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REAL POWER LOSS REDUCTION BY MAINE COON AND PEROGNATHINAE BASED OPTIMIZATION ALGORITHM

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Abstract

This paper proposes Maine Coon and Perognathinae based optimization (MPO) algorithm for solving the power loss lessening problem. Usual behaviour between Maine Coon and Perognathinae is imitated to formulate the MPO algorithm. In the proposed MPO, the crusade of Maine Coon towards Perognathinae as well as the spurt of Perognathinae in the direction of anchorages is replicated. Proposed MPO is population-based procedure which is premeditated by imitating the natural actions of a Maine Coon assaults on Perognathinae and absconding of Perognathinae to the anchorage. The exploration agents in the projected MPO algorithm are alienated into two clusters of Maine Coon's and Perognathinae that examine the problem exploration space with arbitrary activities. The projected MPO algorithm apprises population associates in two segments. In the principal segment, the crusade of Maine Coon's in the direction of Perognathinae is modelled, and in the subsequent segment, the absconding behaviour of Perognathinae to anchorages to protect its life is designed. From a scientific fact of opinion, every associate of the populace is a recommended solution to the problem. In detail, an associate of the population postulates standards for the problem parameters rendering to its location in the exploration space. Proposed MPO algorithm is appraised in IEEE 30 bus system and IEEE 14, 30, 57, 118, 300 bus test systems without considering the voltage constancy index. True power loss lessening, voltage divergence curtailing, and voltage constancy index augmentation has been attained

Keywords

Optimal reactive power, transmission loss, Maine Coon, Perognathinae

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Introduction. Reactive power problem plays an important role in secure and economic operations of power system. In power system lessening of factual power loss is a noteworthy aspect. Lee *et al* [1] has done fuel-cost minimization for power problem. Deeb *et al* [2] found a well-organized method for solving the loss problem by using a reviewed linear programming method. Bjelogrlic *et al* [3] had done use of Newton's optimal power flow in reactive power control. Granville [4] solved the problem by interior point methods. Grudinin [5] had solved the problem by means of successive quadratic programming technique. The works should be noted [6–9]. Mouassa *et al* [10] applied Ant lion algorithm for solving the problem. Mandal *et al* [11] solved the problem by using quasi-oppositional teaching. Khazali *et al* [12] solved the problem by harmony search procedure. Tran *et al* [13] solved problem by innovative enhanced stochastic fractal search procedure. Polprasert *et al* [14] solved the problem by using enhanced pseudo-gradient pursuit particle swarm optimization. Duong *et al* [15] proposed to use an effictive metaheuristic algorithm to calculate the optimal reactive power flow for large-scale power systems. Bhattacharya *et al* [16] solved reactive power flow using biogeography-based optimization. Duman *et al* [17] soled optimal reactive power dispatch using a gravitational search algorithm. Li Wu [18] solved optimal reactive power dispatch with wind power integrated using group search optimizer with intraspecific competition and lévy walk. MATPOWER is available for solving the problems of modelling and optimizing stationary power systems [19]. Dai *et al* [20] used seeker optimization procedure for solving the problem. Subbaraj *et al* [21] used self-adaptive real coded genetic procedure to solve the problem. Pandya *et al* [22] applied Particle swarm optimization to solve the problem. Hussain *et al* [23] applied amended particle swarm optimization to solve the problem. Vishnu *et al* [24] applied an enhanced particle swarm optimization to solve the problem. Basu *et al* [25] applied improved particle swarm optimization for global optimization of unimodal and multimodal functions. Arya *et al* [26] did active power rescheduling for avoiding voltage collapse using modified bare bones particle swarm optimization. Jain *et al* [27] had done a review of particle swarm optimization. Kela *et al* [28] did optimization of radial distribution systems employing differential evolution and bare bones particle swarm optimization. Jain *et al* [29] had done economic load dispatch using adaptive social acceleration constant based particle swarm optimization. Verma *et al* [30] applied modified sigmoid function based gray scale image contrast enhancement using particle swarm optimization. Chiu *et al* [31] have done image reconstruction of a buried conductor by modified particle swarm optimization. Dash *et al* [32] applied hybrid particle swarm optimization and unscented filtering technique for estimation of non-stationary signal parameters. Fahimeh *et al* [33] did optimizing radio frequency identification networks planning by using particle swarm optimization algorithm with fuzzy logic controller and mutation. Biswal *et al* [34] did time frequency analysis and non-stationary signal classification using PSO based fuzzy C-means algorithm. Chaitanya *et al* [35] had done antenna pattern synthesis using the quasi-Newton method, firefly and particle swarm optimization techniques. Pranav *et al* [36] applied a hybrid PSO-ANN-based fault classification system for EHV transmission lines. Kumar *et al* [37] did enhancing the performance of healthcare service in IoT and cloud using optimized techniques. Sahu Barnali *et al* [38] applied adaptive improved binary PSO based learnable Bayesian classifier for dimensionality reduced microarray data. Ayoubi *et al* [39] did synchronization of SA and AV node oscillators using PSO optimized RBF-based controllers and comparison with adaptive control. Mishra *et al* [40] had analysed the performance optimization of PV powered SRM driven water pump using modified Cuk converter. Singh *et al* [41] did unity power factor operated PFC converter-based power supply for computers. Singh *et al* [42] had done multiobjective economic load dispatch problem solved by new PSO. Gupta *et al* [43] did performance analysis of radial distribution systems with UPQC and D-STATCOM. Hazarika *et al* [44] had done a voltage stability index for an interconnected power system based on network partitioning technique. Teeparthi *et al* [45] applied an improved artificial physics optimization algorithm approach for static power system security analysis. Kumar Sharma *et al* [46] did an analysis of mesh distribution systems considering load models and load growth impact with loops on system performance. Chejarla *et al* [47] found multiple solutions for optimal PMU placement using a topology-based method. Kumar *et al* [48] had done about FACTS devices impact on congestion mitigation of power system. Gupta *et al* [49] did comparison of deterministic and probabilistic radial distribution systems load flow. Kanagasabai [50–52] solved real power loss reduction by North American sapsucker algorithm, did real power loss reduction by *Duponchelia fovealis* optimization and enriched squirrel search optimization algorithms, solved optimal reactive power problem by Alaskan Moose Hunting, Larus Livens and Green Lourie swarm optimization algorithms. Omelchenko *et al* [53–55] did development of a design algorithm for the logistics system of product distribution of the mechanical engineering enterprise, the work on organization of logistic systems of scientific productions, and solved the problems and organizational and technical solutions of processing management problems of material and technical resources in a design-oriented organization. Yet many approaches failed to reach the global optimal solution. In this paper Maine Coon and Perognathinae based optimization (MPO) algorithm is proposed to solve the power loss lessening problem. Usual behaviour between Maine Coon and Perognathinae is imitated to formulate the MPO algorithm. In the proposed MPO algorithm, the crusade of Maine Coon towards Perognathinae as well as the spurt of Perognathinae in the direction of anchorages is replicated. Proposed MPO algorithm is population-based procedure which is premeditated by imitating the natural actions of a Maine Coon assaults on Perognathinae and absconding of Perognathinae to the anchorage. The exploration agents in the projected MPO algorithm are alienated into two clusters of Maine Coon's and Perognathinae that examine the problem exploration space with arbitrary activities. The projected MPO algorithm apprises population associates in two segments. In the principal segment, the crusade of Maine Coon's in the direction of Perognathinae is modelled, and in the subsequent segment, the absconding behaviour of Perognathinae to anchorages to protect its life is designed. From a scientific fact of opinion, every associate of the populace is a recommended solution to the problem. In detail, an associate of the population postulates standards for the problem parameters rendering to its location in the exploration space. Consequently, every associate of the population is a vector whose standards regulate the parameters of the problem. Every associate of the populace controls the projected values for the parameters of the problem. Consequently, for every associate of the populace, a rate is quantified for objective function. Grounded on the rates attained for the objective functions, the associates of the populace are categorized from the finest associate with the lowermost rate and sequentially the poorest associate of the populace with the uppermost rate of the objective function. In the proposed MPO algorithm the population matrix possesses two clusters of Maine Coon and Perognathinae. It is presumed that partial population associates and providing improved standards for the objective function establish the populace of Perognathinae and remaining population associates with inferior rates for the objective function establish as Maine Coon population. In the subsequent segment of the proposed MPO algorithm, the absconding of Perognathinae to anchorages is designed. In MPO algorithm, it is presumed that there is an arbitrary anchorage for every Perognathinae, and in these anchorages Perognathinae will hide. The location of the anchorages in the exploration space is arbitrarily generated grounded on modelling the locations of dissimilar associates of the procedure. Proposed MPO algorithm is appraised in IEEE 30 bus system and IEEE 14, 30, 57, 118, 300 bus test systems without considering the voltage constancy index. True power loss lessening, voltage divergence curtailing, and voltage constancy index augmentation has been attained.

