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Real Power Loss Reduction by Enhanced RBS Algorithm

Kanagasabai L.

Department of EEE, Prasad V. Potluri Siddhartha Institute of Technology, Kanuru, Vijayawada, 520007 Andhra Pradesh, India.

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***Corresponding email:**
gklenin@gmail.com

Abstract. In this paper enhanced red-breasted sapsucker (ERBS) algorithm has been proposed to solve the power loss lessening problem. RBS algorithm is designed on the copulate actions of RBS. Male RBS (MRBS) will attract the female with an exclusive tone. Concerning the concentration of the tone female RBS (FMBS) will progress in the direction of the MRBS. Various tone engendered by MRBS will catch the fancy of FRBS, and this action is analogous to data contribution in Evolutionary techniques. Naturally, so many MRBS will put huge efforts simultaneously to attract the FRBS for copulate. RBS has been integrated with the sine-cosine algorithm (SCA) and opposition-based learning (OBL). SCA process shifts resourcefully from exploration to exploitation by acclimatizing the functions. Solutions are frequently streamlined to the premium solution and optimization of the premium region of the exploration zone. OBL is one of the significant optimization procedures to improve the convergence pace of different optimization procedures. The successful execution of the OBL holds the assessment of the opposite population and present population in the analogous generation to find out the better contender solution. The proposed enhanced RBS (ERBS) algorithm is corroborated in IEEE 30 bus test systems. Power discrepancy compressed, power reliability amplified, and power loss condensed.

Keywords: optimal, reactive, transmission, sine-cosine algorithm, opposition.

1 Introduction

Power loss lessening is a fundamental problem in Electrical power systems. Bountiful numeric procedures [1-6] and evolutionary approaches [9-19] solved the real power loss lessening problem. Carpentier [1] done the work on contribution to “à l’étude du dispatching économique” problem. Dommel et al. [2] researched optimal power flow solutions.

Takapoui et al. [3] did work on a simple, effective heuristic for embedded mixed-integer quadratic programming. Abaci et al. [4] solved optimal reactive-power dispatch using a differential search algorithm. Pulluri et al. [5] worked on an enhanced self-adaptive differential evolution-based solution methodology for multiobjective optimal power flow. Sahli et al. [10] applied a hybrid PSO-tabu search to solve the problem.

Mouassa et al. [11] used an ant lion optimizer for solving the optimal reactive power problem. Using quasi-oppositional teaching learning-based optimization, Mandal et al. [12] solved optimal reactive power dispatch. Tran et al. [14] researched optimal reactive power dispatch solutions by using a novel improved stochastic fractal search optimization algorithm.

Polprasert et al. [15] solved optimal reactive power dispatch using improved pseudo-gradient search particle swarm optimization. Muhammad et al. [26] found a solution of optimal reactive power dispatch with FACTS devices. Das et al. [27] solved the optimal reactive power dispatch problem considering load uncertainty using a modified JAYA algorithm.

Das et al. [28] integrated the PV system with optimal reactive power dispatch for voltage security using the JAYA algorithm. Muhammad et al. [29] designed fractional evolutionary processing for reactive power planning with FACTS devices. Shanono et al. [30] did a bibliometric analysis of optimal reactive power dispatch.

Tudose et al. [31] solved single- and multi-objective optimal reactive power dispatch problems using an improved Salp swarm algorithm. Balancing the exploration and exploitation is essential in the progress of the algorithms. Few algorithms are good in exploration, but exploitation property will be poor. Then some algorithms are worthy of exploitation, but it has deprived performance in exploration.

The optimal solution cannot be reached when both exploration and exploitation are not balanced [21-25]. In this article, the ERBS algorithm has been proposed to solve the power loss lessening problem. RBS algorithm is designed on the copulate actions of RBS. MRBS will attract the female with an exclusive tone. Various tone engendered by MRBS will catch the fancy of FRBS, and this action is analogous to data contribution in Evolutionary techniques.

Naturally, so many numbers of MRBS will put huge efforts simultaneously to attract the FRBS for copulate. Mainly, there will be tone variation among MRBS, which subsequently modifies the FRBS direction of movement towards males concerning the concentration of the tone. MRBS and FRBS are considered populations. Initially, MRBS will be in mammoth quantity and the duration of the preliminary stage of copulate – the amount of MRBS diminish owing to copulate.

When iteration increases precisely, the population diminishes. Exploration will be there initially, and regular exploitation will be followed. In the initial phase, FRBS will get fascinated with reverence to the concentration of tone.

