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REAL POWER LOSS REDUCTION BY ENHANCED TRAILBLAZER OPTIMIZATION ALGORITHM

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Abstract

In this paper Teaching learning based Trailblazer optimization algorithm (TLBOTO) is used for solving the power loss lessening problem. Trailblazer optimization algorithm (TOA) is alienated into dual phases for exploration: trailblazer phase and adherent phase. Both phases epitomize the exploration and exploitation phase of TOA correspondingly. Nevertheless, in order to avoid the solution falling in local optimum in this paper Teaching-learning-based optimization (TLBO) is integrated with TOA approach. Learning segment of the TLBO algorithm is added to the adherent phase. Proposed Teaching learning based Trailblazer optimization algorithm (TLBOTO) augment exploration capability of the algorithm and upsurge the convergence speed. Algorithm's exploration competences enhanced by linking the teaching phase and learning. Exploration segment of the trailblazer algorithm identifies the zone with the pre-eminent solution. Subsequently inducing the teaching process, the trailblazer performs as a teacher to teach additional entities and engender a new-fangled entity. The new-fangled unit is equated with the trailblazer, and with reference to the greedy selection norm, the optimal one is designated as the trailblazer to endure exploration. The location of trailblazer is modernized. Legitimacy of the Teaching learning based Trailblazer optimization algorithm (TLBOTO) is substantiated in IEEE 30 bus system (with and devoid of *L*-index). Actual power loss lessening is reached. Proportion of actual power loss lessening is augmented

Keywords

Optimal reactive power, Transmission loss, Teaching, Learning, Trailblazer

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Introduction. In power system Subsiding of factual power loss is a substantial facet. Ample numeric procedures [1–6] and evolutionary approaches (Ant lion optimizer, Hybrid PSO-Tabu search, quasi-oppositional Teaching learning based optimization, harmony search algorithm, stochastic fractal search optimization algorithm, improved pseudo-gradient search particle swarm optimization, Effective Metaheuristic Algorithm, Seeker optimization algorithm, Diversity-Enhanced Particle Swarm Optimization) [7–15] are applied for solving Factual power loss lessening problem. Yet many approaches failed to reach the global optimal solution. In this paper Teaching learning based Trailblazer optimization algorithm (TLBOTO) is applied to solve the Factual power loss lessening problem. Trailblazer optimization algorithm (TOA) emulates the prevailing practices and doggedness rubrics of constellation animals in the common flora and fauna. Trailblazer optimization algorithm is imitated from the reality rules and characteristics of constellation of animals. Adherent track the trailblazer spot (laid by the trailblazer) and their specific intelligence of transportable. Trailblazer and adherent are both uncertain. When algorithms iterations are increased, the trailblazer and adherent roles are inter-changed with orientation to the entity's exploration competencies. Teaching-learning-based optimization (TLBO) is designed based on the imitation of education procedure of the teacher and the responded learning method of the pupils. Its own dual phase, i.e., one is teaching and another is learning. In the Proposed Teaching learning based TLBOTO primarily, trailblazer is deliberated as a teacher and it implements the teaching segment and it swiftly streamline Trailblazer and surge the exploration competence of the technique. Additionally, adherents in are prejudiced by the trailblazer, and also by their own realization. Their performance is comparable to that of pupils in TLBO. Subsequently, adherent implements the learning segment in TLBO. Then the adherent will move forward with obstinacy and surge the exploitation capability of the algorithm. Trial entities use "greedy selection" to produce offspring's. On the contrary, in the education juncture, double entities are capriciously nominated for evaluation, and the entity with deprived performance acquires from the entity with enriched performance, thus turn out in to creating new-fangled entities.

Step length is alienated into dual kinds: stable step length and adjustable step length. Exponential step fits to adjustable step. Exponential step is the amalgamation of exponential utility in arithmetic and step factor in the procedure. Through presenting the factor of exponential step, solution space can be abridged efficiently, which quicken the convergence swiftness. Entities in the adherents will travel in the direction of the trailblazer and the enriched entity nearer to them will streamline the position, instead of capriciously electing the nearer entities to modernize the position. In the meantime, the location of the adherent is steering, the step size is altered to an exponential expansion phase size. Sagacity of Teaching learning based TLBOTO is confirmed by corroborated in IEEE 30 bus system (with and devoid of *L*-index). Factual power loss lessening is achieved. Proportion of factual power loss reduction is augmented.