Problem formulation. Power loss minimization is defined by

$$\min \tilde{F}\left(\overline{d}, \overline{e}\right),$$

where $\min$ is minimization of power loss. Subject to the constraints

$$A\left(\overline{d}, \overline{e}\right) = 0, \ \ B\left(\overline{d}, \overline{e}\right) = 0.$$

Here $\overline{d}, \overline{e}$ are control and dependent variables,

$$d = \left[VLG_1, \ldots, VLG_{Ng}; QC_1, \ldots, QC_{NC}; T_1, \ldots, T_{NT} \right],$$

$$e = \left[PG_{slack}; VL_1, \ldots, VL_{NL}; QG_1, \ldots, QG_{Ng}; SL_1, \ldots, SL_{NT} \right],$$

where VLG is level of the voltage; QC reactive power compensators; T is tap setting of transformers; PG_{slack} is slack generator; VL is voltage on transmission lines; QG is generation unit's reactive power; SL is apparent power.

The fitness function $\left(F_1, F_2, F_3\right)$ is designed for power loss (MW) lessening, voltage deviancy, voltage constancy index (L-index) is defined by:

$$F_1 = P_{\min} = \min \left[\sum_{m}^{NTL} G_m \left[V_i^2 + V_j^2 - 2V_i V_j \cos \text{Ø}_{ij} \right] \right],$$

$$F_2 = \min \left[\sum_{i=1}^{NLB} \left| VL_k - VL_k^{desired} \right|^2 + \sum_{i=1}^{Ng} \left| QG_K - QG_K^{\lim} \right|^2 \right],$$

$$F_3 = \min L_{\max},$$

where NTL is number of transmission line; VL_k is load voltage in k-th load bus; $VL_k^{desired}$ is voltage desired at the k-th load bus; QG_K is reactive power generated at k-th load bus generators; $QG_K^{\lim}$ is reactive power limitation; NLB, Ng are number load and generating units,

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

if

$$\begin{cases} L_j = 1 - \sum_{i=1}^{NPV} F_{ji} \left(V_i / V_j \right), \\ F_{ji} = -\left[Y_1 \right]^1 \left[Y_2 \right], \end{cases}$$

then

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

Parity constraints

$$0 = PG_i - PD_i - V_i \sum_{j \in NB} V_j \left[G_{ij} \cos \left[\text{Ø}_i - \text{Ø}_j \right] + B_{ij} \sin \left[\text{Ø}_i - \text{Ø}_j \right] \right],$$

$$0 = QG_i - QD_i - V_i \sum_{j \in NB} V_j \left[G_{ij} \sin \left[\text{Ø}_i - \text{Ø}_j \right] + B_{ij} \cos \left[\text{Ø}_i - \text{Ø}_j \right] \right].$$

Disparity constraints

$$PG_{slack}^{\min} \le PG_{slack} \le PG_{slack}^{\max}, \quad QG_i^{\min} \le QG_i \le QG_i^{\max}, \quad i \in Ng,$$

$$VL_i^{\min} \le VL_i \le VL_i^{\max}, \quad i \in NL, \quad T_i^{\min} \le T_i \le T_i^{\max}, \quad i \in NT,$$

$$QC^{\min} \le QC \le QC^{\max}, \quad i \in NC, \quad \left|SL_i\right| \le SL_i^{\max}, \quad i \in NTL,$$

$$VG_i^{\min} \le VG_i \le VG_i^{\max}, \quad i \in Ng.$$

Multi objective fitness

$$MOF = F_1 + r_i F_2 + uF_3 =$$

$$= F_1 + \left[\sum_{i=1}^{NL} x_v \left[VL_i - VL_i^{\min} \right]^2 + \sum_{i=1}^{Ng} r_g \left[QG_i - QG_i^{\min} \right]^2 \right] + r_f F_3,$$

u is dependent variables;

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

Maine Coon and Perognathinae based optimization algorithm. Usual behaviour between Maine Coon and Perognathinae is imitated to formulate the MPO algorithm. In the proposed MPO algorithm, the crusade of Maine Coon towards Perognathinae as well as the spurt of Perognathinae in the direction of anchorages is replicated.

Proposed MPO is population-based procedure which is premeditated by imitating the natural actions of a Maine Coon assaults on Perognathinae and absconding of Perognathinae to the anchorage. The exploration agents in the projected MPO algorithm are alienated into two clusters of Maine Coon's and Perognathinae that examine the problem exploration space with arbitrary activities. The projected MPO algorithm apprises population associates in two segments. In the principal segment, the crusade of Maine Coon's in the direction of Perognathinae is modelled, and in the subsequent segment, the absconding behaviour of Perognathinae to anchorages to protect its life is designed. From a scientific fact of opinion, every associate of the populace is a recommended solution to the problem. In detail, an associate of the population postulates standards for the problem parameters rendering to its location in the exploration space. Consequently, every associate of the population is a vector whose standards regulate the parameters of the problem. The population of the procedure is defined by population matrix as follows:

$$Z = \begin{bmatrix} Z_1 \\ \vdots \\ Z_i \\ \vdots \\ Z_N \end{bmatrix}_{N \times m} = \begin{bmatrix} z_{1,1} & \dots & z_{1,m} \\ \vdots & \ddots & \vdots \\ z_{N,1} & \dots & z_{N,m} \end{bmatrix}_{N \times m},$$

where Z_i is is the explore agent; N is population number; m is number of parameters in the problem.

Every associate of the populace controls the projected values for the parameters of the problem. Consequently, for every associate of the populace, a rate is quantified for objective function. The rate attained for the objective function is symbolized by a vector as follows:

$$OFR = \begin{bmatrix} OFR_1 \\ \vdots \\ OFR_i \\ \vdots \\ OFR_N \end{bmatrix}_{N \times 1},$$

where OFR_i functional rate of i-th explore agent.

Grounded on the rates attained for the objective functions, the associates of the populace are categorized from the finest associate with the lowermost rate and sequentially the poorest associate of the populace with the uppermost rate of the objective function. The organized population matrix as well as the categorized objective function is defined as

$$Z^c = \begin{bmatrix} Z_1^c \\ \vdots \\ Z_i^c \\ \vdots \\ Z_N^c \end{bmatrix}_{N \times m} = \begin{bmatrix} z_{1,1}^c & \dots & z_{1,m}^c \\ \vdots & \ddots & \vdots \\ z_{N,1}^c & \dots & z_{N,m}^c \end{bmatrix}_{N \times m}, \quad (1)$$

$$OFR = \begin{bmatrix} OFR_1^c \\ \vdots \\ OFR_N^c \end{bmatrix}_{N \times 1} \begin{bmatrix} \min_{OFR} \\ \vdots \\ \max_{OFR} \end{bmatrix}_{N \times 1}. \quad (2)$$

Here Z^c is classified population rate; Z_i^c is the i-th associate of the classified population.

