Real Power Loss Reduction by Blue Noddy and European Night Crawler Optimization Algorithms

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In this paper Blue noddy optimization (BNO) algorithm and European Night crawler optimization (ENO) algorithm are applied to solve the power loss reduction problem. Key objective is to reduce the power loss with voltage stability enhancement and minimization of voltage deviation. Exodus and Preying behaviour of the Blue noddy has been imitated to formulate the algorithm. In the mathematical formulation of Exodus deed - collusion between the Blue noddy has been avoided and blue noddy will converge in the direction of most excellent companion. Position update of the Blue noddy is based on the most excellent explore agent. Preying behaviour is based on the line and angle of preying. Logically the angle, velocity will be transformed by the Blue noddy and it will do spiral act in the air to seizure the prey. Exploration and Exploitation is augmented through the Exodus and preying behaviour. In ENO algorithm reproduction nature of the European Night crawler is imitated to design the algorithm. European Night crawler population is created through the off-springs with two different kinds of reproduction. The dimension of the adolescent European Night crawler is alike to the parent. In the method Cross over operation has been implemented by considering the parent European Night crawler and Cauchy mutation has been included in order to elude the solution to be trapped under local optima. With and without voltage stability (L –index) proposed BNO and ENO algorithms are verified in IEEE 30 Bus system. Active power loss reduction has been achieved with L-index improvement and voltage deviation minimized.

Povzetek: V tem prispevku sta za reševanje problema zmanjšanja izgube energije uporabljena algoritem BNO za optimizacijo in algoritem ENO (European Night crawler optimization).

1 Introduction

Active power loss reduction is an important problem in Electrical power system. Many methodologies from conventional techniques; Newton, successive quadratic programming, linear programming, interior point (Abril et al., Bjelogrlic et al., Granville, Grudinin, Edalatpanah et al.,) [1-5] to evolutionary and swarm based algorithms; Ant colony, Fish swarm, Frog leaping, Wolf search, Bacterial foraging, Whale optimization, Marine Predators Algorithm, harmony search algorithm (Ebeed et al., Li, Jian et al., Yasir Muhammad et al., Barakat et al., Sahli et al., Mouassa et al., Mandal et al., Khazali et al., Tran et al.,) [6-10] are chronologically applied to solve the problem. Yet various factors are influenced in the poor performance of the techniques. In conventional methods inequality constraints are unable to be included successfully and in evolutionary based algorithms balancing the exploration and exploitation are major task to reach the most excellent solution [11-18]. There should be proper trade-off between exploration and exploitation because when trade-off failed then it not at all possible to reach a better solution [21-25]. This paper proposes Blue noddy optimization (BNO) algorithm and European Night crawler optimization (ENO) algorithm for power loss reduction. Main objective is to reduce the power loss reduction with voltage stability enhancement and Voltage deviation minimization. Blue noddy is extensively dispersed across the Pacific. They feed nearby the shore and capture the fishes and other insects. Naturally Blue noddy possesses the Exodus and Preying behaviour. With respect to seasonal variations Blue noddy will execute the Exodus actions in exploration of food and Blue noddy will apply its intelligence while preying. These two actions has been imitated and modelled to solve the problem. Exploration and exploitation has been balanced through the phases of Exodus and Preying. Preying behaviour of the Blue noddy is mathematically formulation based on the line and angle of preying. Unsurprisingly the angle, velocity will be reformed by the Blue noddy and it will do the spiral performance in the air for detention of the prey. Then in this paper European Night crawler optimization (ENO) algorithm is applied to solve the problem. ENO algorithm has been designed based on the normal actions of European Night crawler. Reproduction nature of the European Night crawler is imitated to design the algorithm. European Night crawler population is created through the off-springs with two different kinds of reproduction. The dimension of the adolescent European Night crawler is alike to the parent. In the procedure when an individual European Night crawler possess the premium fitness then it will pass to the subsequent generation without any modification. In the process Cauchy mutation has been included in order the evade the solution to be trapped under local optima Validity of the Proposed Blue noddy optimization (BNO) algorithm and European Night crawler optimization (ENO) algorithm has been verified in IEEE 30 Bus system by considering L-index (Voltage stability). Then both the BNO and ENO algorithms are evaluated without considering L-index. Power loss reduction has been attained with L-index enhancement and voltage deviation minimized. Mainly percentage of power loss reduction is improved.