Problem formulation. In recent years, the problem of voltage stability and voltage collapse has become a major concern in power system planning and operation. To enhance the voltage stability, voltage magnitudes alone will not be a reliable indicator of how far an operating point is from the collapse point. The reactive power support and voltage problems are intrinsically related. Hence, this paper formulates the reactive power dispatch as a multi-objective optimization problem with loss minimization and maximization of static voltage stability margin as the objectives. Voltage stability evaluation using modal analysis is used as the indicator of voltage stability.

Objective function of the problem is mathematically defined in general mode by

$$\text{Minimization } \tilde{F}\left(\overline{x},\overline{y}\right).$$

$$\text{Subject to}$$

$$E\left(\overline{x},\overline{y}\right)=0;$$

$$I\left(\overline{x},\overline{y}\right)=0.$$

Minimization of the objective function is the key and it defined by "$\tilde{F}$". Both E and I indicate the control and dependent variables of the optimal reactive power problem (ORPD); "x" consist of control variables which are reactive power compensators $\left(Q_c\right)$, dynamic tap setting of transformers — dynamic (T), level of the voltage in the generation units $\left(V_g\right)$:

$$x=\left[VG_1,..,VG_{Ng};QC_1,..,QC_{Nc};T_1,..,T_{N_T}\right];$$

"y" consist of dependent variables which has slack generator PG_{slack}, level of voltage on transmission lines V_L, generation units reactive power Q_G, apparent power S_L:

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

Then the single objective problem formulation is defined as follows. The fitness function $\left(OF_1\right)$ is defined to reduce the power loss (MW) in the system is written as

$$OF_1=P_{\min}=\min\left[\sum_{m}^{NTL}G_m\left[V_i^2+V_j^2-2V_iV_j\cos\varnothing_{ij}\right]\right].$$

Number of transmission line indicated by "NTL", conductance of the transmission line between the i-th, j-th buses, phase angle between buses i and j is indicated by $\varnothing_{ij}$.

Minimization of voltage deviation fitness function (OF_2) is given by

$$OF_2 = \min\left[\sum_{i=1}^{N_{LB}} \left|V_{Lk} - V_{Lk}^{desired}\right|^2 + \sum_{i=1}^{Ng} \left|Q_{GK} - Q_{KG}^{Lim}\right|^2\right].$$

Load voltage in k-th load bus is indicated by V_{Lk}, voltage desired at the k-th load bus is denoted by $V_{Lk}^{desired}$, reactive power generated at k-th load bus generators is symbolized by Q_{GK}, then the reactive power limitation is given by Q_{KG}^{Lim}, then the number load and generating units are indicated by N_{LB} and Ng.

Then the voltage stability index (L-index) fitness function (OF_3) is given by

$$OF_3 = \min L_{\max};$$

$$L_{\max} = \max\left[L_j\right]; j = 1, N_{LB},$$

and

$$L_j = 1 - \sum_{i=1}^{NPV} F_{ji} \frac{V_i}{V_j},$$

$$F_{ji} = -\left[Y_1\right]^1 \left[Y_2\right].$$

Such that

$$L_{\max} = \max\left[1 - \left[Y_1\right]^{-1} \left[Y_2\right] \frac{V_i}{V_j}\right].$$

Then the equality constraints are

$$0 = PG_i - PD_i - V_i \sum_{j \in N_B} V_j \left[G_{ij} \cos\left[\varnothing_i - \varnothing_j\right] + B_{ij} \sin\left[\varnothing_i - \varnothing_j\right]\right];$$

$$0 = QG_i - QD_i - V_i \sum_{j \in N_B} V_j \left[G_{ij} \sin\left[\varnothing_i - \varnothing_j\right] + B_{ij} \cos\left[\varnothing_i - \varnothing_j\right]\right],$$

where N_B is the number of buses; PG and QG are the real and reactive power of the generator; PD and QD are the real and reactive load of the generator; G_{ij} and B_{ij} are the mutual conductance and susceptance between bus i and bus j.

Generator bus voltage V_{Gi} inequality constraint $V_{Gi}^{\min} \le V_{Gi} \le V_{Gi}^{\max}$, $i \in ng$.