In the proposed MPO algorithm the population matrix possesses two clusters of Maine Coon and Perognathinae. It is presumed that partial population associates and providing improved standards for the objective function establish the populace of Perognathinae and remaining population associates with inferior rates for the objective function establish as Maine Coon population. Grounded on this notion, the populaces of Maine Coon and Perognathinae are defined as

$$MC = \begin{bmatrix} MC_1 = Z^c_{N_P+1} \\ \vdots \\ MC_j = Z^c_{N_P+j} \\ \vdots \\ MC_{N_{MC}} = Z^c_{N_P+N_{MC}} \end{bmatrix} = \begin{bmatrix} z^c_{N_P+1,1} & \cdots & z^c_{N_P+1,P} \\ \vdots & \ddots & \vdots \\ z^c_{N_P+N_{MC},1} & \cdots & z^c_{N_P+N_{MC},P} \end{bmatrix}_{N_P \times P}, \quad (3)$$

$$P = \begin{bmatrix} P_1 = Z^c_1 \\ \vdots \\ P_i = Z^c_i \\ \vdots \\ P_{N_P} = Z^c_{N_P} \end{bmatrix} = \begin{bmatrix} z^c_{1,1} & \cdots & z^c_{1,P} \\ \vdots & \ddots & \vdots \\ z^c_{N_P,1} & \cdots & z^c_{N_P,P} \end{bmatrix}_{N_P \times P}, \quad (4)$$

where MC is the Maine Coon population; P is Perognathinae's population; N_P is number of Perognathinae; N_{MC} is the number of Maine Coon.

To modernize the exploration elements, in the principal segment, the alteration of location of Maine Coon is modelled grounded on the normal behaviour of Maine Coon and crusade in the direction of Perognathinae. This segment of the modernization of the projected MPO algorithm is scientifically defined as

$$MC_j^{new} : MC_{j,d}^{new} = MC_{j,d} + R\left(p_{k,d} - QMC_{j,d}\right) \text{ and } j = 1, \quad (5)$$

$$N_{MC,d} = 1, \ldots, MC, \;\; k \in 1, \ldots, N_{MC}, \quad (6)$$

$$Q = circle + \left(1 + Rand\right), \quad (7)$$

$$MC_j = \begin{cases} MC_j^{new}, \left| OFR_{MC,j}^{new} < OFR_{MC,j}, \right. \\ MC_j, \text{ otherwise,} \end{cases} \quad (8)$$

MC_j^{new} is the new position of Maine Coon; $R \in [0,1]$; $p_{k,d}$ is the k-th Perognathinae dimension.

In the subsequent segment of the proposed MPO algorithm, the absconding of Perognathinae to anchorages is designed. In MPO algorithm, it is presumed that there is an arbitrary anchorage for every Perognathinae, and in these anchorages Perognathinae will hide. The location of the anchorages in the exploration space is arbitrarily generated grounded on modelling the locations of dissimilar associates of the procedure. This segment of modernizing the location of Perognathinae is scientifically defined as

$$A_i : a_{i,d} = z_{l,d}, \tag{9}$$

$$N_{p,d} = 1, \ldots, P, \quad l \in 1, \ldots, N, \tag{10}$$

$$P_i^{new} : P_{i,d}^{new} = P_{i,d} + R\left(a_{i,d} - QP_{i,d}\right) \operatorname{sign}\left(OFR_i^p - OFR_i^a\right) \text{ and } i = 1, \tag{11}$$

$$i = 1, \ldots, N_p, \quad d = 1, \ldots, m, \tag{12}$$

$$P_i = \begin{cases} P_i^{new}, \left| OFR_i^{p,new} < OFR_i^p, \right. \\ \qquad P_i, \text{ otherwise.} \end{cases} \tag{13}$$

Here A_i is the anchorage of the Perognathinae; OFR_i^a is the rate of the objective function; P_i^{new} is the new position of the Perognathinae.

Subsequently all associates of the procedure's populace have been rationalised, the procedure pass in to the subsequent iteration and, grounded on equations the iterations of the procedure endure up until the end situation is grasped. The condition for ending the optimization procedures can be a definite number of iterations, or by outlining an adequate error amongst attained elucidations in successive recapitulations. Additionally, the situation for ending the procedure may be within assured stage of time. Figure 1 shows the procedure flow diagram of MPO algorithm:

a. Start
b. Parameters are fixed
c. Fix the number of explore agents
d. Set the number of iterations
e. Arbitrarily engender the preliminary population matrix
f. Calculate the objective functional value
g. For $t = 1, \ldots, T$
h. Based on objective function categorize the population matrix
i. (1)
j. (2)

k. Select the Perognathinae population
l. (4)
m. Select the Maine Coon population
n. (3)
o. First segment: modernize the position of Maine Coon
p. For $j = 1, \ldots, N_{MC}$
q. Modernize the position of the *j*-th Maine Coon
r. (5)
s. (6)
t. (7)
u. (8)
v. End
w. Second segment: modernize the position of Perognathinae
x. For $i = 1, \ldots, N_P$
y. Construct anchorage for the *i*-th Perognathinae
z. (9)
aa. (10)
bb. Modernize the position of the *i*-th Perognathinae
cc. (11)
dd. (12)
ee. (13)
ff. End
gg. End
hh. Output the most excellent optimal solution
ii. End

Simulation results. Projected MPO algorithm is corroborated in IEEE 30 bus system [20]. In Table 1 is shown the loss appraisal, Table 2 shows the voltage aberration evaluation and Table 3 gives the *L*-index assessment. Figures 2 to 4 give the graphical appraisal between the methods. MSO and EMSO abridged the power loss efficiently. 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 (QO-TBO), 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 proportion of the power loss lessening has been enhanced. Predominantly voltage constancy augmentation attained with minimized voltage deviancy.