2 Problem formulation

Power loss minimization is defined by

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

Subject to

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

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

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

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

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,

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

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

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

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

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

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

Equality constraints

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

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

Inequality 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) function has been defined by,

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

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

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

3 Blue noddy optimization algorithm

Blue noddy is sea bird and its natural actions are imitated to formulate the algorithm. Movement of the Blue noddy during Exodus will be in a group mode. Naturally collusion will be avoided while their movement and with respect to the lead Blue noddy others will adjust the position. Direction will be based on the most excellent conditions. These behaviors are imitated and modeled in the Exodus behavior of the Blue noddy.

During the Exodus, Collusion will be evaded between them and it has been mathematically formulated as follows,

$$Collusion_{explore\ agent}(Cn_{ea}) = Blue\ noddy_{agent}(Bn_a) \times Current\ position_{serach\ agent}\ (Cp_{sa}) \cdot (Current\ iteration\ (Ci)) \quad (24)$$

Then the movement of the Bn_a in the exploration phase is given by,

$$Bn_a = Direction\ variable\ \left(Dv_f\right) - \left(Ci \times \left(Dv_f/Maximum_{iterations}\right)\right) \quad (25)$$

Naturally the blue noddy will converge in the direction of most excellent companion Blue noddy and it has been mathematically formulated as follows,

$$Different\ locations\ of\ explore\ agent\ (Dl_{ea}) = Random\ variable\ (Rv_{el}) \times \left(most\ excellent\ fittest\ search\ agent\ (Cp_{msa}) \cdot (Ci) - Current\ position_{serach\ agent}\ (Cp_{sa}) \cdot (Current\ iteration\ (Ci)\right) \quad (26)$$

In the above equation $Random\ variable\ (Rv_{el})$ is accountable for enhanced exploration.

$$Random\ variable\ (Rv_{el}) = 0.50 \times Random\ number\ (R_{nr}); R_{nr} \in [0,1] \quad (27)$$

Blue noddy will update its Position based on the most excellent explore agent and it mathematically formulated as follows,

$$Space\ between\ explore\ agent\ and\ most\ excellent\ fittest\ explore\ agent(S_{sa}) = Collusion_{explore\ agent}(Cn_{ea}) + Different\ locations\ of$$

$explore\ agent\ (Dl_{ea})$ (28)

Preying behaviour of the Blue noddy is mathematically formulation based on the line and angle of preying. Naturally the angle, velocity will be altered by the Blue noddy and it will do spiral performance in the air to capture the prey. This preying behaviour will amplify the Exploitation behaviour of the algorithm and it mathematically formulated as follows,

$$X = Axis \times Sin\ (i) \quad (29)$$

$$Y = Axis\ \times Cos\ (i) \quad (30)$$

$$Z = Axis \times i \quad (31)$$

$$a = p \times e^{kq} \quad (32)$$

Where axis indicates the every shot of the spiral performance, "i" indicates the variables in the range of $0 \leq k \leq 2\pi$ with p and q (constants).

Then the position of the other explore agents are defined as follows,

$$Position\ of\ other\ explore\ agents\ (Po_{ea}) \cdot Current\ iteration\ (Ci) = \begin{pmatrix} pace\ between\ explore\ agent \\ and\ most\ excellent \\ fittest\ explore\ agent (S_{sa}) \times (X+Y+Z) \end{pmatrix} \times most\ excellent\ fittest\ search\ agent\ (Cp_{msa}) \cdot Current\ iteration\ (Ci) \quad (33)$$

a. Start
b. Engender the population
c. Initialization of parameters
d. Compute the fitness value for every explore agent
e. $Cp_{msa} \leftarrow best\ explore\ agent$
f. $While\ (Current\ iteration\ (Ci) < Maximum_{iterations}\ do)$
g. $For\ very\ explore\ agent\ do$
h. $Position\ of\ every\ explore\ agent\ is\ updated$ $Po_{ea} \cdot Ci = \left((S_{sa}) \times (X+Y+Z)\right)\ (Cp_{msa}) \cdot (Ci)$
i. End for
j. $Update\ the\ value\ of\ Collusion_{explore\ agent} (Cn_{ea})\ and\ Random\ variable\ (Rv_{el})$
k. Compute the fitness value for every explore agent
l. $If\ improved\ solution\ is\ existing\ then\ update\ most\ excellent\ fittest\ search\ agent\ (Cp_{msa})$
m. $Ci \leftarrow Ci + 1$
n. End while
o. Yield the Cp_{msa}
p. End