However, at the concluding phase, it will be fascinated in the direction of the most excellent MRBS. FRBS only listens to a single MRBS tone, and at the concluding phase, it is a seal to the FRBS and most excellent concentration tone. RBS is at variance based on the objective function.

MRBS is the most excellent position established in the exploration space, and FRBS is the main investigate representative. The location of the FRBS is entirely grounded on the MRBS. When an enhanced contender solution is attained, subsequently, there will be modernization of the MRBS. RBS arbitrarily instigates, and each RBS is performing as a contender solution. The population and fitness value of RBS is appraised. Most excellent MRBS is considered as ME-population, and it will be mainly striking MRBS, progressively FRBS shift near to particular MRBS.

In the proposed ERBS algorithm, SCA and OBL algorithm has been integrated with the RBS algorithm. SCA process shifts resourcefully from exploration to exploitation by adapting the functions. Solutions are frequently streamlined to the premium solution and optimization of the premium region of the exploration zone. OBL is one of the significant optimization procedures to improve the convergence pace of different optimization procedures.

The successful execution of the OBL holds the assessment of the opposite population and present population in the analogous generation to find the better contender solution. The proposed ERBS algorithm is corroborated in IEEE 30 bus test systems. Power discrepancy compressed, power reliability amplified, and power loss condensed.

2 Research Methodology

2.1 Problem formulation

Power loss minimization is defined by:

$$Min\ \widetilde{OBF}(\bar{r},\bar{u}), \tag{1}$$

subjected to:

$$L(\bar{r},\bar{u}) = 0; \tag{2}$$

$$M(\bar{r},\bar{u}) = 0; \tag{3}$$

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

$$u = \begin{bmatrix} PG_{slack}; VL_1,..,VL_{N_{Load}}; \\ QG_1,..,QG_{Ng}; SL_1,..,SL_{N_T} \end{bmatrix}. \tag{5}$$

The fitness function (F_1, F_2, F_3) is designed for power loss (MW) reduction, Voltage deviation, voltage stability index (L-index) is defined by:

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

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

$$F_3 = Minimize\ L_{MaxImum}; \tag{8}$$

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

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

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

Equality constraints are:

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

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

Inequality constraints are:

$$P_{gslack}^{minimum} \le P_{gslack} \le P_{gslack}^{maximum}; \tag{14}$$

$$Q_{gi}^{minimum} \le Q_{gi} \le Q_{gi}^{maximum}, i \in N_g; \tag{15}$$

$$VL_i^{minimum} \le VL_i \le VL_i^{maximum}, i \in NL; \tag{16}$$

$$T_i^{minimum} \le T_i \le T_i^{maximum}, i \in N_T; \tag{17}$$

$$Q_c^{minimum} \le Q_c \le Q_C^{maximum}, i \in N_C; \tag{18}$$

$$|SL_i| \le S_{L_i}^{maximum}, i \in N_{TL}; \tag{19}$$

$$VG_i^{minimum} \le VG_i \le VG_i^{maximum}, i \in N_g. \tag{20}$$

Multi objective fitness:

$$\begin{aligned} MOF &= F_1 + r_i F_2 + uF_3 = \\ &= F_1 + \{\textstyle\sum_{i=1}^{NL} x_v [VL_i - VL_i^{min}]^2 + \\ &+ \textstyle\sum_{i=1}^{NG} r_g [QG_i - QG_i^{min}]^2\} + r_f F_3; \end{aligned} \quad (21)$$

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

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

2.2 RBS algorithm

RBS algorithm is designed on the copulate actions of RBS. MRBS will attract the female with an exclusive tone. Concerning the concentration of the tone FRBS will progress in the direction of the MRBS.

Modulation in the tone will vary with time, and this tone concentration induces the FRBS to progress gradually in the direction of the MRBS for copulating.

Various tones engendered by MRBS will catch the fancy of FRBS, and this action is analogous to data contribution in Evolutionary techniques.

Naturally, so many male RBSs will put huge efforts simultaneously to attract the FRBS for copulate. There will mainly be tone variation among MRBS, which subsequently modifies the FRBS direction of movement towards males concerning the concentration of the tone.