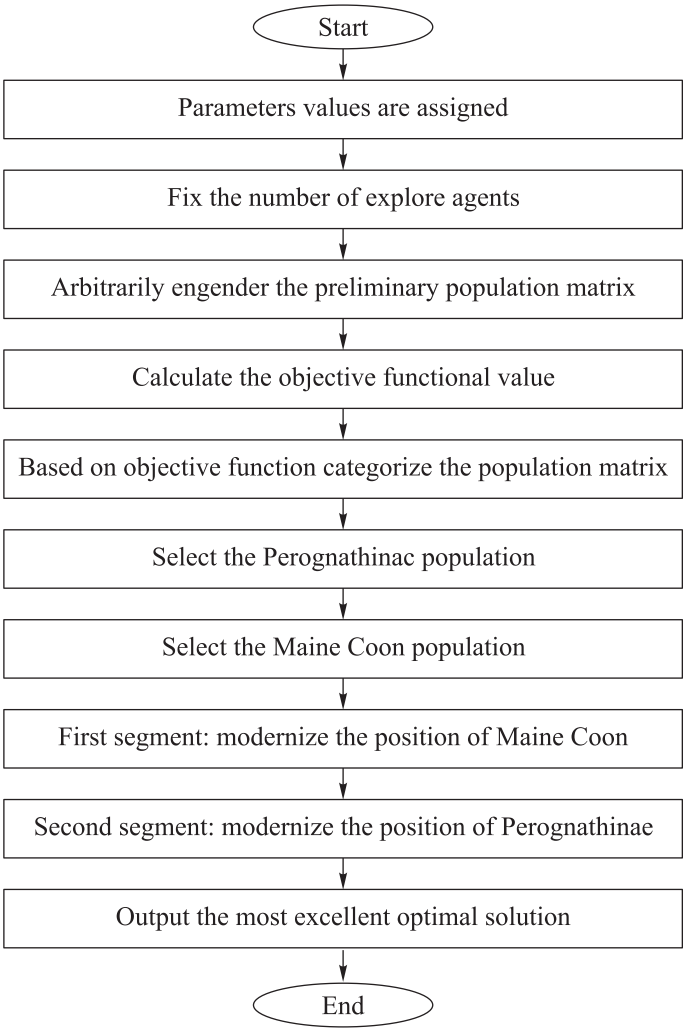

Fig. 1. Procedure flow diagram of MPO algorithm

The Table 1 and Fig. 2 show the appraisal of power loss and assessment done with Basic PSO-TS [10], Standard TS [10], Basic PSO [10], ALO [11], Basic QO-TLBO [12], Standard TLBO [12], Standard GA [13], Basic PSO [13], HAS [13], Standard FS [14], IS-FS [14] and Standard FS [15].

Table 1

Assessment of entire power loss

Algorithm	Power loss, MW	Algorithm	Power loss, MW
Basic PSO-TS [10]	4.5213	Basic PSO [13]	4.9239
Standard TS [10]	4.6862	HAS [13]	4.9059
Basic PSO [10]	4.6862	Standard FS [14]	4.5777

End of the Table 1

Algorithm	Power loss, MW	Algorithm	Power loss, MW
ALO [11]	4.5900	IS-FS [14]	4.5142
Basic QO-TLBO [12]	4.5594	Standard FS [16]	4.5275
Standard TLBO [12]	4.5629	MPO	4.4555
Standard GA [13]	4.9408		

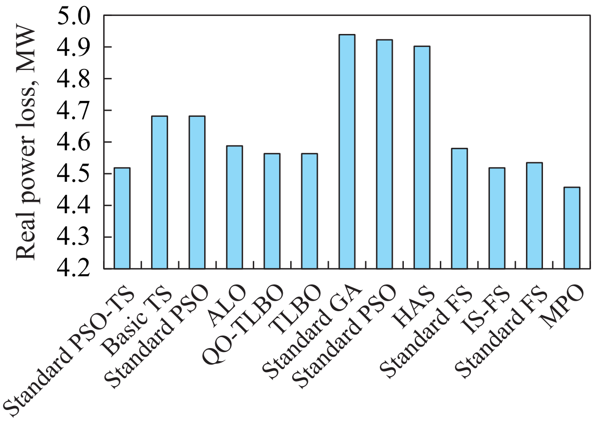

Fig. 2. Assessment of real power loss, MW

Table 2 and Fig. 3 show the evaluation of voltage deviancy and assessment done with Basic PSO-TVIW [15], Basic PSO-TVAC [15], Standard PSO-TVAC [15], Basic PSO-CF [15], PG-PSO [15], SWT-PSO [15], PGSWT-PSO [15], MPG-PSO [15], QO-TLBO [12], TLBO [12], Standard FS [14], ISFS [14] and Standard FS [16].