Load bus voltage V_{Li} inequality constraint: $V_{Li}^{\min} \le V_{Li} \le V_{Li}^{\max}$, $i \in nl$. Switchable reactive power compensations Q_{Ci} inequality constraint: $Q_{Ci}^{\min} \le Q_{Ci} \le Q_{Ci}^{\max}$, $i \in nc$. Reactive power generation Q_{Gi} inequality constraint: $Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max}$, $i \in ng$. Transformers tap setting T_i inequality constraint: $T_i^{\min} \le T_i \le T_i^{\max}$, $i \in nt$. Transmission line flow S_{Li} inequality constraint: $S_{Li}^{\min} \le S_{Li}^{\max}$, $i \in nl$. Here nc, ng and nt are numbers of the switchable reactive power sources, generators and transformers.

The equality constraints are satisfied by running the power flow program. The active power generation P_{gi}, generator terminal bus voltages V_{gi} and transformer tap settings t_k are the control variables and they are self-restricted by the optimization algorithm. The active power generation at slack bus P_{sl}, load bus voltage V_{load} and reactive power generation Q_{gi} are the state variables and are restricted by adding a quadratic penalty term to the objective function.

Then the multi-objective fitness (MOF) function has been defined by

$$\mathrm{MOF} = OF_1 + x_i OF_2 + y OF_3 =$$

$$= OF_1 + \left[\sum_{i=1}^{NL} x_v \left[VL_i - VL_i^{\min} \right]^2 + \sum_{i=1}^{NG} x_g \left[QG_i - QG_i^{\min} \right]^2 \right] + x_f OF_3;$$

$$VL_i^{\min} = \begin{cases} VL_i^{\max} & VL_i > VL_i^{\max}, \\ VL_i^{\min} & VL_i < VL_i^{\min}; \end{cases}$$

$$QG_i^{min} = \begin{cases} QG_i^{\max} & QG_i > QG_i^{\max}, \\ QG_i^{\min} & QG_i < QG_i^{\min}. \end{cases}$$

Teaching learning based Trailblazer optimization algorithm. Trailblazer optimization algorithm (TOA) imitates the existing practices and persistence rubrics of cluster animals in the normal flora and fauna. Trailblazer optimization algorithm is imitated from the existence rules and physiognomies of cluster of animals. In the Trailblazer optimization algorithm, cluster of animals are alienated into dual types of characters rendering to the entity's fitness value: trailblazer and adherent. The Trailblazer is accountable for discovering the way onward to attain the pre-eminent food in any location, and leave a spot around especially for the adherent's reference. Adherent track the trailblazer based on the spot port by the trailblazer and their individual intelligence of transportable. Trailblazer and adherent are both ambiguous. When algorithms iterations are increased, the trailblazer and adherent roles are inter-changed with orientation to the entity's exploration competences. During this segment trailblazers will turn out to be adherent. Equally, adherent will be as a trailblazer.

In the exploration phase the Trailblazer will modernize the location and it mathematically defined as

$$Y_T^{k+1} = Y_T^k + \mathrm{Random}_3\left(Y_T^k - Y_T^{k-1}\right) + B,$$

where Y_T^{k+1} epitomizes the modernized position vector of Trailblazer; Y_T^k signifies the present position vector of Trailblazer; Y_T^{k-1} characterizes the preceding position vector of Trailblazer; k embodies the present sum of iterations, $\mathrm{Random}_3 \in [0,1]$.

Subsequent to the modernization of location exploitation phase will be there and it numerically defined as

$$Y_i^{k+1} = Y_i^k + \alpha\,\mathrm{Random}_1\left(Y_j^k - Y_i^k\right) + \beta\,\mathrm{Random}_2\left(Y_T^k - Y_i^k\right) + \varepsilon;\ \ i \geq 2.0,$$

where Y_i^{k+1} epitomizes the new-fangled position vector of i-th entity after the location modernizing; Y_i^k position vector of i-th entity; Y_j^k characterizes the position vector of neighbouring entities; Y_T^k signifies the present position vector of Trailblazer; Random_1 and $\mathrm{Random}_2 \in [0,1]$; α is the interface coefficient; β is the fascination coefficient,

$$\varepsilon = \left(1 - \frac{1}{k_{\max}}\right) g_1 S_{ij};\ \ S_{ij} = Y_i - Y_j;$$

$$B = g_2 e^{2k/k_{\max}}.$$

Here g_1, $g_2 \in [-1,1]$; S_{ij} is the space among the two entities; B, ε will deliver arbitrary walk steps for all entities; $k, k_{\max}$ are the present and maximum number of iterations.

