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Novel Commercial Pilot Preparation, Mindarinae and Formica Fusca Rapport Inspired, Red-footed Booby Optimization Algorithms for Real Power Loss Reduction and Voltage Stability Expansion

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Abstract

In this paper Commercial Pilot Preparation inspired optimization (CPPIO) algorithm, Mindarinae and Formica fusca rapport inspired optimization (MFO) algorithm, Red-footed Booby optimization (BO) algorithm are applied to solve the problem. Key objective of the problem is Real power loss reduction, Voltage deviation minimization and Voltage stability enhancement. Main segment of the CPPIO modernization is grounded on the choice of trainer by the beginner and at that time the preparation done by the designated trainer to the beginner. Amongst the beginner population, chosen quantities of the preeminent associates are deliberated as trainers and remaining as beginner. Preparation of the beginner to become as commercial pilot by the trainer is the exploration segment of the algorithm. Mindarinae and Formica fusca rapport inspired optimization algorithm combines dissimilar exploration stratagems, which pretend the dissimilar cooperative actions which exist in the natural lifecycle of Mindarinae and Formica fusca. Thus, algorithm employs dissimilar entities that permit sustenance each other and can track dissimilar exploration courses. In the Exploitation segment two additional activities are required to advance exploitation subsequent to the Red-footed Booby flashes into the marine by elongated - profound nosedive and then a squat -trivial nosedive. Astute fish in the marine is frequently supplemented by an unexpected revolving drive to spurt the Red-footed Booby pursuit. Commercial Pilot Preparation inspired optimization (CPPIO) algorithm, Mindarinae and Formica fusca rapport inspired optimization (MFO) algorithm, Red-footed Booby optimization (BO) algorithm are verified in G01–G24 benchmark functions, Six, IEEE bus test systems and in Practical Unified Egyptian Transmission Network. In six bus IEEE test systems real power loss obtained by proposed algorithm is CPPIO- 11. 0069 (MW), MFO-11. 0043 (MW) and BO -11. 0036 (MW). In IEEE 30 bus system CPPIO- 4.49012 (MW), MFO-4.49009 (MW) and BO -4.49005 (MW). In IEEE 57 bus system CPPIO- 21.67901 (MW), MFO-21.67893 (MW) and BO -21.67889 (MW). In IEEE 118 bus system CPPIO- 113.54321 (MW), MFO-113.54305 (MW) and BO -113.54298 (MW). In IEEE 300 bus system CPPIO- 360.0601 (MW), MFO-360.0589 (MW) and BO -360.0581 (MW). In IEEE 354 bus system CPPIO- 336.5153 (MW), MFO-336.5133 (MW) and BO -336.5129 (MW). In Practical Unified Egyptian Transmission Network CPPIO- 29. 0526 (MW), MFO-29. 0509 (MW) and BO -29. 0495 (MW). Real power loss reduction, Voltage deviation minimization and Voltage stability enhancement has been attained in the electrical power transmission network.

Keywords: Commercial Pilot Preparation, Mindarinae, Formica fusca, rapport

1. Introduction

Numerous Conventional methodologies [1-6] applied to solve the problem. Then various types of swarm based algorithms [7-14] applied. Numerous evolutionary based techniques [15-21] are employed. Further these decades many types of procedures [22 -34] which are all inspired by nature are applied to various engineering and management domains. Recently many researchers are employing the physics and chemistry based algorithms [34-50] in multiple areas.

1.1. Planned methods

In this paper Commercial Pilot Preparation inspired optimization (CPPIO) algorithm, Mindarinae and Formica fusca rapport inspired optimization (MFO) algorithm, Red-footed Booby optimization (BO) algorithm are applied to solve the power loss lessening problem.

1.2. Importance of the methods

Commercial Pilot Preparation inspired optimization (CPPIO) algorithm:

- Preparation of the beginner to become as commercial pilot by the trainer
- Beginner prefiguring from trainer talents
- Personal preparation of the beginner

Mindarinae and Formica fusca rapport inspired optimization (MFO) algorithm:

- Mindarinae and Formica fusca rapport inspired optimization algorithm envisages double divergent sorts of entities that are Mindarinae and Formica fusca.
- Preeminent Mindarinae which are named as spearhead create clusters comprise of enduring Mindarinae and Formica fusca.

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- Mindarinae and Formica fusca rapport inspired optimization algorithm combines dissimilar exploration stratagems, which pretend the dissimilar cooperative actions which exist in the natural lifecycle of Mindarinae and Formica fusca. Thus, algorithm employs dissimilar entities that permit sustenance each other and can track dissimilar exploration courses. These possessions create the algorithm to be more suitable for solving the problem.

Table 1. Application of methods.

Author	Published year	Applied technique
Costa [1]	1997	Primal-dual method
Sasson et al [2]	1973	Hessian Matrix
Jan et al [3]	1995	Newton-Raphson
Belati et al [4]	2003	Newton method
Dhivya et al [5]	2013	Primal dual interior point
Capitanescu et al [6]	2007	Interior point
Dong et al [8]	2022	Gaussian bare-bones bat algorithm
Wahab et al [9]	2022	Chaotic Turbulent Flow of Water-Based Algorithm
Muhammad et al [21]	2021	Fractional evolutionary
Hassan[et al 22]	2022	Rao-3 Algorithm
Elsayed et al [23]	2021	Improved Heap-Based Optimizer
Bhongade et al [24]	2020	BAT algorithm
Constante et al [25]	2021	Branch-and-Bound Algorithm
Chaitanya et al [26]	2021	Modified Ant Lion Optimizer
Raghuwanshi et al [40]	2019	KLM

Red-footed Booby optimization (BO) algorithm:

- In the Exploration segment; Red-footed Booby quest for victim in the marine by commencing from the midair, and as soon as Red-footed Booby discover victim, they regulate the nosedive outline rendering to the profundity of the victim. An elongated - profound nosedive and then a squat -trivial nosedive will be executed by the Red-footed Booby.
- In the Exploitation segment two additional activities are required to advance exploitation subsequent to the Red-footed Booby flashes into the marine by elongated - profound nosedive and then a squat -trivial nosedive.
- If the grasping capability of the Red-footed Booby is inside the range towards the acquiring victim, the location is rationalised with an impulsive revolving; or else, the Red-footed Booby is inept to grasp this malleable fish and accomplishes a Levy crusade to examine for the subsequent target in arbitrary mode.

1.3. Commercial Pilot Preparation inspired optimization (CPPIO) algorithm

In this paper Commercial Pilot Preparation inspired optimization (CPPIO) algorithm is used to solve the problem. Commercial Pilot Preparation (training) is a brainy procedure in which a trainee is educated and obtains driving talents. A trainee as a student pilot can select from numerous trainers while getting training in Pilot Preparation (training) institute. Preparation of the beginner to become as commercial pilot by the trainer is the exploration segment of the algorithm. Fig 1 shows the image representation of Commercial Pilot Preparation.