Table 2

Comparison of voltage deviancy

Algorithm	Voltage deviancy, PU	Algorithm	Voltage deviancy, PU
Basic PSO-TVIW [15]	0.1038	MPG-PSO [15]	0.0892
Basic PSO-TVAC [15]	0.2064	QO-TLBO [12]	0.0856
Standard PSO-TVAC [15]	0.1354	TLBO [12]	0.0913
Basic PSO-CF [15]	0.1287	Standard FS [14]	0.1220
PG-PSO [15]	0.1202	ISFS [14]	0.0890
SWT-PSO [15]	0.1614	Standard FS [16]	0.0877
PGSWT-PSO [15]	0.1539	MPO	0.0819

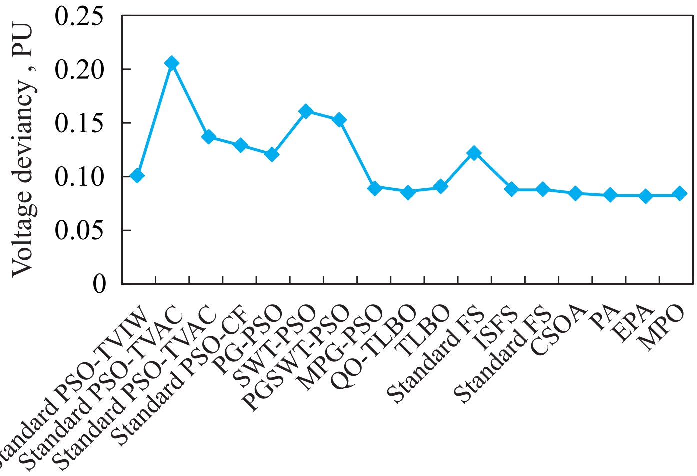

Fig. 3. Appraisal of voltage deviancy, PU

Table 3 and Fig. 4 shows the voltage constancy and assessment done with Basic PSO-TVIW [15], Basic PSO-TVAC [15], Standard PSO-TVAC [15], Basic PSO-CF [15], PG-PSO [15], SWT-PSO [15], PGSWT-PSO [15], MPG-PSO [15], QO-TLBO [12], Standard TLBO [12], ALO [11], ABC [11], Standard GWO [11], Basic BA [11], Standard FS [14], IS-FS [14] and Standard FS [15].

Table 3

Appraisal of voltage constancy

Algorithm	Voltage constancy (L-index), PU	Algorithm	Voltage constancy (L-index), PU
Basic PSO-TVIW [15]	0.1258	ALO [11]	0.1161
Basic PSO-TVAC [15]	0.1499	ABC [11]	0.1161
Standard PSO-TVAC [15]	0.1271	Standard GWO [11]	0.1242
Basic PSO-CF [15]	0.1261	Basic BA [11]	0.1252
PG-PSO [15]	0.1264	Standard FS [14]	0.1252
SWT-PSO [15]	0.1488	IS-FS [14]	0.1245
PGSWT-PSO [15]	0.1394	Standard FS [16]	0.1007
MPG-PSO [15]	0.1241	MPO	0.1001
QO-TLBO [12]	0.1191	ALO [11]	0.1161
Standard TLBO [12]	0.1180	ABC [11]	0.1161

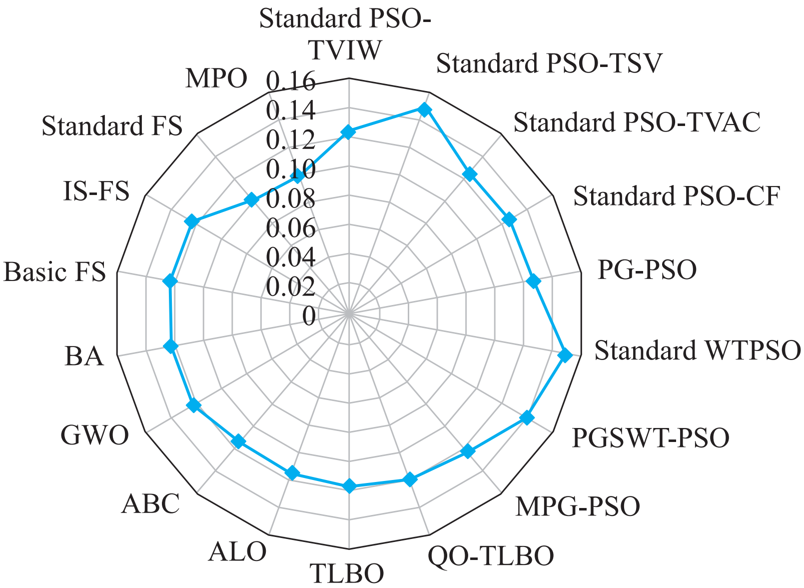

Fig. 4. Assessment of voltage constancy, PU

Then projected MPO algorithm is substantiated in IEEE 14, 30, 57, 118 and 300 bus test systems deprived of L-index. Loss appraisal is shown in Tables 4 to 8. Figure 5 to 9 gives graphical comparison between the approaches with orientation to power loss. Proposed algorithms are compared with Adapted PSO, PSO, EP, SARGA, CGA, AGA, EPSO, CLPSO, AGA, FEA and CSO.

Table 4 and Fig. 5 shows the actual power loss appraisal for IEEE 14 bus system without considering voltage constancy and assessment done with Base case [23], Adapted PSO [23], PSO [23], EP [22] and SARGA [21].