4 European night crawler optimization algorithm

European Night crawler optimization (ENO) algorithm has been designed based on the natural actions of European Night crawler. Reproduction nature of the European Night crawler is imitated to model the algorithm. Population generation of the European Night crawler is through the off-springs with two different kinds of reproduction. The length of the adolescent European Night crawler is similar to the parent. In the process- when an individual European Night crawler possess the most excellent fitness then it will pass to the subsequent generation without any alteration.

Generally European Night crawler possesses both male and female sex organs and it can produce the adolescent European Night crawler by itself. Mathematical formulation of the above approach can be defined as,

$$En_{i1,j} = En_{maximum,j} + E_{minimum,j} - \alpha En_{i,j}\ ;\ \alpha \in [0,1] \quad (34)$$

Where $En_{i1,j}$the jth element of the European Night crawler and factor is α determines the distance between the parent and offspring

Cross over operation has been implemented by considering the parent European Night crawler as $P_{En} = 2$ and adolescent European Night crawler as $A_{En} = 1$. Then two parent European Night crawler $P_{En}\ 1\ and\ P_{En}\ 2$ are chosen by roulette wheel selection method and it mathematically expressed as,

$$P_{En} = \begin{bmatrix} P_{En_1} \\ P_{En_2} \end{bmatrix} \quad (35)$$

Then "2" off-springs $En_{12}\ and\ En_{22}$ are produced from the "2" parents and it defined as,

$$If\ random\ > 0.50\ ,\ En_{12,j} = P_{En_{1,j}}\ and\ En_{22,j} = P_{En_{2,j}} \quad (36)$$

Or else

$$En_{12,j} = P_{En_{2,j}}\ and\ En_{22,j} = P_{En_{1,j}} \quad (37)$$

Then En_{i2} is defined as,

$$En_{i2} = \begin{cases} En_{12}\ for\ random_1 < 0.50 \\ En_{22}\quad otherwise \end{cases} \quad (38)$$

The next generation European Night crawler (En_i') is defined after the generation of $En_{i1}\ and\ En_{i2}$

$$En_i' = \beta En_{i1} + (1-\beta) En_{i2} \quad (39)$$

Through the factor $'\beta'$ proportion between $En_{i1}\ and\ En_{i2}$ is adjusted by balancing the global and local search effectively.

$$\beta^{ct+1} = \gamma \cdot \beta^{ct} \quad (40)$$

Where "ct" is the existing generation and in the preliminary stage $ct = 0\ and\ \beta = 1$

In the procedure Cauchy mutation has been included in order to avoid the solution to be trapped under local optima and it has been defined as,

$$weight_j = \left(\sum_{i=1}^{N\ population} En_{i,j}\right) / N\ population \quad (41)$$

Then the jth element of the last European Night crawler is defined as

$$En_{i,j}'' = En_{i,j}' + \left(weight_j = \left(\sum_{i=1}^{N\ population} En_{i,j}\right) / N\ population\right) * G \quad (42)$$

Where "G" is the random number and it haggard from the Cauchy distribution $\tau = 1\ where\ \tau\ scale\ parameter$

a. Start
b. Initialization of parameters
c. Engender the population of European Night crawler

d. Feasibility and Deception of the European Night crawler population to be checked
e. Compute the value of the objective function
f. Arrange the obtained values of objective function in ascending order
g. Find the most excellent population
h. Save the most excellent population ('N')
i. Engender the offs-springs through reproduction
j. Produce the off-springs by including the cross over operation
k. Obtain the New-fangled European Night crawler by the weighted summation of two off-springs
l. Apply Cauchy mutation to the New-fangled European Night crawler to acquire the last European Night crawler for subsequent generation
m. New-fangled population's feasibility is checked
n. Repeat the steps "I" to "m" until definite number of population reached
o. Repeat the step "f"
p. Poor population are replaced by most excellent population
q. Repeat the steps "d", "e" and "f"
r. Repeat the steps form "g" to "h" until finest solution obtained
s. End

5 Simulation study

Projected Blue noddy optimization (BNO) algorithm and European Night crawler optimization (ENO) algorithm has been tested in standard IEEE 30 bus system [20]. In Table 1 shows the loss comparison, Table 2 shows the voltage deviation comparison and Table 3 gives the L-index comparison. Figures – 1to 3 gives the graphical comparison between the methodologies with reference to power loss, voltage stability improvement, voltage deviation.