Tone concentration (TC) is defined as:

$$TC = \frac{Tone\ supremacy}{Zone}. \quad (24)$$

Proliferation velocity of the tone mathematically described as:

$$TC = \frac{source\ of\ Proliferation\ velocity}{4\pi r^2}. \quad (25)$$

Based on the space Concentration of the Tone is calculated by

$$\begin{aligned} Space &= ||Tone\ location\ (Z_{tl}) - \\ &- Location\ of\ \text{RBS which hear the tone}\ (Z^h)||. \end{aligned} \quad (26)$$

Concerning tone concentration, fascination will occur between males and females, leading to copulation. RBS fitness value has been calculated. FRBS will get fascinated by the most excellent MRBS, and the prettiness is considered to be similar to fitness value. Tone source is essential because minor space will augment tone strength, which is similar to sound emission. Expanse amplifies; subsequently, the pace of concentration of tone diminishes. MRBS and FRBS are considered populations. Initially, MRBS will be in mammoth quantity, and in the duration of the preliminary stage of copulating, the amount of MRBS will diminish owing to copulate. When iteration increases precisely, the population diminishes. Exploration will be there initially, and regular exploitation will be followed. In the initial phase, FRBS will get fascinated with reverence to the concentration of tone. However, at the concluding phase, it will be fascinated in the direction of the most excellent MRBS. FRBS only listens to a single MRBS tone, and at the concluding phase, it is a seal to the FRBS and most excellent concentration tone. RBS is at variance based on the objective function.

Male RBS is the most excellent position established in the exploration space, and FRBS is the main investigate representative. The location of the FRBS is entirely grounded on the MRBS. When an enhanced contender solution is attained, subsequently, there will be modernization of the MRBS. RBS arbitrarily instigates, and each RBS is performing as a contender solution. The population and fitness value of RBS is appraised. Most excellent MRBS is considered as ME-population, and it will be mainly striking MRBS, progressively FRBS shift near to particular MRBS.

Progress of the RBS is modernized by:

$$\begin{aligned} z_i^{t+1} &= z_i^t + R^{\frac{\mu_i^t}{2}} \times \\ &\times \left[\left(z_{ME_{pop}}^t - z_i^t\right) + \gamma_{mrsj} * \left(z_{mrsj}^t - z_i^t\right)\right], \end{aligned} \quad (27)$$

where z_i^t – the preceding location of RBS; z_{ME-pop}^t indicates the location of most excellent RBS; z_{mrsj}^t specifies the location of MRBS; μ_i^t is coefficient of RBS in *t*-th iteration; *R* is random:

$$\mu_i^t = R \times Factor\ value, \quad (28)$$

where the factor is 0.79 to 0 during the iterations.

$\mu_i^t > 1$ and $\mu_i^t \leq 1$ specify the location of FRBS which attaining the MRBS:

$$\gamma = \frac{1}{1 + Tone\ concentration_j^i}, \quad (29)$$

where γ signifies the lure possibility grounded on the tone concentration with reverence to location (close to or remote); γ possesses enormous consequence over the exploitation segment.

Tangent sigmoid *Ts* is employed in the procedure:

$$E = Ts\left(1 - \frac{present\ iter.\ no}{max\ no\ of\ iter.}\right). \quad (30)$$

Quantity of MRBS in the iteration is defined as:

$$\begin{aligned} &Quantity\ of\ Male\ Red-breasted\ sapsucker = \\ &\{Ring[\frac{max\ quantity\ of\ Red-breasted\ sapsuckersapsucker}{2} \times \\ &\times \left(1 - \frac{present\ iter.\ no}{max\ no\ of\ iter.}\right)] + 1. \end{aligned} \quad (31)$$

The most excellent MRBS based on ME-population is described as:

$$z_i^{t+1} = z_i^t + R * \mu_i^t * \left(z_{ME\_pop}^t - z_i^t\right) + \gamma_{ME\_pop}. \quad (32)$$

Alteration in the path and location is based on the concentration of stone, and in addition, if some danger brings into being from others, then RBS will shift from the position:

$$T_\gamma = 0.8 \frac{\sum_n^{n-1} \gamma_{ME_{pop}}^i}{n-1}, \quad (33)$$

where T_γ indicates the threshold:

$$z_{shift}^{i} = LB - (LB - UB)R, \quad (34)$$

where *LB*, *UB* are lower and upper bound:

Based on tone adaptableness, the RBS locate, and as soon as there is an elevated concentration of tone from the most excellent MRBS subsequently the FRBS will progress towards it:

$$P_{ME-pop.Progress\,rate} = \beta\left(1 - \frac{present\ iter.\ no}{max\ no\ of\ iter.}\right), \quad (35)$$

where $P_{ME-pop.Progress\,rate}$ specifies the possibility of RBS population progress:

$$ME_{pop.Progress\,rate} = = \begin{cases} 1\ if\ space \le P_{ME-pop.\ progress\,rate}; \\ 0 \quad otherwise. \end{cases} \quad (36)$$