The main segment of the CPPIO modernization is grounded on the choice of trainer by the beginner and at that time the preparation done by the designated trainer to the beginner. Amongst the beginner population, chosen quantities of the preeminent associates are deliberated as trainers and remaining as beginner. Selecting the trainer and learning the talents of that trainer will tip to the crusade of population associates to dissimilar ranges in the exploration region. This will upsurge the beginner exploration ability in the global examination and detection of the optimal zone. CPPIO approach modernization is grounded on the beginner emulating the trainer and talents of the trainer. This procedure passages CPPIO associates to dissimilar locations in the exploration region, thus aggregating the CPPIO exploration ability. Personal preparation of the beginner is act as exploitation segment in the procedure. In this segment CPPIO modernization is grounded on the Personal preparation of the beginner to progress and augment pilot abilities. Each beginner attempts to get nearer to the preeminent abilities in this segment.

Fig 1. Image representation of Commercial Pilot Preparation.

1.4. Mindarinae and Formica fusca rapport inspired optimization (MFO) algorithm

Then in this paper Mindarinae and Formica fusca rapport inspired optimization (MFO) algorithm is applied to solve the problem. Proposed MFO approach imitates the affinity between Mindarinae and Formica fusca. Novel features are combined assorted entities containing of Mindarinae and Formica fusca that alive in numerous gatherings composed and have dissimilar regionalized knowledge performances and purposes. Fig 2 shows the image representation of Mindarinae and Formica fusca rapport

Fig 2. Image representation of Mindarinae and Formica fusca rapport.

Enthused by environment, gathering grounded info interchange and by means of dissimilar exploration stratagems together with concentrating on the entity's individual information, erudition from additional gathering's associates and info distribution with neighboring gatherings are castoff. This rapport tips to converging to the universal optima and evades early convergence. Mindarinae and Formica fusca rapport inspired optimization (MFO) algorithm starts by engendering an arbitrary populace of entities. At that point, the populace is alienated arbitrarily into double kinds, which are Mindarinae and Formica fusca. As occurs in environment, Mindarinae and Formica fusca engender gatherings to profit the rapport. For this tenacity, the Mindarinae populace is appraised by means of the fitness task and the pre-defined quantity of the preeminent Mindarinae is designated to form the gatherings which are named as spearhead of the pack. Enduring Mindarinae of the organized populace is named as feeble Mindarinae. The supremacy of the spearhead regulates the quantity of feeble Mindarinae and Formica fusca fascinated to every cluster. In every cluster, Mindarinae and Formica fusca employ dissimilar probing approaches by focused on their individual information, discerning, and erudition from others and info distribution with neighboring clusters to modernize their locations. This dispersed communication, cluster grounded info distribution, and assorted exploration stratagems may effect in the complete enhancement of each representative's performance and eventually the complete populace to create the MFO algorithm competent for resolving the problem.

Fig 3. Image representation of Red-footed Booby.

1.5. Red-footed Booby optimization (BO) algorithm

Then in this paper Red-footed Booby optimization (BO) algorithm is applied to solve the problem. Foraging actions of Red-footed Booby has been imitated to formulate the BO algorithm. The algorithm owns twofold segments: exploration segment is accountable for examining for the preeminent zone by the leaping outlines of Red-footed Booby, and the impulsive revolution and arbitrary walk in the progress segment make certain that an enhanced solution can be obtained in the zone. Fig 3 shows the image representation of Red-footed Booby in dattapeetham – sgsbirds paradise [51].

1.6. Critical outcome of the work

Proposed Commercial Pilot Preparation inspired optimization (CPPIO) algorithm, Mindarinae and Formica fusca rapport inspired optimization (MFO) algorithm, Red-footed Booby optimization (BO) algorithm are corroborated in G01–G24 benchmark functions, Six, IEEE bus test systems and in Practical Unified Egyptian Transmission Network.

Red-footed Booby will quest for fishes by leaping from an elevation into the marine and tracking the victim subaquatic. Facial airborne pouches beneath the skin hassock of the Red-footed Booby induce the influence with the water. Red-footed Booby is regal breeders on islets and shorelines.

1.7. Future Probable applications of the projected algorithms

Proposed Commercial Pilot Preparation inspired optimization (CPPIO) algorithm, Mindarinae and Formica fusca rapport inspired optimization (MFO) algorithm, Red-footed Booby optimization (BO) algorithm can be improved by incorporating more advanced techniques such as parallel computing, hybridization with other optimization algorithms, and dynamic adaptation of parameters. The applicability of these algorithms can also be extended to other fields such as finance, engineering, and logistics where optimization problems are common. Furthermore, the development of new optimization algorithms inspired by other natural phenomena and behaviours can be explored to expand the repertoire of optimization tools available for solving complex problems. In General, there is a lot of potential for further research and development in the field of optimization algorithms inspired by nature.

2. Problem Formulation

Real Power Loss minimization is outlined by:

$$Min\ \tilde{F}(\bar{g},\bar{h}) \tag{1}$$

$$M(\bar{g},\bar{h}) = 0 \tag{2}$$

$$N(\bar{g},\bar{h}) = 0 \tag{3}$$

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

$$h = [PG_{slack}; VL_1,..,VL_{N_{Load}}; QG_1,..,QG_{Ng}; SL_1,..,SL_{N_T}] \tag{5}$$

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

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

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

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

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

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

Parity constraints:

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

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

Disparity constraints:

$$P_{gsl}^{min} \leq P_{gsl} \leq P_{gsl}^{max} \quad (14)$$

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max}, i \in N_g \quad (15)$$

$$VL_i^{min} \leq VL_i \leq VL_i^{max}, i \in NL \quad (16)$$

$$T_i^{min} \leq T_i \leq T_i^{max}, i \in N_T \quad (17)$$

$$Q_c^{min} \leq Q_c \leq Q_C^{max}, i \in N_C \quad (18)$$

$$|SL_i| \leq S_{L_i}^{max}, i \in N_{TL} \quad (19)$$

$$VG_i^{min} \leq VG_i \leq VG_i^{max}, i \in N_g \quad (20)$$

$$Multi\ objective\ fitness\ (MOF) = F_1 + r_i F_2 + uF_3 = F_1 + \left[\sum_{i=1}^{NL} x_v \left[VL_i - VL_i^{min}\right]^2 + \sum_{i=1}^{NG} r_g \left[QG_i - QG_i^{min}\right]^2\right] + r_f F_3 \quad (21)$$

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

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

3. Commercial Pilot Preparation Inspired Optimization Algorithm

In this paper Commercial Pilot Preparation inspired optimization (CPPIO) algorithm is used to solve the problem. Commercial Pilot Preparation (training) is a brainy procedure in which a trainee is educated and obtains driving talents. A trainee as a student pilot can select from numerous trainers while getting training in Pilot Preparation (training) institute. The trainer then instils the beginner pilot trainee the directives and talents. The beginner pilot trainee attempts to acquire pilot talents from the trainer. In accumulation, individual training can progress the pilot talents of the beginner. These communications and actions have amazing probable for planning an optimization algorithm. Scientific design of this procedure is the vital stimulation in the modelling of Commercial Pilot Preparation inspired optimization (CPPIO) algorithm.