Then Projected Blue noddy optimization (BNO) algorithm and European Night crawler optimization (ENO) algorithm verified in IEEE 30 bus test system [19] without considering voltage stability (L- index). Loss comparison is shown in Table 4. Figure 4 gives graphical comparison between the methodologies with reference to power loss.

Table 5 shows the convergence characteristics of the Blue noddy optimization (BNO) algorithm and European Night crawler optimization (ENO) algorithm. Figure 5 shows the graphical representation of the characteristics. Blue noddy optimization (BNO) algorithm and European Night crawler optimization (ENO) algorithm reduced the power loss efficiently. Comparison of loss has been done with PSO, modified PSO, improved 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), improved stochastic fractal search optimization algorithm (ISFS), harmony search (HS), improved pseudo-gradient search particle swarm optimization and cuckoo search

Method	Power loss (MW)
BPSO-TS [10]	4.5213
TS [10]	4.6862
BPSO [10]	4.6862
ALO [11]	4.5900
QO-TLBO [12]	4.5594
TLBO [12]	4.5629
SGA [13]	4.9408
BPSO [13]	4.9239
HAS [13]	4.9059
S-FS [14]	4.5777
IS-FS [14]	4.5142
SFS [16]	4.5275
BNO	4.5012
ENO	4.5010

Table 1: Comparison of Real power loss for IEEE 30 bus system.

Method	Voltage deviation (PU)
BPSO-TVIW [15]	0.1038
BPSO-TVAC [15]	0.2064
SPSO-TVAC [15]	0.1354
BPSO-CF [15]	0.1287
PG-PSO [15]	0.1202
SWT-PSO [15]	0.1614
PGSWT-PSO [15]	0.1539
MPG-PSO [15]	0.0892
QO-TLBO [12]	0.0856
TLBO [12]	0.0913
S-FS [14]	0.1220
ISFS [14]	0.0890
SFS [16]	0.0877
BNO	0.0865
ENO	0.0863

Table 2: Comparison of voltage deviation for IEEE 30 bus system.

Method	L-index (PU)
BPSO-TVIW [15]	0.1258
BPSO-TVAC [15]	0.1499
SPSO-TVAC [15]	0.1271
BPSO-CF [15]	0.1261
PG-PSO [15]	0.1264
SWT-PSO [15]	0.1488
PGSWT-PSO [15]	0.1394
MPG-PSO [15]	0.1241
QO-TLBO [12]	0.1191
TLBO [12]	0.1180
ALO [11]	0.1161
ABC [11]	0.1161
GWO [11]	0.1242
BA [11]	0.1252
S-FS [14]	0.1252
IS-FS [14]	0.1245
SFS [16]	0.1007
BNO	0.1002
ENO	0.1000

Table 3: Comparison of Voltage stability index for IEEE 30 bus system.