Subsequently, the location of FRBS is described as

$$z_{ME_{pop.progress\,rate}}^{i} = z_i^t + ME_{pop.progress\,rate} \times \times \{(z_{ME\ pop}^{t} - z_{space})R\}. \quad (37)$$

The corresponding procedure is as follows:

a. Start
b. RBS population initialized
c. Red-breasted sapsucker fitness value computed
d. Calculate T_γ
e. $while\ (iter < max\ no\ of iter)$
f. The quantity of MRBS is calculated by
$$Quantity\ of\ Male\ Red-breasted\ sapsucker = = Ring[\frac{max\ quantity\ of\ Red-breasted\ sapsuckersapsucker}{2} \times \times * \left(1 - \frac{present\ iter.\ no}{max\ no\ of\ iter.}\right)] + 1.$$
g. Categorize the RBS
h. For every RBS; decide MRBS
i. $\gamma = \frac{1}{1 + Tone\ concentration_j^i}.$
j. $\mu_i^t = R \times Factor\ value.$
k. Location of the RBS modernized by
l. $$z_i^{t+1} = z_i^t + R\frac{\mu_i^t}{2} \times \times \left[\left(z_{ME_{pop}}^t - z_i^t\right) + \gamma_{mrsj} * \left(z_{mrsj}^t - z_i^t\right)\right],$$
m. Calculate the progression of RBS
n. $$ME_{pop.Progress\,rate} = = \begin{cases} 1\ if\ space \le P_{ME-pop.\ progress\,rate}; \\ 0 \quad otherwise. \end{cases}$$
o. $$z_{ME_{pop.progress\,rate}}^{i} = z_i^t + ME_{pop.progress\,rate} \times \times \{(z_{ME\ pop}^{t} - z_{space})R\}.$$
p. End if
q. Modify the location of FRBS
r. Once the most excellent solution is established, subsequently modernize ME_{pop}
s. End for
t. $iter = iter + 1$
u. End while
v. End
w. Revisit the ME_{pop}

In the proposed ERBS algorithm, SCA and OBL algorithms have been integrated with RBS.

SCA [32] processes shift resourcefully from exploration to exploitation by adapting the functions. Solutions are frequently streamlined to the premium solution and optimization of the premium region of the exploration zone.

$$\vec{Z}_i^{m+1} = \vec{Z}_i^m + R_1 Sin(R_2)\left|R_3 \times E_i^m - \vec{Z}_i^m\right|; \quad (38)$$

$$\vec{Z}_i^{m+1} = \vec{Z}_i^m + R_1 Cos(R_2)\left|R_3 \times E_i^m - \vec{Z}_i^m\right|; \quad (39)$$

$$\vec{Z}_i^{m+1} = \begin{cases} \vec{Z}_i^m + R_1 Sin(R_2)\left|R_3 E_i^m - \vec{Z}_i^m\right| R_4 < 0.50; \\ \vec{Z}_i^m + R_1 Cos(R_2)\left|R_3 E_i^m - \vec{Z}_i^m\right| R_4 \ \ge 0.50, \end{cases}; \quad (40)$$

where $\vec{Z}_i^m$ is the present position at *m*-th iteration with E_i^m population.

OBL [33] is one of the significant optimization procedures to improve the convergence pace of different optimization procedures. The successful execution of the OBL holds the assessment of the opposite population and present population in the analogous generation to find out the better contender solution.

Fix ON ($ON \in [g, h]$) by an actual number and ON^o (opposite number) is described as follows:

$$N^o = g + h - ON. \quad (41)$$

Exploration augmented by:

$$ON_i^o = g_i + h_i - ON_i, \quad (42)$$

where $(ON_1, ON_2, ..ON_d)$ is a spot in "*d*" exploration space; $N_i \in [x_i, y_i]$; $i \to \{1,2,3,..d\}$.

The corresponding procedures are as follows:

a. Start
b. Initialize parameters
c. Engender opposite population; For $j = 1$; population size: for $i = 1$; umber of control variables
d. $ON_i^o = g_i + h_i - ON_i$

a. Categorize the present and opposite population from most excellent to poor
b. RBS population initialized
c. RBS fitness value computed
d. Calculate T_γ
e. $T_\gamma = 0.8\frac{\sum_n^{n-1} \gamma_{ME\ pop}^i}{n-1}$
f. $while\ (iter < max\ no\ of iter)$
g. The quantity of RBS is calculated by
$$Quantity\ of\ Male\ Red-breasted\ sapsucker = = Ring[\frac{max\ quantity\ of\ Red-breasted\ sapsuckersapsucker}{2} \times \times * \left(1 - \frac{present\ iter.\ no}{max\ no\ of\ iter.}\right)] + 1.$$
h. Categorize the RBS
i. For every RBS; decide MRBS
j. $\gamma = \frac{1}{1 + Tone\ concentration_j^i}$
k. $\mu_i^t = R \times Factor\ vaue$

