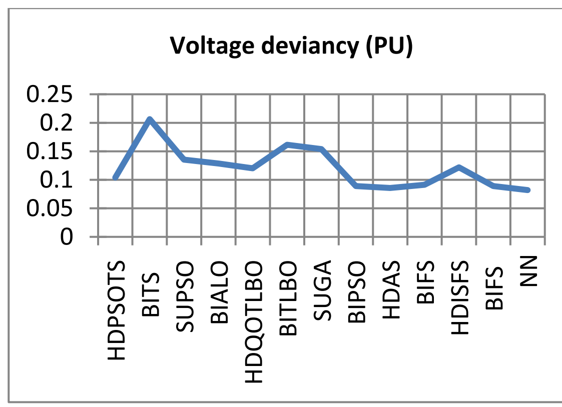

Fig 3. Review of Electrical energy eccentricity.

Table 3. Review of Electrical energy constancy

Technique	Electrical energy fidelity (PU)
HDPSOTS [30]	0.1258
BITS [30]	0.1499
SUPSO [30]	0.1271
BIALO [31]	0.1261
HDQOTLBO [32]	0.1264
BITLBO [32]	0.1488
SUGA [33]	0.1394
BIPSO [33]	0.1241
HDAS [33]	0.1191
BIFS [34]	0.1180
HDISFS [35]	0.1161
BIFS [36]	0.1161
NN	0.1001

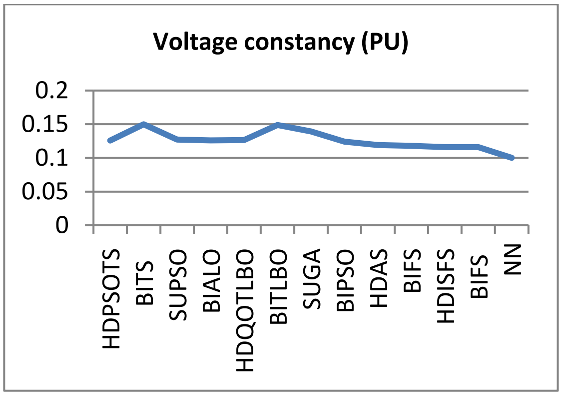

Fig 4. Valuation of electrical energy reliability.

Table 4. Valuation outcome

Variable	Loss (MW)	Ratio of loss dwindling
BC [14]	13.550	0.000
IRPSO [14]	12.293	9.2000
BIPSO [13]	12.315	9.1000
BIEP [13]	13.346	1.500
HDSARGA [12]	13.216	2.500
NN	10.013	26.1033

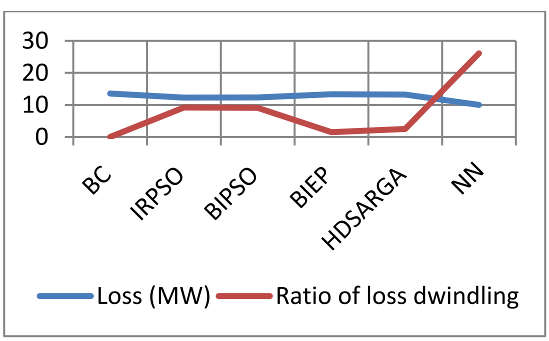

Fig 5. Loss evaluation

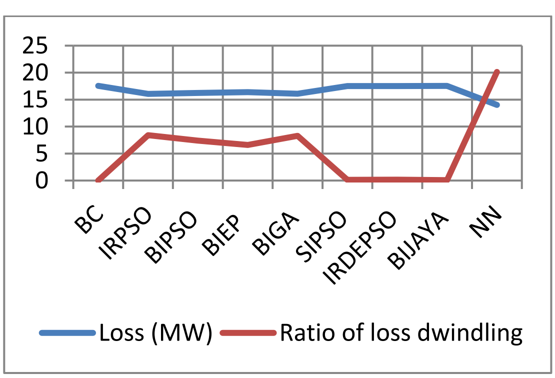

Fig 6. Review of Loss

Then the Neural Network (NN) method is substantiated in IEEE 14, 30, 57, 118 and 300 bus test systems deprived of Power reliability. Loss review is shown in Tables 4 to 8. Figure 5 to 9 gives l comparisons.