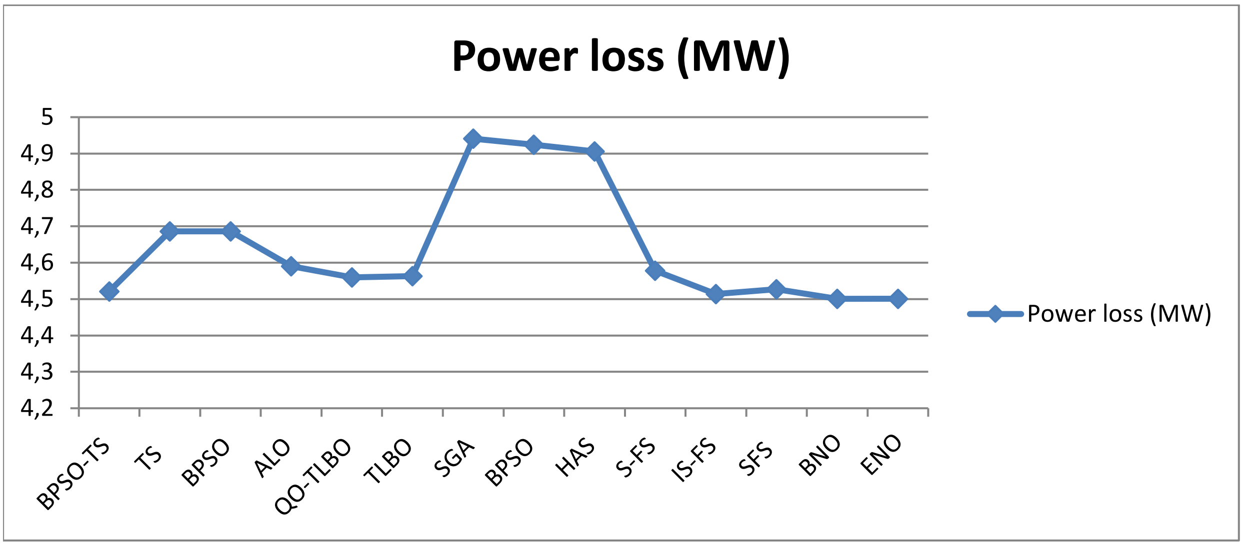

Figure 1: Comparison of real power loss.

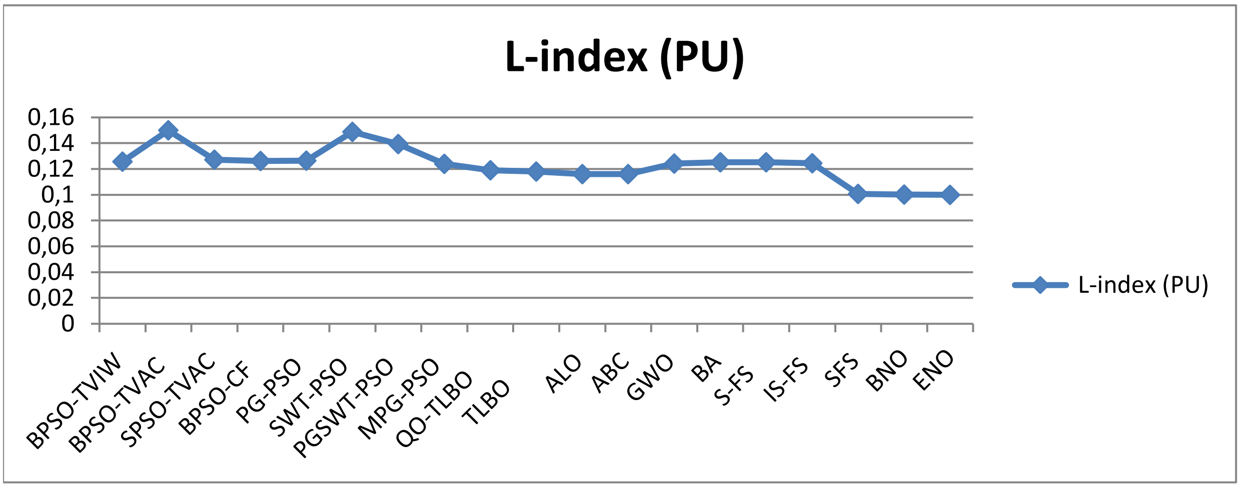

Figure 2: Comparison of voltage stability index.