l. Location of the RBS modernized by

m. $$z_i^{t+1} = z_i^t + R\frac{\mu_i^t}{2} \times$$
$$\times \left[\left(z^t_{ME_{pop}} - z_i^t\right) + \gamma_{mrsj} * \left(z^t_{mrsj} - z_i^t\right)\right],$$

n. $\vec{Z}_i^{m+1} = \vec{Z}_i^m + R_1 Sin(R_2)\left|R_3 \times E_i^m - \vec{Z}_i^m\right|$

o. $\vec{Z}_i^{m+1} = \vec{Z}_i^m + R_1 Cos(R_2)\left|R_3 \times E_i^m - \vec{Z}_i^m\right|$

p. $\vec{Z}_i^{m+1} = \begin{cases} \vec{Z}_i^m + R_1 Sin(R_2)\left|R_3 E_i^m - \vec{Z}_i^m\right| R_4 < 0.50; \\ \vec{Z}_i^m + R_1 Cos(R_2)\left|R_3 E_i^m - \vec{Z}_i^m\right| R_4 \ \geq 0.50, \end{cases}$

q. Calculate the progression of RBS

r. $$ME_{pop.\text{Progress}\,rate} =$$
$$= \begin{cases} 1 \; if \; space \leq P_{ME-pop.\;progress\,rate}; \\ \qquad 0 \quad otherwise. \end{cases}$$

s. $$z^i_{ME_{pop.progress\,rate}} = z_i^t + ME_{pop.progress\,rate} \times$$
$$\times \left\{\left(z^t_{ME\,pop} - z_{space}\right)R\right\}.$$

t. End if

u. Modify the location of FRBS

v. Once the most excellent solution is established, subsequently modernize ME_{pop}

w. End for

x. $iter = iter + 1$

y. End while

z. End

aa. Revise the ME_{pop}

3 Results

Projected RBS and ERBS algorithms have been corroborated in IEEE 30 bus system [20].

Table 1 shows the loss appraisal, Table 2 – the voltage aberration evaluation, and Table 3 – the L-index assessment.

Table 1 – Assessment of entire power loss

Technique	Power loss, MW
Basic PSO-TS [10]	4.52
Standard TS [10]	4.68
Basic PSO [10]	4.69
Ant LO [11]	4.59
Basic QO-TLBO [12]	4.56
Standard TLBO [12]	4.56
Standard GA [13]	4.94
Basic PSO [13]	4.92
HAS [13]	4.91
Standard FS [14]	4.58
IS-FS [14]	4.51
Standard FS [16]	4.53
RBS	4.50
ERBS	4.50

Figures 1–3 give the graphical appraisal of the methods. MSO and EMSO abridged the power loss efficiently.

Table 2 – Comparison of voltage aberration

Technique	Voltage deviancy, PU
Basic PSO-TVIW [15]	0.104
Basic PSO-TVAC [15]	0.206
Standard PSO-TVAC [15]	0.135
Basic PSO-CF [15]	0.129
PG-PSO [15]	0.120
SWT-PSO [15]	0.161
PGSWT-PSO [15]	0.154
MPG-PSO [15]	0.089
QO-TLBO [12]	0.086
TLBO [12]	0.091
Standard FS [14]	0.122
ISFS [14]	0.089
Standard FS [16]	0.088
RBS	0.086
ERBS	0.085

Table 3 – Appraisal of voltage constancy

Technique	Voltage constancy L-index, PU
Basic PSO-TVIW [15]	0.126
Basic PSO-TVAC [15]	0.150
Standard PSO-TVAC [15]	0.127
Basic PSO-CF [15]	0.126
PG-PSO [15]	0.126
SWT-PSO [15]	0.149
PGSWT-PSO [15]	0.139
MPG-PSO [15]	0.124
QO-TLBO [12]	0.119
Standard TLBO [12]	0.118
ALO [11]	0.116
ABC [11]	0.116
Standard GWO [11]	0.124
Basic BA [11]	0.125
Standard FS [14]	0.125
IS-FS [14]	0.125
Standard FS [16]	0.101
RBS	0.100
ERBS	0.100