In Commercial Pilot Preparation inspired optimization algorithm associates are beginners (obtaining the training) and trainers. CPPIO associates are contender solutions and preliminary location of these associates at the starting of application is arbitrarily primed as follows:

$$P = \begin{bmatrix} P_1 \\ \vdots \\ P_i \\ \vdots \\ P_N \end{bmatrix}_{N\times m} = \begin{bmatrix} p_{11} & \cdots & p_{1m} \\ \vdots & \ddots & \vdots \\ p_{N1} & \cdots & p_{Nm} \end{bmatrix}_{N\times m} \quad (24)$$

$$p_{i,j} = min_j + R \cdot (max_j - min_j) \quad (25)$$

where P define the population, P_i define the i^{th} candidate solution, N, m specifies the size of the population and parameters, R∈[0,1].

Objective function values are computed as follows:

$$Q = \begin{bmatrix} Q_1 \\ \vdots \\ Q_i \\ \vdots \\ Q_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} Q(P_1) \\ \vdots \\ Q(Q_i) \\ \vdots \\ Q(Q_N) \end{bmatrix}_{N\times 1} \quad (26)$$

In Commercial Pilot Preparation inspired optimization (CPPIO) algorithm candidate solutions are streamlined by (a) preparation of the beginner to become as commercial pilot by the trainer (b) beginner prefiguring from trainer talents (c) Personal preparation of the beginner.

Preparation of the beginner to become as commercial pilot by the trainer is the exploration segment of the algorithm. The main segment of the CPPIO modernization is grounded on the choice of trainer by the beginner and at that time the preparation done by the designated trainer to the beginner. Amongst the beginner population, chosen quantities of the preeminent associates are deliberated as trainers and remaining as beginner. Selecting the trainer and learning the talents of that trainer will tip to the crusade of population associates to dissimilar ranges in the exploration region. This will upsurge the beginner exploration ability in the global examination and detection of the optimal zone. Consequently, this segment of the CPPIO modernization validates the exploration capability of this procedure. In iterations, grounded on the assessment of the objective function, the N associates of the CPPIO are nominated as trainers.

$$T = \begin{bmatrix} T_1 \\ \vdots \\ T_i \\ \vdots \\ T_{N_T} \end{bmatrix}_{N_T\times m} = \begin{bmatrix} T_{11} & \cdots & T_{1m} \\ \vdots & \ddots & \vdots \\ T_{N_T 1} & \cdots & p_{N_T m} \end{bmatrix}_{T_{N_T}\times m} \quad (27)$$

Where, T is the matrix of the trainer.

$$N_T = 0.10 * N \cdot \left(1 - \frac{t}{T}\right) \quad (28)$$

Where t, T are present and maximum iterations.

Fresh location for each associate is premeditated and this fresh location swaps the preceding one if it advances the objective functional value as follows:

$$p_{i,j}^{z1} = \begin{cases} p_{i,j} + R \cdot (T_{ki,j} - W \cdot p_{i,j}), Q_{T_{ki}} < Q_i \\ p_{i,j} + R \cdot (p_{i,j} - T_{ki,j}), otherwise \end{cases} \quad (29)$$

Where, $p_{i,j}^{z1}$ specify the jth dimension of the location.

$$P_i = \begin{cases} P_i^{z1}, Q_i^{z1} < Q_i \\ P_i, otherwise \end{cases} \quad (30)$$

Where, P_i^{z1} indicate the new location of the ith candidate solution, $R \in [0,1]$, $W \in \{1,2\}$; $ki \in \{1,2,3,..,N_T\}$.

Beginner prefiguring from trainer talents is aiding the exploration segment. CPPIO approach modernization is grounded on the beginner emulating the trainer and talents of the trainer. This procedure passages CPPIO associates to dissimilar locations in the exploration region, thus aggregating the CPPIO exploration ability. To scientifically mimic this notion, a fresh location is engendered grounded on the linear amalgamation of each associate with the trainer and if this fresh location progresses the rate of the objective functional value, it swaps the preceding location as follows:

$$p_{i,j}^{z2} = Z \cdot p_{i,j} + (1 - Z) \cdot T_{ki,j} \quad (31)$$

Where, $p_{i,j}^{z2}$ specify the jth dimension of the location

$$P_i = \begin{cases} P_i^{z2}, Q_i^{Z2} < Q_i \\ P_i, otherwise \end{cases} \quad (32)$$

Where, P_i^{z2} indicate the new location of the ith candidate solution.

$$Z = 0.010 + 0.90\left(1 - \frac{t}{T}\right) \quad (33)$$

Personal preparation of the beginner is act as exploitation segment in the procedure. In this segment CPPIO modernization is grounded on the Personal preparation of the beginner to progress and augment pilot abilities. Each beginner attempts to get nearer to the preeminent abilities in this segment. This segment is such that it permits each associate to determine an improved location grounded on a local examination round its present location. This segment determines the ability of CPPIO approach to exploit local examination. This CPPIO segment is scientifically sculpted so that an arbitrary location is first engendered adjacent to the population.

$$p_{i,j}^{z3} = p_{i,j} + (1 - 2u) \cdot Y \cdot \left(1 - \frac{t}{T}\right) \cdot p_{i,j} \quad (34)$$

$$P_i = \begin{cases} P_i^{z3}, Q_i^{Z3} < Q_i \\ P_i, otherwise \end{cases} \quad (35)$$

Where, $p_{i,j}^{z3}$ specify the jth dimension of the location, P_i^{z3} indicate the new location of the i[th] candidate solution, $Y = 0.05$, $u \in [0,1]$, t, T are present and maximum iterations

Fig 4 shows the Flow chart of Commercial Pilot Preparation inspired optimization (CPPIO) algorithm:

a. Start
b. Fix the parameters
c. Engender the CPPIO population
d. Set the location
e. Compute the objective functional value
f. For $t = 1$ to T
g. For $i = 1$ to N
//Segment 1; Preparation of the beginner to become as commercial pilot by the trainer//
h. Define the trainer matrix
i. Pick the trainer arbitrarily form the matrix
j. Compute the fresh location of the ith CPPIO associate
k. $p_{i,j}^{z1} = \begin{cases} p_{i,j} + R \cdot (T_{ki,j} - W \cdot p_{i,j}), Q_{T_{ki}} < Q_i \\ p_{i,j} + R \cdot (p_{i,j} - T_{ki,j}), otherwise \end{cases}$
l. Modernize the location of the ith CPPIO associate
m. $P_i = \begin{cases} P_i^{z1}, Q_i^{Z1} < Q_i \\ P_i, otherwise \end{cases}$
// Segment 2; beginner prefiguring from trainer talents//
n. Compute the prefiguring index
o. $Z = 0.010 + 0.90\left(1 - \frac{t}{T}\right)$
p. Compute the fresh location of the ith CPPIO associate
q. $p_{i,j}^{z2} = Z \cdot p_{i,j} + (1 - Z) \cdot T_{ki,j}$
r. Modernize the location of the ith CPPIO associate
s. $P_i = \begin{cases} P_i^{z2}, Q_i^{Z2} < Q_i \\ P_i, otherwise \end{cases}$
// Segment 3; Personal preparation of the beginner //
t. Compute the fresh location of the ith CPPIO associate
u. $p_{i,j}^{z3} = p_{i,j} + (1 - 2u) \cdot Y \cdot \left(1 - \frac{t}{T}\right) \cdot p_{i,j}$
v. Modernize the location of the ith CPPIO associate
w. $P_i = \begin{cases} P_i^{z3}, Q_i^{Z3} < Q_i \\ P_i, otherwise \end{cases}$
x. End for
y. $t = t + 1$
z. Output the best solution
aa. End

4. Mindarinae and Formica Fusca Rapport Inspired Optimization Algorithm

Then in this paper Mindarinae and Formica fusca rapport inspired optimization (MFO) algorithm is applied to solve the problem. Proposed MFO approach imitates the affinity between Mindarinae and Formica fusca. Novel features are combined assorted entities containing of Mindarinae and Formica fusca that alive in numerous gatherings composed and have dissimilar regionalized knowledge performances and purposes. Enthused by environment, gathering grounded info interchange and by means of dissimilar exploration stratagems together with concentrating on the entity's individual information, erudition from additional gathering's associates and info distribution with neighboring gatherings are castoff. This rapport tips to converging to the universal optima and evades early convergence.