Table 4

Assessment of results (IEEE 14 bus)

Algorithm	True loss, MW	Ratio of loss diminution
Base case [23]	13.550	0
Adapted PSO [23]	12.293	9.2
PSO [22]	12.315	9.1
EP [22]	13.346	1.5
SARGA [21]	13.216	2.5
MPO	9.9999	26.2

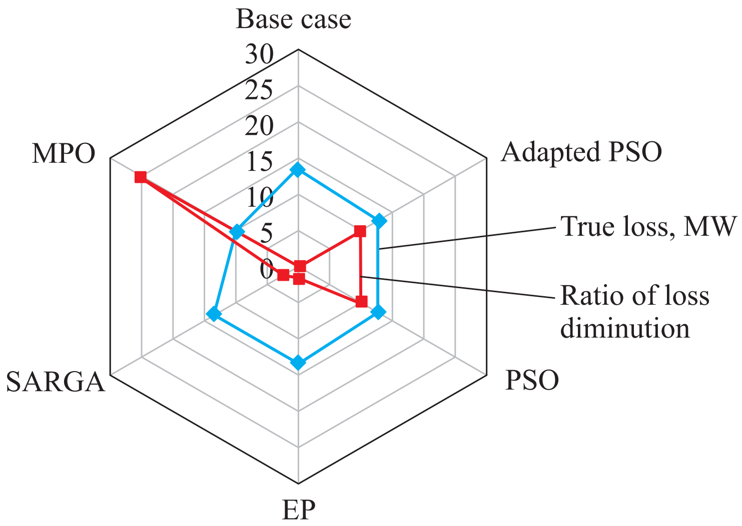

Fig. 5. Power loss appraisal (IEEE 14 bus system)

Table 5 and Fig. 6 shows the actual power loss appraisal for IEEE 30 bus system without considering voltage constancy and assessment done with Base case value [23], M-PSO[23], Basic-PSO [22], EP [20], S-GA [21], PSO [24], DEPSO [24] and JAYA [24].

Table 5

Appraisal of loss (IEEE 30 bus system)

Algorithm	Actual power loss, MW	Proportion of lessening in power loss
Base case value [23]	17.5500	0
M-PSO [23]	16.0700	8.40000
Basic PSO [22]	16.2500	7.40000
EP [20]	16.3800	6.60000
S-GA [21]	16.0900	8.30000
PSO [24]	17.5246	0.14472
DEPSO [24]	17.5200	0.17094
JAYA [24]	17.5360	0.07977
MPO	13.1900	24.8433

The Table 6 and Fig. 7 show the actual power loss appraisal for IEEE 57 bus system without considering voltage constancy and assessment done with Base case [23], Adapted PSO [23], PSO [22], CGA [21] and AGA [21].

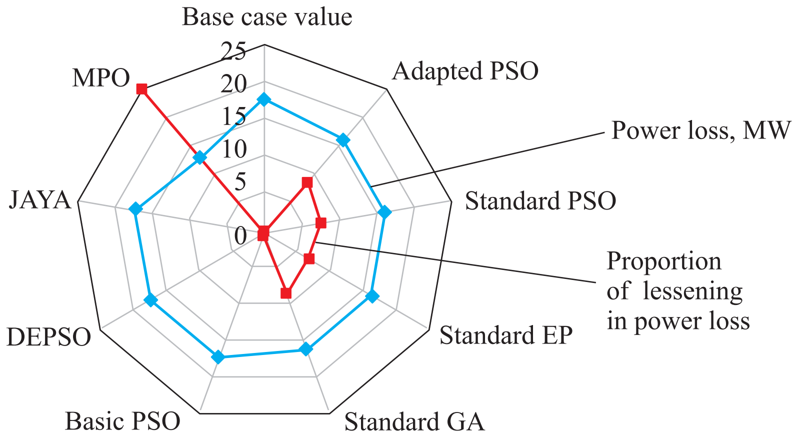

Fig. 6. Appraisal of power loss (IEEE 30 bus system)

Table 6

Assessment of parameters

Algorithm	True loss, MW	Ratio of loss diminution
IEEE 57 bus system		
Base case [23]	27.800	0
Adapted PSO [23]	23.510	15.400
PSO [22]	23.860	14.100
CGA [21]	25.240	9.2000
AGA [21]	24.560	11.600
MPO	20.009	28.0251
IEEE 118 bus system		
Base case [23]	132.8	0.00
Adapted PSO [23]	117.19	11.700
PSO [22]	119.34	10.100
EPSO [20]	131.99	0.600
CLPSO [20]	130.96	1.300
MPO	110.90	16.4909

Table 6 and Fig. 8 shows the real power loss appraisal for IEEE 118 bus system without considering voltage constancy and assessment done with Base case [23], Adapted PSO [23], PSO [22], EPSO [20] and CLPSO [20].