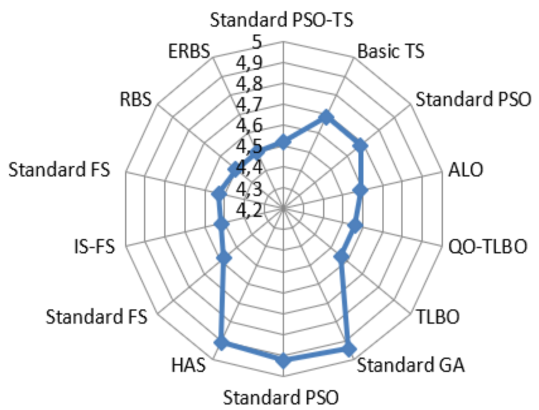

Figure 1 –Assessment of power loss, MW

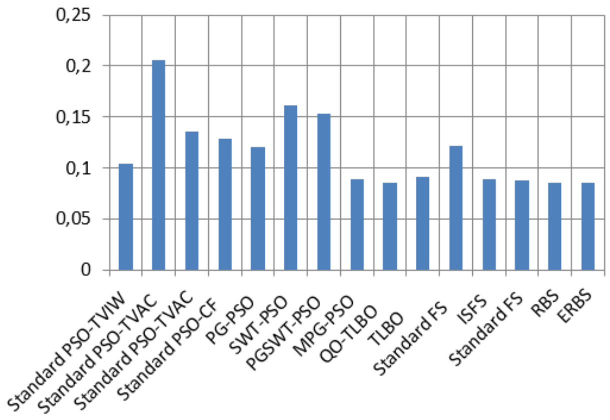

Figure 2 – Appraisal of voltage aberration, PU

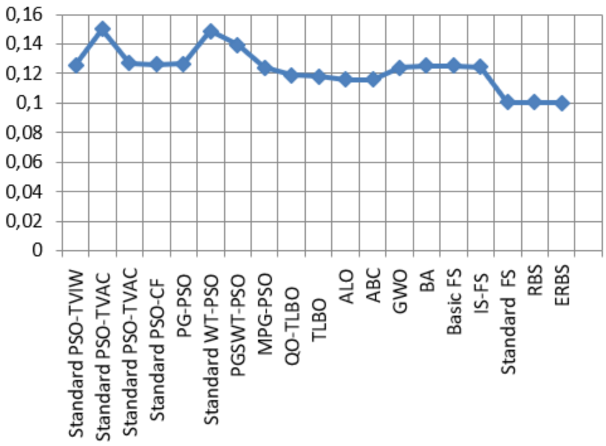

Figure 3 – Assessment of voltage constancy index, PU

Appraisal of loss has been done with PSO, adapted PSO, enhanced PSO, comprehensive learning PSO, Adaptive genetic algorithm, Canonical genetic algorithm, enhanced genetic algorithm, Hybrid PSO-Tabu search (PSO-TS), Ant lion (ALO), quasi-oppositional teaching learning-based (QOTBO), enhanced stochastic fractal search optimization algorithm (ISFS), harmony search (HS), upgraded pseudo-gradient search particle swarm optimization and cuckoo search algorithm. Power loss abridged competently, and the proportion of the power loss lessening has been enhanced. Predominantly voltage constancy augmentation attained with minimized voltage deviancy.

Then Projected RBS and ERBS algorithm substantiated in IEEE 14, 30, 57, 118, and 300 bus test systems [19] deprived of L-index. Loss appraisal is shown in Tables 4–8.

Figures 4–8 give a graphical comparison between the approaches with orientation to power loss. Proposed RBS and ERBS are compared with Adapted PSO, PSO, EP, SARGA, CGA, AGA, EPSO, CLPSO, AGA, FEA, and CSO.

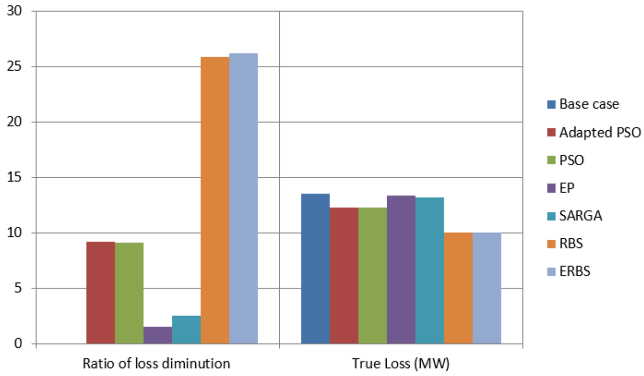

Figure 4 – Power loss appraisal (IEEE 14 bus system)