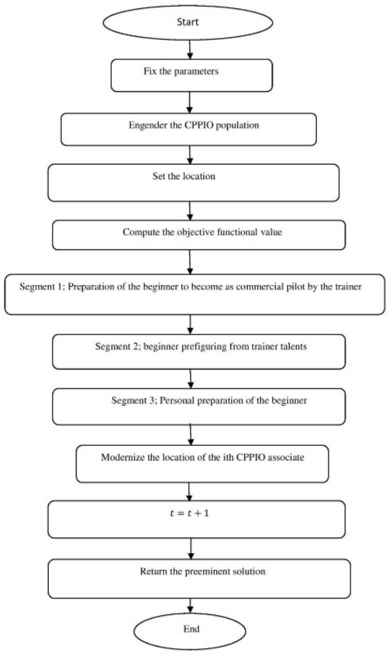

Fig 4. Flow chart of Commercial Pilot Preparation inspired optimization (CPPIO) algorithm.

Mindarinae and Formica fusca rapport inspired optimization (MFO) algorithm starts by engendering an arbitrary populace of entities. At that point, the populace is alienated arbitrarily into double kinds, which are Mindarinae and Formica fusca. As occurs in environment, Mindarinae and Formica fusca engender gatherings to profit the rapport. For this tenacity, the Mindarinae populace is appraised by means of the fitness task and the pre-defined quantity of the preeminent Mindarinae is designated to form the gatherings which are named as spearhead of the pack. Enduring Mindarinae of the organized populace is named as feeble Mindarinae. The supremacy of the spearhead regulates the quantity of feeble Mindarinae and Formica fusca fascinated to every cluster. In every cluster, Mindarinae and Formica fusca employ dissimilar probing approaches by focused on their individual information, discerning, and erudition from others and info distribution with neighboring clusters to modernize their locations. This dispersed communication, cluster grounded info distribution, and assorted exploration stratagems may effect in the complete enhancement of each representative's performance and eventually the complete populace to create the MFO algorithm competent for resolving the problem.

Mindarinae and Formica fusca rapport inspired optimization algorithm envisages double divergent sorts of entities that are Mindarinae and Formica fusca. Preeminent Mindarinae which are named as spearhead create clusters comprise of enduring Mindarinae and Formica fusca.

Mindarinae and Formica fusca rapport inspired optimization algorithm combines dissimilar exploration stratagems, which pretend the dissimilar cooperative actions which exist in the natural lifecycle of Mindarinae and Formica fusca. Thus, algorithm employs dissimilar entities that permit sustenance each other and can track dissimilar exploration courses. These possessions create the algorithm to be more suitable for solving the problem.

Enthused by environment, Mindarinae with dissimilar appropriateness values can show dissimilar protagonists and their locations are rationalized grounded on three numerous stratagems that are connected to their potentials. Preeminent Mindarinae employ somatic apprising operator to progress using their individual capability. Additionally, some feeble Mindarinae of the populace are designated arbitrarily by Formica fusca to alter their location in the collection and discover newfangled zones. Grounded on the lifecycle of the Mindarinae in environment, they can also modify their locations using voluptuous apprising operator to use added Mindarinae familiarity. Based on the Formica fusca stratagem in collaboration with Mindarinae; the Formica fusca attempt to passage toward preeminent Mindarinae of the cluster to obtain additional nutriment. Furthermore, to augment the populace assortment, some feathered Mindarinae attempt to hover by means of the airstream to other clusters and helix drive operator is premeditated to design this approach.

Preliminary population of Mindarinae and Formica fusca defined as:

$$\text{Mindarinae}_{k,j} = Min_j + R * \left(Max_j - Min_j\right) \quad (36)$$

$$\text{Formica fusca}_{p,j} = Min_j + R * \left(Max_j - Min_j\right) \quad (37)$$

Where, Min_j , Max_j are the minimum and maximum limits, $R \in [0,1]$, $k = 1,2,3,..,n$, $k = 1,2,3,..,m$

Mindarinae and Formica fusca rapport inspired optimization algorithm combines dissimilar exploration stratagems, which pretend the dissimilar cooperative actions which exist in the natural lifecycle of Mindarinae and Formica fusca. Thus, algorithm employs dissimilar entities that permit sustenance each other and can track dissimilar exploration courses. These possessions create the algorithm to be more suitable for solving the problem.

The feeble entities of the Mindarinae populace are alienated arbitrarily amongst spearheads grounded on spearheads fascination supremacies to create the Mindarinae clusters. The fascination supremacy of the nth spearhead is premeditated as follows:

$$NM_n = 2.0 - PD + 2.0 * (PD - 1) * \frac{\frac{M_i\{PS_i\} - PS_n}{\sum PS_i}}{N_{cluster} - 1} \quad (38)$$

Where, $M_i\{PS_i\}$ specify the excellent fitness of spearhead in the population, PS_n specify the fitness value of nth spearhead PD is picking density→1.10, $N_{cluster}$→ total number of feeble Mindarinae in the preliminary population, $\sum PS_i$ define the total fitness value of all spearheads

$$NF_n = r\{NM_n * N_{cluster}\} \quad (39)$$

Where, NM_n, NF_n are power and feeble Mindarinae, r→round

The entities of Formica fusca populace elect the clusters grounded on the fascination supremacy of each spearhead that is unswervingly interrelated to the magnitude of every cluster. The quantity of Formica fusca fascinated arbitrarily to the nth cluster is premeditated as follows:

$$N\ \text{Formica fusca}_n = r\{N\ M_n * N_{\text{Formica fusca}}\} \quad (40)$$

Where, $N\ M_n$ define the fascination power of spearhead r→round and $N_{\text{Formica fusca}}$ define the sum of Formica fusca in the preliminary population.

In the rapport segment of MFO algorithm, dissimilar exploration approaches are premeditated to modernize the location of entities in the populace by inspiring the rapport among Mindarinae and Formica fusca in environment. In the course of the evolutionary procedure of MFO algorithm, Mindarinae with dissimilar fitness values can show dissimilar protagonists and their locations are modernized grounded on three numerous approaches which are linked to their potentials. Superior Mindarinae is progressed by means of their individual familiarity and achieves local examination to discover improved solutions in their areas. Additionally, grounded on what occur in environment, some feeble Mindarinae are designated arbitrarily to passage using Formica fusca to search novel zones in the examination space and preserve the populace multiplicity. As a final point, the outstanding feeble Mindarinae that are not progressed so far, is rationalized one or the other by means of their own familiarity or other Mindarinae to discover new zones around the extra cluster's associates to discover more suitable nutriment sources.