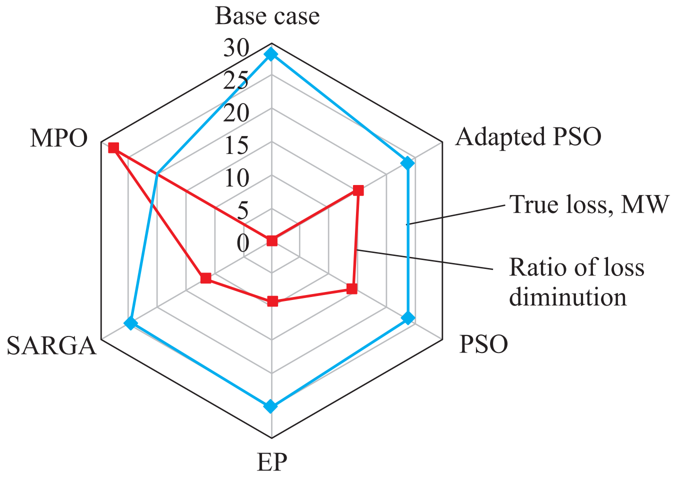

Fig. 7. Power loss appraisal (IEEE 57 bus system)

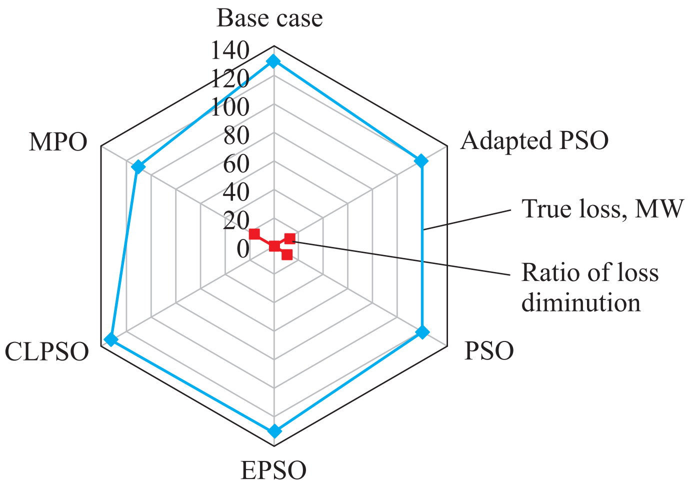

Fig. 8. Power loss appraisal (IEEE 118 bus system)

The Table 7 and Fig. 9 show the real power loss appraisal for IEEE 300 bus system without considering voltage constancy and assessment done with AGA [34], FEA [34] and CSO [33].

Table 7

Power loss appraisal (IEEE 300 bus system)

Algorithm	True loss, MW
AGA [34]	646.299800
FEA [35]	650.602700
CSO [34]	635.894200
MPO	624.112348

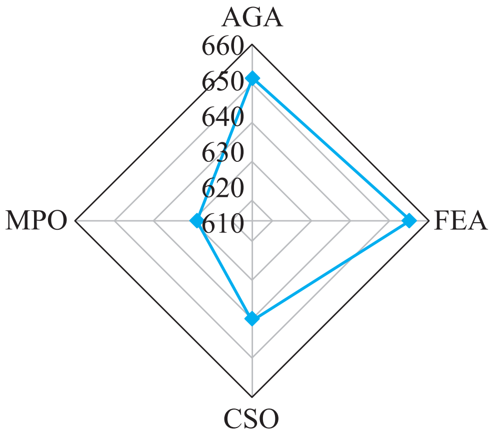

Fig. 9. Power loss appraisal (IEEE 300 bus system)

Conclusion. MPO algorithm successfully solved the power loss lessening problem. In the proposed MPO algorithm, the crusade of Maine Coon towards Perognathinae as well as the spurt of Perognathinae in the direction of anchorages is replicated. Proposed MPO algorithm is population-based procedure which is premeditated by imitating the natural actions of a Maine Coon assaults on Perognathinae and absconding of Perognathinae to the anchorage. The exploration agents in the projected MPO algorithm are alienated into two clusters of Maine Coon's and Perognathinae that examine the problem exploration space with arbitrary activities. The projected MPO algorithm apprises population associates in two segments. In the principal segment, the crusade of Maine Coon's in the direction of Perognathinae is modelled, and in the subsequent segment, the absconding behaviour of Perognathinae to anchorages to protect its life is designed. From a scientific fact of opinion, every associate of the populace is a recommended solution to the problem. In detail, an associate of the population postulates standards for the problem parameters rendering to its location in the exploration space. Consequently, every associate of the population is a vector whose standards regulate the parameters of the problem. Every associate of the populace controls the projected values for the parameters of the problem. Consequently, for every associate of the populace, a rate is quantified for objective function. Grounded on the rates attained for the objective functions, the associates of the populace are categorized from the finest associate with the lowermost rate and sequentially the poorest associate of the populace with the uppermost rate of the objective function. In the proposed MPO algorithm the population matrix possesses two clusters of Maine Coon and Perognathinae. It is presumed that partial population associates and providing improved standards for the objective function establish the populace of Perognathinae and remaining population associates with inferior rates for the objective function establish as Maine Coon population. In the subsequent segment of the proposed MPO algorithm, the absconding of Perognathinae to anchorages is designed. In MPO, it is presumed that there is an arbitrary anchorage for every Perognathinae, and in these anchorages Perognathinae will hide. The location of the anchorages in the exploration space is arbitrarily generated grounded on modelling the locations of dissimilar associates of the procedure. Subsequently all associates of the procedure's populace have been rationalised, the procedure pass in to the subsequent iteration and, grounded on Equations the iterations of the procedure endure up until the end situation is grasped. The condition for ending the optimization procedures can be a definite number of iterations, or by outlining an adequate error amongst attained elucidations in successive recapitulations. Additionally, the situation for ending the procedure may be within assured stage of time. Proposed MPO algorithm is appraised in IEEE 30 bus system and IEEE 14, 30, 57, 118, 300 bus test systems without considering the voltage constancy index. True power loss lessening, voltage divergence curtailing, and voltage constancy index augmentation have been attained.

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