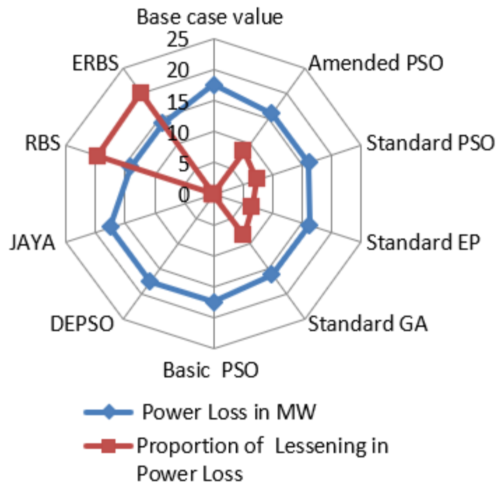

Figure 5 – Appraisal of power loss (IEEE 30 bus system)

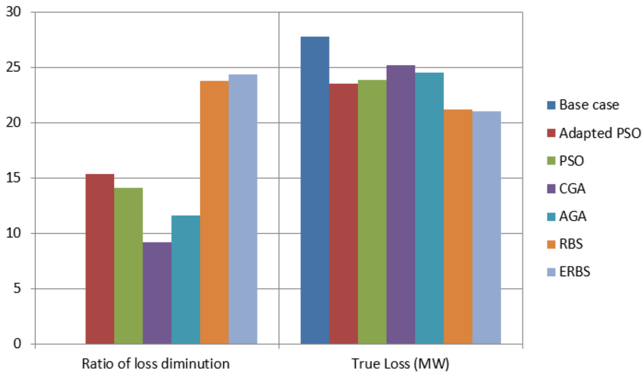

Figure 6 – Power loss appraisal (IEEE 57 bus system)

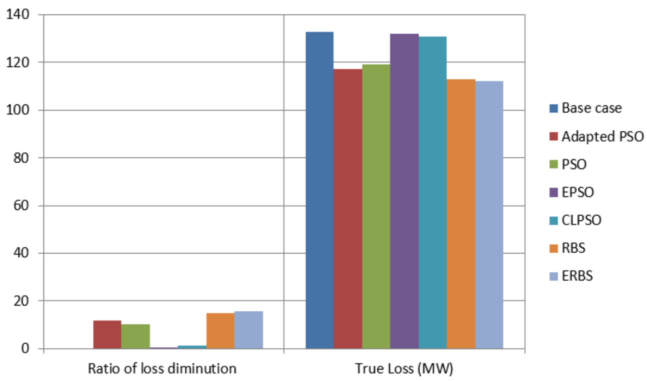

Figure 7 – Power loss appraisal (IEEE 118 bus system)

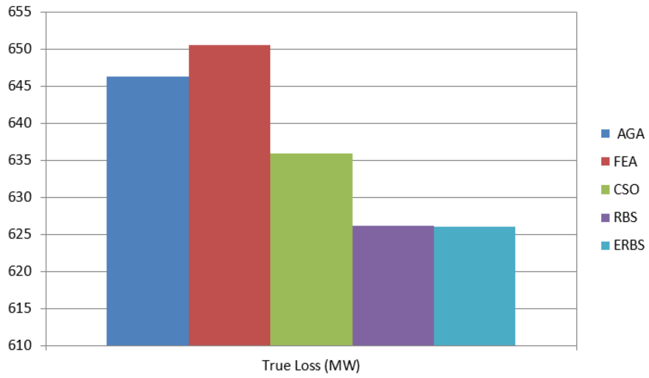

Figure 8 – Power loss appraisal (IEEE 300 bus system)

Table 4 – Assessment of results (IEEE 14 bus system)

Parameter	Base case [24]	Adapted PSO [24]	PSO [23]	EP [23]	SARGA [22]	RBS	ERBS
Ratio of loss diminution	0.000	9.2000	9.1000	1.500	2.500	25.892	26.169
True Loss (MW)	13.550	12.293	12.315	13.346	13.216	10.029	10.004

Table 5 – Appraisal of loss (IEEE 30 bus system)

Parameter	Actual power loss, MW	The proportion of lessening in power loss
Base case value [24]	17.5500	0.000
M-PSO [24]	16.0700	8.400
Basic-PSO [23]	16.2500	7.400
EP [21]	16.3800	6.600
S -GA [22]	16.0900	8.300
PSO [25]	17.5246	0.145
DEPSO [25]	17.52	0.171
JAYA [25]	17.536	0.080
RBS	14.100	19.658
ERBS	14.034	20.034

Table 6 – Assessment of parameters (IEEE 57 bus system)

Parameter	Base case [24]	Adapted PSO [24]	PSO [23]	CGA [22]	AGA [22]	RBS	ERBS
Ratio of loss diminution	0.00	15.40	14.10	9.20	11.60	23.76	24.33
True loss, MW	27.80	23.51	23.86	25.24	24.56	21.20	21.04