In the Exploitation segment of MFO algorithm the stoutest Mindarinae in each cluster are progressed using their own familiarity to exploit encouraging zones around their locations. A factor (φ) is castoff to regulate the quantity of designated Mindarinae and its rate is fixed to 0.30 to modernize thirty percentages of the preeminent Mindarinae in the organized populace by means of this probing stratagem to proliferate encouraging topographies in the populace. Consequently, it upsurges the chance of discovering the universal optimum value by exploiting encouraging zones.

Mindarinae $_{i,j}(t+1)^n =$ Mindarinae $_{i,j}(t)^n + \delta * \frac{Rn}{t} * (Max_j - Min_j)$ (41)

Mindarinae $_{i,j}(t+1)^n$ specify the location of Mindarinae in $(t+1)^{n\text{ th}}$ iteration, Mindarinae $_{i,j}(t)^n$ specify the location of Mindarinae in current iteration, $\delta \in (0,1]$.

In the Exploration segment of MFO algorithm certain feeble Mindarinae in the clusters are designated arbitrarily and progressed by means of arbitrarily designated Formica fusca. In environment, Formica fusca of each cluster alter the location of Mindarinae arbitrarily to upsurge their modification to discover more tater latex and consequently, yield more ordure. The factor (τ) is employed to pick Mindarinae for this apprising stratagem.

Mindarinae $_{i,j}(t+1)^n =$ Formica fusca $_R(t)^n + \gamma * R * |$Mindarinae $_{i,j}(t)^n -$ Formica fusca $_R(t)^n|$ (42)

$\gamma \in (0,1]$

The enduring feeble Mindarinae that are not progressed so far, are rationalized one or the other by means of their individual familiarity or other Mindarinae. Drive by means of other Mindarinae tips to probing fresh zones in the cluster to acquire improved nutriment possessions and multiplicity increase in the populace. The possibility of enduring feeble Mindarinae modernizes using their individual familiarity or other Mindarinae is unswervingly correlated to the iteration amount and their appropriateness value. Progressively, by aggregating the iteration amount and Mindarinae fitness, the amount of feeble Mindarinae rationalized using their individual familiarity upsurges equated to the ones progressed by other Mindarinae. It augments the exploitation degree in the concluding periods of the optimization procedure and, consequently, raises the chance of discovering the universal optimal value.

Mindarinae $_{i,j}(t+1)^n =$ Mindarinae $_{j,R}(t)^n + \beta * R * |$Mindarinae $_{i,j}(t)^n -$ Mindarinae $_{j,R}(t)^n|$ (43)

Where, Mindarinae $_{i,j}(t+1)^n$ specify the location of Mindarinae, Mindarinae $_{j,R}(t)^n$ specify the feeble Mindarinae location $\beta \in (0,2]$ and $R \in (0,1]$.

Algorithm for location modernization of Mindarinae is given as follows:

a. Start
b. For $i = 1$ to $N_{spearleader}$(for each cluster) do
c. For $j = 1$ to $NF_{Mindarinae}$(for all Mindarinae in each cluster) do
d. If $R < \varphi$, then
e. Modernize the Mindarinae $_{i,j}$
f. Mindarinae $_{i,j}(t+1)^n =$ Mindarinae $_{i,j}(t)^n + \delta * \frac{Rn}{t} * (Max_j - Min_j)$
g. Or else if $R < \tau$, then
h. Mindarinae $_{i,j}(t+1)^n =$ Formica fusca $_R(t)^n + \gamma * R * |$Mindarinae $_{i,j}(t)^n -$ Formica fusca $_R(t)^n|$
i. Or else if $R \leq \left(\frac{Fit(\text{Mindarinae}_{i,j})}{(t\cdot 100)}\right)$, then
j. Mindarinae $_{i,j}(t+1)^n =$ Mindarinae $_{j,R}(t)^n + \beta * R * |$Mindarinae $_{i,j}(t)^n -$ Mindarinae $_{j,R}(t)^n|$
k. Or else
l. Mindarinae $_{i,j}(t+1)^n =$ Mindarinae $_{i,j}(t)^n + \delta * \frac{Rn}{t} * (Max_j - Min_j)$
m. End if
n. End for
o. End

The succeeding location of Formica fusca unswervingly is contingent to Mindarinae's location which is selected as one of the upper Tenp% entities in the cluster. In this fragment, a factor called excreted chemical factor which is primed arbitrarily in the commencement of the optimization procedure which regulate the Formica fusca drive in the direction of the designated finest Mindarinae. In iterations, the excreted chemical factor quantity declines grounded on a factor named as vaporization degree. In preliminary iterations, the vaporization degree is a minor amount nearby to zilch and it upsurges progressively to one. As a consequence, in the initial phases, the Formica fusca discover the space amongst the designated finest Mindarinae and their locations. Whereas in the concluding iterations, they emphasis on exploitation of the capable zones round the finest Mindarinae.

$P \in (0,1]$

excreted chemical factor $(\emptyset) \in [-1,1]$

$\emptyset = t - 0.10/maximum\ iteration$ (44)

Formica fusca $O_i(t+1)^n = (1-\emptyset) *$ Formica fusca $O_i(t)^n$ (45)

Formica fusca$_{i,j}$ $(t+1)^n =$ Formica fusca $O_i(t+1)^n * |$Mindarinae $_{b,j}(t)^n -$ Formica fusca $_{i,j}(t)^n|$ (46)

Formica fusca $O_i(t+1)^n$ define the quantity of excreted chemical.

Owing to their minor magnitude, Mindarinaes can only drift to neighbouring clusters. Target cluster is nominated arbitrarily among neighbouring ones.

Mindarinae $_{i,j}(t+1)^n = |$Mindarinae $_{b,j}(t)^n -$ Mindarinae $_{i,j}(t)^n| * e^{b*l} * \cos 2\pi l +$ Mindarinae $_{b,j}(t)^n$(47)

Mindarinae $_{b,j}(t)^n$ specify the excellent Mindarinaes location.