Trailblazer optimization algorithm

a. Begin
b. Parameters are initialized
c. Preliminary population fitness values are computed
d. Find the Trailblazer
e. While $k <$ maximum number of iterations
f. Random variables; α and $\beta \in [1,2]$
g. Position of the Trailblazer modernize

$$Y_T^{k+1} = Y_T^k + \mathrm{Random}_3\left(Y_T^k - Y_T^{k-1}\right) + B$$

h. Check the limit conditions
i. If new-fangled Trailblazer is better than previous Trailblazer, then

j. Modernize the Trailblazer
k. End
l. For $i = 2.0$ to maximum number of populations
m. Modernize the location of the entities

$$Y_i^{k+1} = Y_i^k + \alpha\,\text{Random}_1\left(Y_j^k - Y_i^k\right) + \beta\,\text{Random}_2\left(Y_T^k - Y_i^k\right) + \varepsilon,\ \ i \geq 2.0$$

n. Check the limit conditions
o. End
p. Compute the fitness values of new-fangled entities
q. Find the most excellent fitness value
r. If most excellent fitness < fitness of Trailblazer, then
s. Trailblazer = Most excellent entity; Fitness = Most excellent fitness
t. End
u. For $i = 2.0$ to maximum number of populations
v. If new-fangled fitness of entity(i) < fitness of entity(i), then
w. Modernize the entities
x. End
y. End
z. Engender new-fangled B and ε
aa. End

Teaching-learning-based optimization is modelled by the imitation of education process [16] of the teacher and the reciprocated learning procedure of the pupils and it possess dual phase, i.e., one is teaching and another is learning.

Teaching segment mimic the instruction procedure of the teacher. In the population the pre-eminent individual is designated as the teacher. The teacher ensures his or her superlative actions to transport the mediocre level of the pupil to more attention and action though which progress the whole class has been done and it mathematically defined as follows:

$$y^{new} = y^{old} + \text{Random}\left(y^{teacher} - t\,\text{eaching feature}\cdot\text{mean}\right);\ \text{Random} \in [0,1],$$

where y^{new} indicates the agent educated from the pre-eminent agent; y^{old} symbolize the entity picked for learning,

$$\text{Teaching feature} = \text{rotund}\left[1 + \text{random}\left(0,1\right)\left\{2-1\right\}\right].$$

In the procedure of reciprocated education, two dissimilar entities y^{r1}, y^{r2} are arbitrarily nominated from the population, the benefit and drawbacks of the dual entities are equated, and then the superior entities are nominated for education (learning):

$$y^{new} = \begin{cases} y^{old} + \text{random}\left(y^{r1} - y^{old}\right) & f\left(y^{r1}\right) < f\left(y^{r2}\right); \\ y^{old} + \text{random}\left(y^{r2} - y^{old}\right) & \text{otherwise.} \end{cases}$$

Investigational entities use "greedy selection" to engender offspring's. Conversely, in the education stage, double entities are arbitrarily designated for appraisal, and the entity with deprived performance acquires from the entity with improved performance, thus producing new-fangled entities.

Step length [17] is alienated into dual kinds: stable step length and adjustable step length. Exponential step fits to adjustable step. Exponential step is the amalgamation of exponential utility in arithmetic and step factor in the procedure. Through presenting the factor of exponential step, solution space can be abridged efficiently, which quicken the convergence swiftness.