Table 7 – Assessment of results (IEEE 118 bus system)

Parameter	Base case [24]	Adapted PSO [24]	PSO [23]	EPSO [21]	CLPSO [21]	RBS	ERBS
Ratio of loss diminution	0.00	11.70	10.10	0.60	1.30	14.97	15.56
True loss, MW	132.80	117.19	119.34	131.99	130.96	112.92	112.14

Table 8 – Power loss appraisal (IEEE 300 bus system)

Parameter	AGA [35]	FEA [35]	CSO [34]	RBS	ERBS
True loss, MW	646.30	650.60	635.89	626.15	626.09

4 Discussion

Projected RBS and ERBS algorithms compressed the power loss resourcefully. With and devoid of power stability index, proposed algorithms performed well. The ratio of power loss diminution improved sufficiently, and assessment has been done with other standard reported algorithms.

At first, the projected RBS and ERBS algorithm was substantiated in IEEE 30 bus system with considering voltage stability. Appraisal of loss has been done with PSO, adapted PSO, enhanced PSO, comprehensive learning PSO, Adaptive genetic algorithm, Canonical genetic algorithm, enhanced genetic algorithm, Hybrid PSO-Tabu search (PSO-TS), Ant lion (ALO), quasi-oppositional teaching learning-based (QOTBO), enhanced stochastic fractal search optimization algorithm (ISFS), harmony search (HS), upgraded pseudo-gradient search particle swarm optimization and cuckoo search algorithm.

Then Projected RBS and ERBS algorithm was substantiated in IEEE 14, 30, 57, 118, and 300 bus test systems deprived of L-index. Loss appraisal and graphical comparison between the approaches with orientation to power loss are reported. Proposed RBS and ERBS are compared with Adapted PSO, PSO, EP, SARGA, CGA, AGA, EPSO, CLPSO, AGA, FEA, and CSO. The ratio of power loss reduction has been improved.

5 Conclusions

ERBS algorithm condensed the power loss with amplifying of power constancy. MRBS and FRBS are considered populations. Initially, MRBS will be in mammoth quantity and the duration of the preliminary stage of copulate – the amount of MRBS diminish owing to copulate.

When iteration increases precisely, the population diminishes. Exploration will be there initially, and regular exploitation will be followed. In the initial phase, FRBS will get fascinated with reverence to the concentration of tone; however, at the concluding phase, it will be fascinated in the direction of the most excellent MRBS. FRBS only listens to a single MRBS tone, and at the concluding phase, it is a seal to the FRBS and most excellent concentration tone. RBS is at variance based on the objective function. MRBS is the most excellent position established in the exploration space, and FRBS is the main investigate representative. The location of the FRBS is entirely grounded on the MRBS.

When an enhanced contender solution is attained, subsequently, there will be modernization of the MRBS. RBS arbitrarily instigates, and each RBS is performing as a contender solution. The population and fitness value of RBS is appraised. Most excellent MRBS is considered ME-population, and it will be mainly striking MRBS, progressively FRBS shift near to particular MRBS.

In the proposed ERBS algorithm, SCA and OBL algorithm has been integrated with RBS. SCA process shifts resourcefully from exploration to exploitation by adapting the functions. Solutions are frequently streamlined to the premium solution and optimization of the premium region of the exploration zone.

OBL is one of the significant optimization procedures to improve the convergence pace of different optimization procedures. The successful execution of the OBL holds the assessment of the opposite population and present population in the analogous generation to find the better contender solution. ERBS and RBS algorithms are verified in IEEE 30 bus test system with and devoid of L-index.

Both algorithms commendably reduced the power loss, and the percentage of real power loss lessening has been enhanced. Convergence characteristics show the better performance of the proposed optimization algorithms. The comparison of power loss has been made with other standard reported algorithms.

Nomenclature

OBF – minimization of the objective function;
r – consist of control variables;
Q_c – reactive power compensators;
T – dynamic tap setting of transformers;
V_g – level of the voltage in the generation units;
u – consist of dependent variables;
PG_{slack} – slack generator;
V_L – voltage on transmission lines;
Q_G – generation unit's reactive power;
S_L – apparent power;
NTL – number of the transmission line;
V_{Lk} – load voltage in *k*-th load bus;
$V_{Lk}^{desired}$ – voltage desired;
Q_{GK} – reactive power;
Q_{KG}^{Lim} – reactive power limitation;
N_{LB}, N_g – number load and generating units;
T – transformer tap.

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