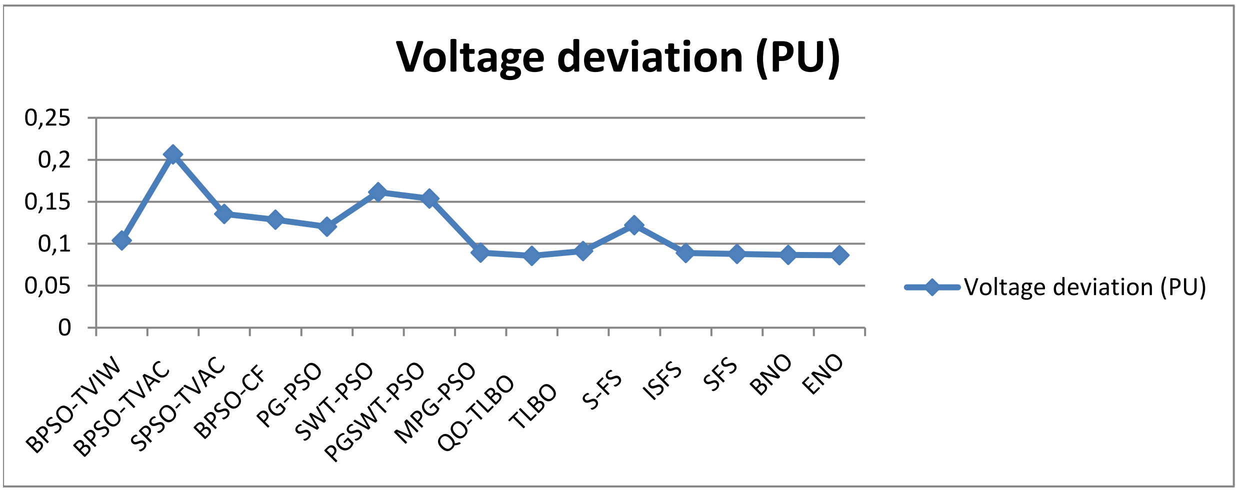

Figure 3: Comparison of Voltage deviation.

algorithm. Power loss reduced efficiently and percentage of the power loss reduction has been improved. Mainly voltage stability enhancement achieved with minimized voltage deviation.

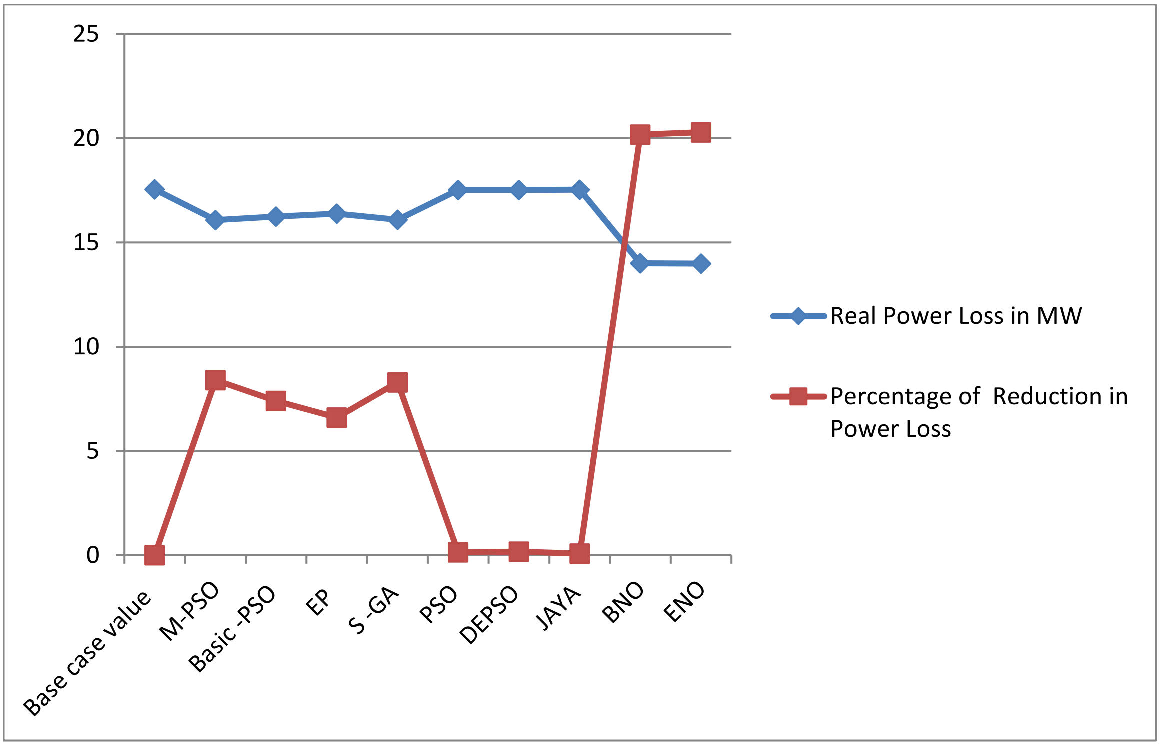

Figure 5: Comparison of Real Power Loss between methodologies (Tested in IEEE 30 bus system).