Table 5 Review of loss

Variable	Loss (MW)	Ratio of loss dwindling
BC[14]	17.5500	0.0000
IRPSO[14]	16.0700	8.40000
BIPSO [13]	16.2500	7.4000
BIEP [11]	16.3800	6.60000
BIGA [12]	16.0900	8.30000
SIPSO [15]	17.5246	0.14472
IRDEPSO [15]	17.52	0.17094
BIJAYA [15]	17.536	0.07977
NN	14.017	20.1310

Table 6. Assessment

Variable	Loss (MW)	Ratio of loss dwindling
BC [14]	27.8	0.00
IRPSO [14]	23.51	15.400
BIPSO [13]	23.86	14.100
CLGA[12]	25.24	9.200
AIGA [12]	24.56	11.600
NN	21.019	24.3920

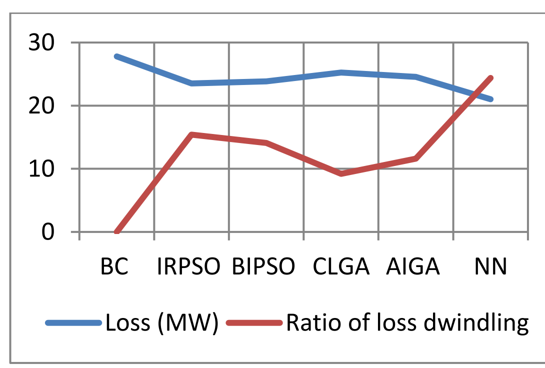

Fig 7. Loss review.

Table 7. Valuation of results

Variable	Loss (MW)	Ratio of loss winding
BC[14]	132.8	0.00
IRPSO [14]	117.19	11.700
BIPSO [13]	119.34	10.100
BIEPSO [11]	131.99	0.600
BICLPSO [11]	130.96	1.300
NN	112.009	15.6558

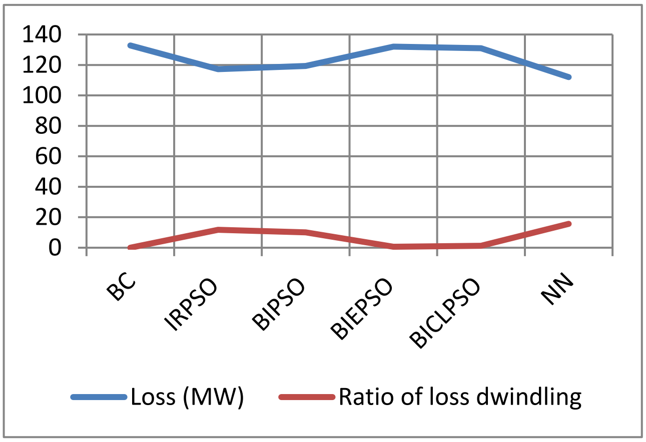

Fig 8. Loss review

Table 8. Loss evaluation

Variable	Loss (MW)
AIGA [17]	646.299800
FREA [17]	650.602700
BICSO [18]	635.894200
NN	625.100279

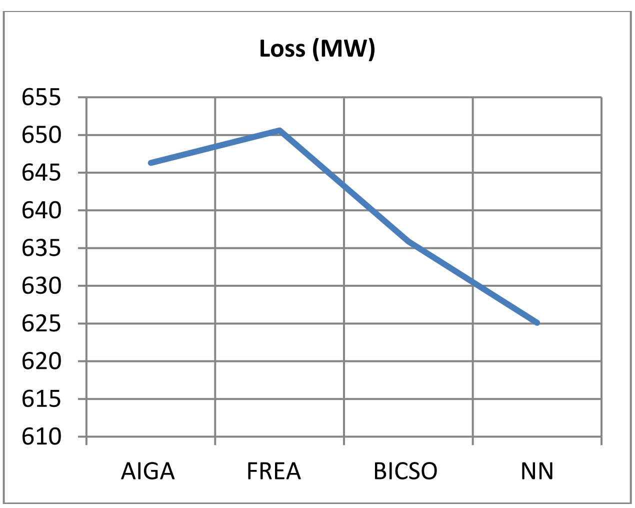

Fig 9. Loss assessment.

5. CONCLUSION

Neural Network (NN) method condensed the Actual power loss resourcefully. NN is fabricated independently for every representative, to epitomize the examining location. The neural accomplishments are defined with reference to action dissemination between neurons and exterior response. Neural network ordered model poised of numerous tasks of Gaussian possibility concentration, which relate to the groups. Training populace with N statistics facts $(N \geq H)$, which are situated at the center locations of trellises. In the direction of designate the objective possibility map convincingly, the formed statistics necessity be in accord with the objective possibility map, so the quantity of statistics facts positioned at a trellis ought to be relational to its committed objective possibility. In order to attain the noble guesstimate the factors of each Gaussian constituent requisite to be assessed. The K-means technique is principally utilized to engender K preliminary groups with great resemblance unevenly, and on this foundation the probability of intensification method is espoused to guesstimate the factors by compelling the probability stage and the intensification stage iteratively up until attaining the convergence situation. Certain energetic adaptive approaches, such as the abolition, combine or putrefaction of Gaussian representations can be acquainting with into the iterative stage in order to improve the accurateness. Consequently the quantity of prototypes is stretchy in accord with the situation.

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