In the proposed Teaching learning based TLBOTO primarily, trailblazer is considered as a teacher and implements the teaching segment and it rapidly modernize Trailblazer and upsurge the exploration capability of the procedure. Furthermore, adherents in are prejudiced by the trailblazer, and also by their own realization. Their performance is comparable to that of pupils in TLBO. Consequently, adherent executes the learning segment in TLBO. Then the adherent will move onward with tenacity and upsurge the exploitation capability of the algorithm. Then the swiftness of the adherent tracking the Trailblazer can be accustomed. An exponential phase length is smeared to the adherent to track the Trailblazer diligently. Algorithm's exploration competences enhanced by linking the teaching phase and learning. Exploration segment of the trailblazer algorithm identifies the zone with the pre-eminent solution. Subsequently inducing the teaching process, the trailblazer performs as a teacher to teach additional entities and engender a new-fangled entity. The new-fangled unit is equated with the trailblazer, and with reference to the greedy selection norm, the optimal one is designated as the trailblazer to endure exploration. The location of trailblazer is modernized. Linking the learning segment of the teaching and learning algorithm upsurges the exploiting ability of the procedure. In the exploiting segment of the trailblazer algorithm entity modernizes the position in the direction of the Trailblazer and the entities closer to it. At this period, the entity has no intellectual capability and is an arbitrary transportable behaviour. Add the learning procedure to the entities in the adherents to create them to possess human intellectual capability. In this method, the entities in the adherents will travel in the direction of the trailblazer and the enhanced entity nearer to them will modernize the position, instead of arbitrarily choosing the nearer entities to modernize the position. In the meantime, the location of the adherent is steering, the step size is altered to an exponential development phase size. The location of numbers is rationalized rendering to

$$Y_i^{k+1} = Y_i^k + \alpha\,\mathrm{Random}_1\left(Y_{new}^k - Y_i^k\right) + \beta\,\mathrm{Random}_2\left(Y_T^k - Y_i^k\right) + \varepsilon,\ \ i \ge 2.0;$$

$$\varepsilon = \left(1 - \frac{1}{k_{\max}}\right) g_1 S_{ij};\ S_{ij} = Y_i - Y_j,$$

where Y_{new}^k epitomizes the location vector of the new-fangled entity and it engendered after reciprocated learning.

Teaching learning based Trailblazer optimization algorithm

a. Begin
b. Parameters are initialized
c. Preliminary population fitness values are computed
d. Fine the Trailblazer
e. While $k <$ maximum number of iterations
f. Random variables; α and $\beta \in [1, 2]$
g. For $i = 1.0$ to maximum number of populations
h. Engender new-fangled entity

$$y^{new} = y^{old} + \mathrm{Random}\left(y^{teacher} - \text{teaching feature} \cdot \text{mean}\right);\ \mathrm{Random} \in [0,1]$$

i. End
j. Compute the new-fangled agent fitness value
k. Check the limit conditions
l. If the new-fangled better than Trailblazer, then
m. Modernize the position of the new-fangled agent

$$Y_T^{k+1} = Y_T^k + \mathrm{Random}_3\left(Y_T^k - Y_T^{k-1}\right) + B$$

$$y^{new} = y^{old} + \mathrm{Random}\left(y^{teacher} - \text{teaching feature} \cdot \text{mean}\right);\ \mathrm{Random} \in [0,1]$$

n. Else
o. Modernize the position of the Trailblazer

$$Y_T^{k+1} = Y_T^k + \mathrm{Random}_3\left(Y_T^k - Y_T^{k-1}\right) + B$$

$$y^{new} = y^{old} + \mathrm{Random}\left(y^{teacher} - \text{teaching feature} \cdot \text{mean}\right);\ \mathrm{Random} \in [0,1]$$

p. End

q. Compute the fitness value of Y_{new}^{k} and Y_{T}^{k}
r. Check the limit conditions
s. If new-fangled Trailblazer is better than previous Trailblazer, then
t. Modernize the Trailblazer
u. End
v. For $i = 2.0$ to maximum number of populations
w. Compute the fitness value of neighbouring entity $\left(Y_j^k \text{ and } Y_i^k\right)$
x. if fitness value of $Y_i^k < Y_j^k$, then
y. Obtain the new entity by

$$y^{new} = \begin{cases} y^{old} + \text{random}\left(y^{r1} - y^{old}\right) f\left(y^{r1}\right) < f\left(y^{r2}\right), \\ y^{old} + \text{random}\left(y^{r2} - y^{old}\right) \text{ otherwise} \end{cases}$$

z. End
aa. Modernize the location of entities
bb. Check the limit conditions

$$Y_i^{k+1} = Y_i^k + \alpha\,\text{Random}_1\left(Y_{new}^k - Y_i^k\right) + \beta\,\text{Random}_2\left(Y_T^k - Y_i^k\right) + \varepsilon, \quad i \geq 2.0$$

cc. Compute the fitness values of new-fangled entities
dd. Find the most excellent fitness value
ee. If most excellent fitness < fitness of Trailblazer, then
ff. Trailblazer = Most excellent entity; Fitness = Most excellent fitness
gg. End
hh. For $i = 2.0$ to maximum number of populations
ii. If new-fangled fitness of entity (i) < fitness of entity (i), then
jj. Modernize the entities
kk. End
ll. End
mm. Engender new-fangled B and ε
nn. End