IEEE 30 Bus system	Real power Loss in MW (With L-index)	Real power Loss in MW (without L-index)	Time in Sec (with L-index)	Time in sec (without L-index)	Number of iterations (with L-index)	Number of iterations (withou L-index)
BNO	4.5012	14.01	18.09	16.16	19	16
ENO	4.5010	13.989	17.99	15.91	17	15

Table 4: Convergence characteristics.

Parameter	Real Power Loss in MW	Percentage of Reduction in Power Loss
Base case value [24]	17.5500	0.0000
M-PSO[24]	16.0700	8.40000
Basic -PSO [23]	16.2500	7.4000
EP [21]	16.3800	6.60000
S -GA [22]	16.0900	8.30000
PSO [25]	17.5246	0.14472
DEPSO [25]	17.52	0.17094
JAYA [25]	17.536	0.07977
BNO	14.01	20.17
ENO	13.989	20.29

Table 5: Comparison of loss with reference to IEEE −30 system.

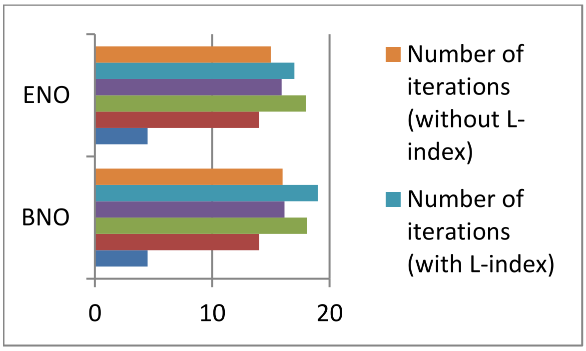

Figure 4: Convergence characteristics.

6 Conclusion

Blue noddy optimization (BNO) algorithm and European Night crawler optimization (ENO) algorithm condensed the power loss with escalation of voltage stability. In BNO Exodus and Preying behavior of blue noddy has been imitated to formulate the algorithm. Blue noddy congregated in the direction of most excellent companion and Position updating is done based on the most excellent explore agent. In preying behaviour angle, velocity is altered by the Blue noddy and spiral performance done in the air to confiscation of the prey. Both Exodus and Preying phases will amplify the exploration and exploitation in the procedure of the algorithm. In ENO algorithm population generation of the European Night crawler is through the off-springs with two different kinds of reproduction. The length of the young European Night crawler is analogous to the parent. In the process - when an individual European Night crawler possess the most excellent fitness then it passed to the successive generation without any variation. Blue noddy optimization (BNO) algorithm and European Night crawler optimization (ENO) algorithm is verified in IEEE 30- bus test system with L-index and devoid of L-index. Both algorithms commendably reduced the power loss and percentage of real power loss lessening has been improved. Convergence characteristics show the better performance of the proposed BNO and ENO optimization algorithms. Comparison of power loss has been done with other standard reported algorithms. Percentage of real power loss reduction of BNO and ENO is 20.17, 20.29.

Scope of future work

In future proposed Blue noddy optimization (BNO) algorithm and European Night crawler optimization (ENO) algorithm can be applied to other problems in Power system optimization and control. Then the validity of the algorithms can be tested in large systems and sequentially it can be applied to practical systems.

Nomenclature

OBF- Minimization of the Objective function.
L and M- control and dependent variables of the optimal reactive power problem
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 transmission line indicated by conductance of the transmission line between the i^{th} and j^{th} buses, $\emptyset_{ij}$. Phase angle between buses i and j
V_{Lk} $-$Load voltage in k^{th} load bus
$V_{Lk}^{desired}$ $-$Voltage desired at the k^{th} load bus,
$Q_{GK} -$ Reactive power generated at k^{th} load bus generators,
Q_{KG}^{Lim} $-$ Reactive power limitation,
N_{LB} and Ng - number load and generating units
Tt – Transformer tap
Gen volt- Generator Voltage

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