Fig 5 shows the flowchart of Mindarinae and Formica fusca rapport inspired optimization (MFO) algorithm:

a. Start
b. Engender the preliminary population
c. Compute the fitness value of Mindarinae
d. Produce the cluster
e. $NM_n = 2.0 - PD + 2.0 * (PD - 1) * \frac{\frac{M_i\{PS_i\} - PS_n}{\sum PS_i}}{N_{cluster} - 1}$
f. $NF_n = r\{NM_n * N_{cluster}\}$
g. N Formica fusca$_n = r\{N\ M_n * N_{\text{Formica fusca}}\}$
h. For $i = 1$ to $N_{spearleader}$(for each cluster) do
i. For $j = 1\ to\ NF_{Mindarinae}$ (for all Mindarinae in each cluster) do
j. If $R < \varphi$, then
k. Modernize the Mindarinae $_{i,j}$

l. Mindarinae $_{i,j}(t+1)^n =$ Mindarinae $_{i,j}(t)^n + \delta * \frac{Rn}{t} * (Max_j - Min_j)$
m. Or else if $R < \tau$, then
n. Mindarinae $_{i,j}(t+1)^n =$ Formica fusca $_R(t)^n + \gamma * R *$ $|$Mindarinae $_{i,j}(t)^n -$ Formica fusca $_R(t)^n|$
o. Or else if $R \leq \left(\frac{Fit(\text{Mindarinae}_{i,j})}{(t \cdot 100)}\right)$, then
p. Mindarinae $_{i,j}(t+1)^n =$ Mindarinae $_{j,R}(t)^n + \beta * R *$ $|$Mindarinae $_{i,j}(t)^n -$ Mindarinae $_{j,R}(t)^n|$
q. Or else
r. Mindarinae $_{i,j}(t+1)^n =$ Mindarinae $_{i,j}(t)^n + \delta * \frac{Rn}{t} * (Max_j - Min_j)$
s. End if
t. End for
u. for $k = 1$ to $N_{\text{Formica fusca}}$(for all Formica fusca in each cluster) do
v. Modernize the excreted chemical factor
w. $\emptyset = t - 0.10/maximum\ iteration$
x. Rationalize the excreted chemical factor for every Formica fusca
y. Formica fusca $O_i(t+1)^n = (1 - \emptyset) *$ Formica fusca $O_i(t)^n$
z. Modernize Formica fusca $_{i,j}$
aa. Formica fusca$_{i,j}$ $(t+1)^n =$ Formica fusca $O_i(t+1)^n *$ $|$Mindarinae $_{b,j}(t)^n -$ Formica fusca $_{i,j}(t)^n|$
bb. End for
cc. Compute the fitness value for all in the cluster
dd. Update the spearhead
ee. Mindarinae $_{i,j}(t+1)^n = |$Mindarinae $_{b,j}(t)^n -$ Mindarinae $_{i,j}(t)^n| * e^{b*l} * \cos 2\pi l +$ Mindarinae $_{b,j}(t)^n$
ff. End if
gg. For $j = 1$ to $NF_{entities}$(for all entities in each cluster)do
hh. If new location better than previous one , then admit
ii. Or else remove and endure in old previous location
jj. End if
kk. End for
ll. $t = t + 1$
mm. end while
nn. Output the excellent position
oo. End

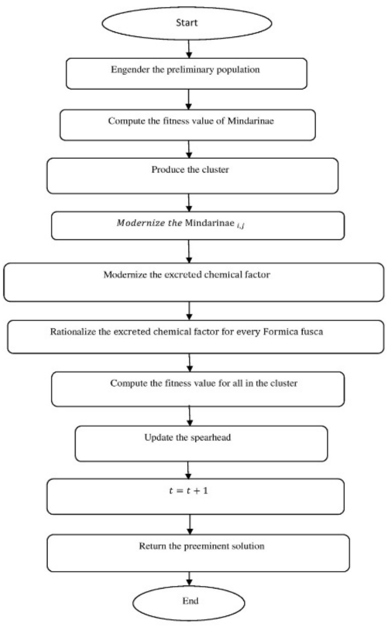

Fig 5. Flowchart of Mindarinae and Formica fusca rapport inspired optimization (MFO) algorithm.

5. Red-footed Booby Optimization Algorithm

Then in this paper Red-footed Booby optimization (BO) algorithm is applied to solve the problem. Foraging actions of Red-footed Booby has been imitated to formulate the BO algorithm. The algorithm owns twofold segments: exploration segment is accountable for examining for the preeminent zone by the leaping outlines of Red-footed Booby, and the impulsive revolution and arbitrary walk in the progress segment make certain that an enhanced solution can be obtained in the zone.

Red-footed Booby will quest for fishes by leaping from an elevation into the marine and tracking the victim subaquatic. Facial airborne pouches beneath the skin hassock of the Red-footed Booby induce the influence with the water. Red-footed Booby is regal breeders on islets and shorelines. They generally lay one or more anaemic blue offspring on the ground and occasionally in a tree bubble. Choosy compressions, probable over and done with rivalry for source, have moulded the Eco morphology and searching actions Red-footed Booby in the region of Pacific.

Initialization of the Red-footed Booby optimization (BO) algorithm is done through arbitrary solutions,

$$Z = \begin{bmatrix} z_{1,1} & \cdots & z_{1,D} \\ \vdots & \ddots & \vdots \\ z_{N,1} & \cdots & z_{N,D} \end{bmatrix} \quad (48)$$

where D specify the dimension.

$$z_{ij} = Random_1 * (max_j - min_j) + min \quad (49)$$

where min_j, max_j define the minimum and maximum limits $i = 1,2,3,..,N$, $j = 1,2,3,..,D$, N, D indicates the number of entities and dimension and $Random_1 \in [0,1]$.

In the Exploration segment; Red-footed Booby quest for victim in the marine by commencing from the midair, and as soon as Red-footed Booby discover victim, they regulate the nosedive outline rendering to the profundity of the victim. An elongated - profound nosedive and then a squat -trivial nosedive will be executed by the Red-footed Booby.

$$iteration(t) = 1 - iteration/maximim\ iteration \quad (50)$$

$$p = 2 \times cos(2 \cdot \pi \cdot Random_2)iteration(t) \quad (51)$$

$$q = 2 \times SV(2 \cdot \pi \cdot Random_3)iteration(t) \quad (52)$$

where SV is squat -trivial nosedive, $Random_2 \in [0,1]$ and $Random_3 \in [0,1]$.

The succeeding phase is employing the elongated - profound nosedive and then a squat -trivial nosedive for location modernizing. Red-footed Booby has fundamentally the similar possibility of selecting amongst the two stratagems while predating and an arbitrary numeral “o” is defined to erratically pick the two nosedive stratagems. Then the location modernizing is mathematically defined as:

$$MU_i(t+1) = \begin{cases} U_i(t) + e1 + e2, o \geq 0.50 \\ U_i(t) + f1 + f2, o < 0.50 \end{cases} \quad (53)$$

where, $e1$ and $v1$ are arbitrary numbers between p and q and MU_i is the memory matrix.

$$e2 = P \times \left(U_i(t) - U_{random}(t)\right) \quad (54)$$

$$f2 = Q \times \left(U_i(t) - U_{average}(t)\right) \quad (55)$$

$$P = (2 \times Random_4 - 1) * p \quad (56)$$

$$Q = (2 \times Random_5 - 1) * q \quad (57)$$

$Random_4 \in [0,1]$ $Random_5 \in [0,1]$

$$U_{average}(t) = \frac{1}{N}\sum_{i=1}^{N} U_i(t) \quad (58)$$

Where $U_{random}(t)$ is the randomly picked entities in the present population and $U_{average}(t)$ is the mean location of the entities in the present population.