Simulation results. With considering L-index (voltage constancy), Teaching learning based TLBOTO is corroborated in IEEE 30 bus system [18]. Appraisal of loss has been done with PSO, amended PSO, enhanced PSO, widespread learning PSO, Adaptive genetic algorithm, Canonical genetic algorithm, enriched genetic algorithm, Hybrid PSO-Tabu search (PSO-TS), Ant lion (ALO), quasi-oppositional teaching learning based (QOTBO), improved stochastic fractal search optimization algorithm (ISFS), harmony search (HS), improved pseudo-gradient search particle swarm optimization and cuckoo search algorithm. Power loss abridged competently and proportion of the power loss lessening has been enriched. Predominantly voltage constancy enrichment achieved with minimized voltage deviancy. In Table 1 shows the loss appraisal, Table 2 shows the voltage deviancy evaluation and Table 3 gives the L-index assessment. Figures 1 to 3 gives graphical appraisal.

Table 1

Assessment of factual power loss lessening

Technique	Actual Power loss (MW)
Standard PSO-TS [8]	4.5213
Basic TS [8]	4.6862
Standard PSO [8]	4.6862
ALO [9]	4.5900
QO-TLBO [10]	4.5594
TLBO [10]	4.5629
Standard GA [11]	4.9408
Standard PSO [11]	4.9239
HAS [11]	4.9059
Standard FS [12]	4.5777
IS-FS [12]	4.5142
Standard FS [14]	4.5275
TOA	4.5007
TLBOTO	4.5002

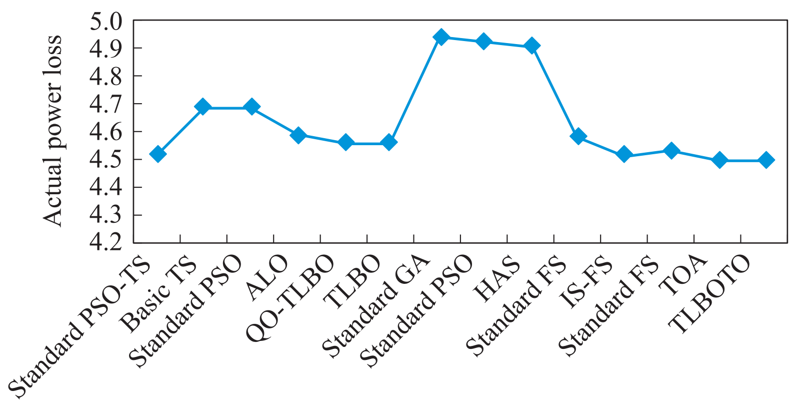

Fig. 1. Appraisal of actual power loss

Table 2

Evaluation of voltage deviation

Technique	Voltage deviancy (PU)
Standard PSO-TVIW [13]	0.1038
Standard PSO-TVAC [13]	0.2064
Standard PSO-TVAC [13]	0.1354
Standard PSO-CF [13]	0.1287
PG-PSO [13]	0.1202
SWT-PSO [13]	0.1614
PGSWT-PSO [13]	0.1539
MPG-PSO [13]	0.0892
QO-TLBO [10]	0.0856
TLBO [10]	0.0913
Standard FS [12]	0.1220
ISFS [12]	0.0890
Standard FS [14]	0.0877
TOA	0.0845
TLBOTO	0.0836