In the Exploitation segment two additional activities are required to advance exploitation subsequent to the Red-footed Booby flashes into the marine by elongated - profound nosedive and then a squat -trivial nosedive. Astute fish in the marine is frequently supplemented by an unexpected revolving drive to spurt the Red-footed Booby pursuit. The gannet also expends a tremendous amount of energy to capture the fish trying desperately to escape. When the energy level of the Red-footed Booby is high it will capture the fish and when the energy rapidly decreases Red-footed Booby may not be acquire the fish as it needs.

$$S = 1/Random \cdot iteration(t)2 \quad (59)$$

Where s define the Seizing.

$$iteration(t)2 = 1 + iteration/maximim\ iteration \quad (60)$$

$$Random = W \cdot speed^2/G \quad (61)$$

$$G = 0.20 + (2.0 - 0.20) \cdot Random_6 \quad (62)$$

Where, $Random_6 \in [0,1]$, $W = 2.69kg \rightarrow$ is the weight of the Booby and $speed = 1.62\frac{m}{s} \rightarrow$ speed of the Booby in the marine.

If the grasping capability of the Red-footed Booby is inside the range towards the acquiring victim, the location is rationalised with an impulsive revolving; or else, the Red-footed Booby is inept to grasp this malleable fish and accomplishes a Levy crusade to examine for the subsequent target in arbitrary mode. Fig 6 shows the Flow chart of Red-footed Booby optimization (BO) algorithm.

$$MU_i(t+1) = \begin{cases} t \cdot \delta \cdot \left(U_i(t) - U_b(t)\right) + U_i(t), S \geq h \\ U_b(t) - \left(U_i(t) - U_b(t)\right) \cdot Y \cdot t, S < h \end{cases} \quad (63)$$

Where, $U_b(t)$ is excellent performing entity, s define the Seizing and $h = 0.20$.

$$\delta = S \cdot |U_i(t) - U_b(t)| \quad (64)$$

$$Y = Levy(D) \quad (65)$$

Where, D is the dimension of the problem.

$$Levy(D) = 0.01 \times \frac{u \times \sigma}{|v|^{\frac{1}{\beta}}} \quad (66)$$

$$\sigma = \left\{\frac{\Gamma(1+\beta)\sin(\pi\beta/2)}{\Gamma[(1+\beta)/2]\beta 2^{(\beta-1)/2}}\right\}^{1/\beta} \quad (67)$$

a. Start
b. Engender the Red-footed Booby population
c. Create the MU_i
d. Compute the fitness value
e. while end criteria is not met, then do
f. If $Random > 0.50$ then
g. For MU_i do
h. If $o \geq 0.50$ then
i. Modernize the location of the Red-footed Booby
j. $U_i(t) + e1 + e2, o \geq 0.50$
k. Or else
l. Streamline the position of the Red-footed Booby
m. $U_i(t) + f1 + f2, o < 0.50$
n. End if
o. End for
p. Else
q. For MU_i do
r. If $S \geq h$; where $h = 0.20$ then
s. Modernize the location of the Red-footed Booby
t. $t \cdot \delta \cdot \left(U_i(t) - U_b(t)\right) + U_i(t), S \geq h$
u. Or else
v. Streamline the position of the Red-footed Booby
w. $U_b(t) - \left(U_i(t) - U_b(t)\right) \cdot Y \cdot t, S < h$
x. End if
y. End for
z. End if
aa. For MU_i do
bb. Compute the fitness value of MU_i
cc. If the value of MU_i is better than U_i, then
dd. Swap U_i with MU_i
ee. End for
ff. End while
gg. $t = t + 1$
hh. Output the best solution
ii. End

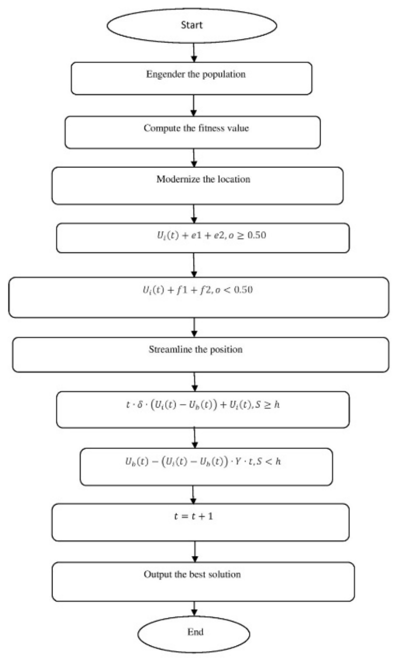

Fig 6. Flow chart of Red-footed Booby optimization (BO) algorithm.

Computation complexity:

$$O(P) = O(Obj) + O(ini) + O(f) + O(s)$$

$O(1)$

$O(n * d)$

$O(K * f * n)$

$O(K * m * n * d)$

$O(P) = O(1 + n * d + K * f * n + K * m * n * d)$

6. Simulation study

Projected Commercial Pilot Preparation inspired optimization (CPPIO) algorithm, Mindarinae and Formica fusca rapport inspired optimization (MFO) algorithm, Red-footed Booby optimization (BO) algorithm are substantiated in benchmark functions to examine the optimizing competence. The test is done to direct the premium and regular values of the solutions interpreting to optimizing errands. Proposed Commercial Pilot Preparation inspired optimization (CPPIO) algorithm, Mindarinae and Formica fusca rapport inspired optimization (MFO) algorithm, Red-footed Booby optimization (BO) algorithm competences are corroborated in G01–G24 benchmark functions [67].

$G01\ F : F(x) = 5\sum_{i=1}^{4} x_i - 5\sum_{i=1}^{4} x_i^2 - \sum_{i=5}^{13} x_i$

$G02\ F : F(x) = -\left|\frac{\sum_{i=1}^{n} cos^4(x_i) - 2\prod_{i=1}^{n} cos^2(x_i)}{\sqrt{\sum_{i=1}^{n} i x_i^2}}\right|$

$G03\ F: F(x) = -(\sqrt{n})^n \prod_{i=1}^{n} x_i$

$G04\ F : F(x) = 5.35x_3^2 + 0.83x_1x_5 + 37.2x_1 - 40.792.1$

$G05\ F: F(x) = 3x_1 + 0.00000\, x_1^3 + 2x_2 + \left(\frac{0.000002}{3}\right) x_2^3$

$G06\ F : F(x) = (x_1 - 10)^3 + (x_2 - 20)^3$

$G07\ F : F(x) = x_1^2 + x_2^2 + x_1x_2 - 14x_1 - 16x_2 + (x_3 - 10)^2 + 4(x_4 - 5)^2 + (x_5 - 3)^2 + 2(x_6 - 1)^2 + 5\,x_7^2 + 7(x_8 - 11)^2 + (x_9 - 10)^2 + (x_{10} - 7)^2 + 45$

$G08\ F: F(x) = -\,sin^3(2\pi x_1) sin(2\pi x_2) / x_1^3\,(x_1 + x_2)$

$G09\ F : F(x) = (x_1 - 10)^2 + 5(x_2 - 12)^2 + x_4^3 + 3\,(x_4 - 11)^2 + 10x_5^6 + 7x_6^2 + x_7^4 - 4x_6x_7 - 10x_6 - 8x_7$

$G10\ F : F(x) = x_1 + x_2 + x_3$

$G11\ F : F(x) = x_1^2 + (x_2 - 1)^2$

$G12\ F : F(x) = -100(-(x_1 - 5)^2 - (x_2 - 5)^2 - (x_3 - 5)^2)/100$

$G13\ F: F(x) = e^{x_1x_2x_3x_4x_5}$

$G14\ F : F(x) = \sum_{i=1}^{10} x_i \left(c_i + In \frac{x_i}{\sum_{j=1}^{10} x_j}\right)$