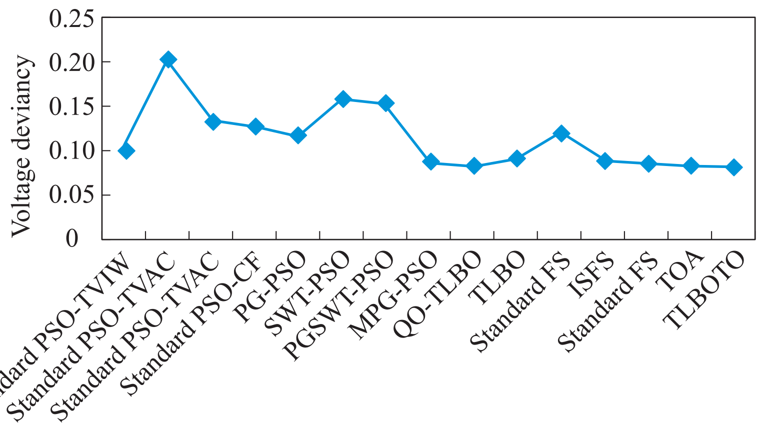

Fig. 2. Appraisal of voltage deviation

Table 3

Assessment of voltage constancy

Technique	Voltage constancy (PU)
Standard PSO-TVIW [13]	0.1258
Standard PSO-TVAC [13]	0.1499

End of the Table 3

Technique	Voltage constancy (PU)
Standard PSO-TVAC [13]	0.1271
Standard PSO-CF [13]	0.1261
PG-PSO [13]	0.1264
Standard WT-PSO [13]	0.1488
PGSWT-PSO [13]	0.1394
MPG-PSO [13]	0.1241
QO-TLBO [10]	0.1191
TLBO [10]	0.1180
ALO [9]	0.1161
ABC [9]	0.1161
GWO [9]	0.1242
BA [9]	0.1252
Basic FS [12]	0.1252
IS-FS [12]	0.1245
Standard FS [14]	0.1007
TOA	0.1006
TLBOTO	0.1002

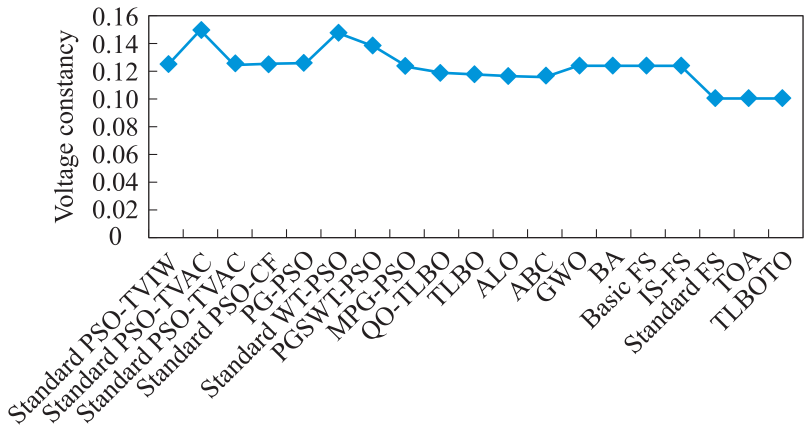

Fig. 3. Appraisal of voltage constancy

Then Projected Teaching learning based TLBOTO is corroborated in IEEE 30 bus test system deprived of *L*-index. Loss appraisal is shown in Table 4. Figure 4 gives graphical appraisal between the approaches with orientation to actual power loss.

Table 4

Assessment of true power loss

Parameter	Actual Power Loss in MW	Proportion of Lessening in Power Loss
Base case value [19]	17.5500	0
Amended PSO[19]	16.0700	8.40000
Standard PSO [20]	16.2500	7.40000
Standard EP [21]	16.3800	6.60000
Standard GA [22]	16.0900	8.30000
Basic PSO [23]	17.5246	0.14472
DEPSO [23]	17.5200	0.17094
JAYA [23]	17.5360	0.07977
TOA	14.0210	20.1000
TLBOTO	13.9820	20.3300

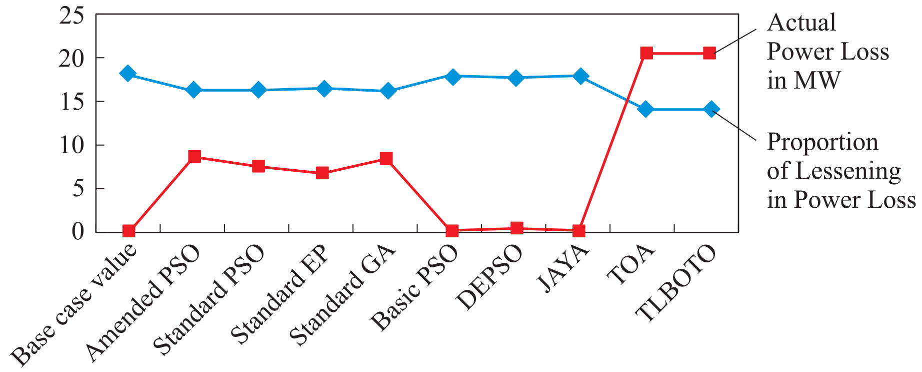

Fig. 4. Appraisal of actual power loss in MW and proportion of lessening in power loss

Table 5 shows the convergence characteristics of Teaching learning based TLBOTO. Figure 5 shows the graphical representation of the characteristics.

Table 5

Convergence characteristics

IEEE 30 bus system	Actual power loss in MW with *L*-index / without *L*-index	Proportion of lessening in power loss, %	Time, sec, with *L*-index / without *L*-index	Number of iterations with *L*-index / without *L*-index
TOA	4.5007/14.021	20.10	18.67 / 15.92	29 / 24
TLBOTO	4.5002 / 13.982	20.33	14.04 / 11.31	23 / 20

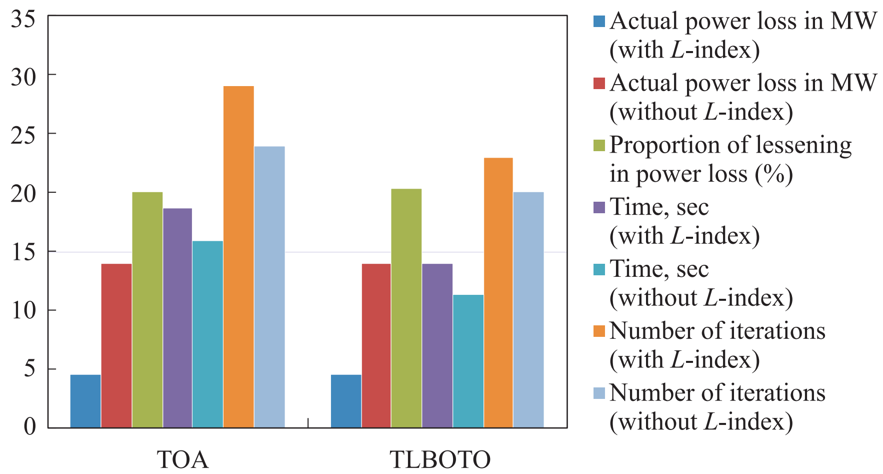

Fig. 5. Convergence characteristics of Teaching learning based TLBOTO

Conclusion. Teaching learning based TLBOTO condensed the factual power loss dexterously. Teaching learning based TLBOTO corroborated in IEEE 30 bus test system with and also deprived of voltage constancy. In the Proposed Teaching learning based Trailblazer optimization algorithm (TLBOTO) primarily, trailblazer is considered as a teacher and implements the teaching segment and it rapidly modernize Trailblazer and upsurge the exploration capability of the procedure. Exploration segment of the trailblazer algorithm identifies the zone with the pre-eminent solution. Subsequently inducing the teaching process, the trailblazer performs as a teacher to teach additional entities and engender a new-fangled entity. The new-fangled unit is equated with the trailblazer, and with reference to the greedy selection norm, the optimal one is designated as the trailblazer to endure exploration. The location of trailblazer is modernized. Linking the learning segment of the teaching and learning algorithm upsurges the exploiting ability of the procedure. In the exploiting segment of the trailblazer algorithm entity modernizes the position in the direction of the Trailblazer and the entities closer to it. At this period, the entity has no intellectual capability and is an arbitrary transportable behaviour. Add the learning procedure to the entities in the adherents to create them to possess human intellectual capability. In this method, the entities in the adherents will travel in the direction of the trailblazer and the enhanced entity nearer to them will modernize the position, instead of arbitrarily choosing the nearer entities to modernize the position. Teaching learning based TLBOTO creditably condensed the power loss and proportion of factual power loss lessening has been upgraded. Convergence characteristics show the better performance of the proposed TLBOTO algorithm. Assessment of power loss has been done with other customary reported algorithms.

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