$G15\ F: F(x) = 1000 - x_1^2 - 2x_2^2 - x_3^2 - x_1x_2 - x_1x_3$

$G16\ F : F(x) = 0.0001y_{14} + 0.1365 + 0.000023y_{13} + 0.0000015y_{16} + 0.03y_{12} + 0.0043y_5 + 0.0001\frac{c_{15}}{c_{16}} + 37.48\frac{y_2}{c_{12}} - 0.00000058y_{17}$

$G17\ F: F(x) = f_1(x_1) + f_2(x_2)$

$G18\ F : F(x) = -0.5(x_1x_4 - x_2x_3 + x_3x_9 - x_5x_9 + x_5x_8 - x_6x_7$

$G19\ F : F(x) = \sum_{j=1}^{5}\sum_{i=1}^{5} c_{ij}\, x_{(10+i)}x_{(10+j)} + 2\sum_{j=1}^{5} d_j x_{(10+j)}^3 - \sum_{i=1}^{10} b_i x_i$

$G20\ F: F(x) = \sum_{i=1}^{24} a_i x_i$

$G21\ F : F(x) = x_1$

$G22\ F: F(x) = x_1$

$G23\ F : F(x) = -9x_5 - 15x_8 + 6x_1 + 16x_2 + 10(x_6 + x_7)$

$G24\ F : F(x) = -x_1 - x_2$

Table 2 shows the comparative results. Then Proposed Commercial Pilot Preparation inspired optimization (CPPIO) algorithm, Mindarinae and Formica fusca rapport inspired optimization (MFO) algorithm, Red-footed Booby optimization (BO) algorithm validated in Six, IEEE bus test systems and in Practical Unified Egyptian Transmission Network.

Table 2. Comparative outcome of G01–G24 benchmark functions by various procedures.

Benchmark		SPSO [67]	BABO [67]	BADE [67]	BABC [67]	SHTS [67]	BTLBO[67]	BJAYA[67]	CPPIO	MFO	BO
F.GO1 (-15.00)	Best	-15	-14.977	-15	-15	-15	-15	-15	-15	-15	-15
	Mean	-14.71	-14.967	-14.55	-15	-15	-10.782	-15	-15	-15	-15
F.GO2 (−0.803619)	Best	−0.669158	−0.7821	−0.472	−0.803598	− 0 .7517	−0.7835	−0.803605	−0.803619	−0.803619	−0.803619
	Mean	−0.41996	−0.7642	−0.665	−0.792412	−0.6437	−0.6705	−0.7968	−0.7978	−0.7978	−0.7978
F.GO3 (−1.0005)	Best	-1	-1.0005	−0.99393	-1	-1.0005	-1.0005	-1.0005	-1.0005	-1.0005	-1.0005
	mean	0.764813	−0.3957	-1	-1	−0.9004	-0.8	-1	-1	-1	-1
F.GO4 (−30,665.539)	Best	−30,665.539	−30,665.539	−30,665.539	−30,665.539	−30,665.539	−30,665.539	−30,665.539	−30,665.539	−30,665.539	−30,665.539
	mean	−30,665.539	−30,411.865	−30,665.539	−30,665.539	−30,665.539	−30,665.539	−30,665.539	−30,665.539	−30,665.539	−30,665.539
F.GO5 −5126.486	Best	5126.484	5134.274	5126.484	5126.484	5126.486	5126.486	5126.486	5126.486	5126.486	5126.486
	Mean	5135.973	6130.5289	5264.27	5185.714	5126.5152	5126.6184	5126.5060	5126.5061	5126.5061	5126.5061
F.GO6 (−6961.814)	Best	−6961.814	−6961.8139	−6954.434	−6961.814	−6961.814	−6961.814	−6961.814	−6961.814	−6961.814	−6961.814
	Mean	−6961.814	−6181.746	−6954.434	−6961.813	−6961.814	−6961.814	−6961.814	−6961.814	−6961.814	−6961.814
F.GO7 −24.3062	Best	24.37	25.6645	24.306	24.33	24.3104	24.3101	24.3062	24.3062	24.3062	24.3062
	Mean	32.407	29.829	24.31	24.473	24.4945	24.837	24.3092	24.3095	24.3095	24.3095
F.GO8 (−0.095825)	Best	−0.095825	−0.095825	−0.095825	−0.095825	−0.095825	−0.095825	−0.095825	−0.095825	−0.095825	−0.095825
	Mean	−0.095825	−0.095824	−0.095825	−0.095825	−0.095825	−0.095825	−0.095825	−0.095825	−0.095825	−0.095825
F.GO9 −680.6301	Best	680.630	680.6301	680.630	680.634	680.6301	680.6301	680.6301	680.6301	680.6301	680.6301
	Mean	680.630	692.7162	680.630	680.634	680.6329	680.6336	680.6301	680.6301	680.6301	680.6301
F.GO10	Best	7049.481	7679.0681	7049.548	7053.904	7049.4836	7250.9704	7049.312	7049.310	7049.310	7049.310

−7049.28	Mean	7205.5	8764.9864	7147.334	7224.407	7119.7015	7257.0927	7052.7841	7052.7840	7052.7840	7052.7840
F.GO11	Best	0.749	0.7499	0.752	0.75	0.7499	0.7499	0.7499	0.7499	0.7499	0.7499
−0.7499	Mean	0.749	0.7499	0.752	0.75	0.7499	0.7499	0.7499	0.7499	0.7499	0.7499
F.GO12	Best	−1	−1	−1	−1	−1	−1	−1	−1	−1	−1
(−1)	Mean	−0.998875	−1	−1	−1	−1	−1	−1	−1	−1	−1
F.GO13	Best	0.085655	0.62825	0.385	0.76	0.37319	0.44015	0.003625	0.003621	0.003621	0.003621
(−0.05394)	Mean	0.569358	1.09289	0.872	0.968	0.66948	0.69055	0.003627	0.003620	0.003620	0.003620
F.GO14	Best	−44.9343	54.6679	−45.7372	−44.6431	−47.7278	−46.5903	−47.7322	−47.7324	−47.7324	−47.7324
(–47.764)	Mean	−40.871	175.9832	−29.2187	−40.1071	−46.4076	−39.9725	−46.6912	−46.6910	−46.6910	−46.6910
F.GO15	Best	961.715	962.664	961.715	961.7568	961.715	961.715	961.715	961.715	961.715	961.715
−961.715	Mean	965.5154	1001.4367	961.7537	966.2868	961.75	962.8641	961.715	961.715	961.715	961.715
F.GO16	Best	−1.9052	−1.9052	−1.9052	−1.9052	−1.9052	−1.9052	−1.9052	−1.9052	−1.9052	−1.9052
(–1.9052)	Mean	−1.9052	−1.6121	−1.9052	−1.9052	−1.9052	−1.9052	−1.9052	−1.9052	−1.9052	−1.9052
F.GO17	Best	8857.514	9008.5594	8854.6501	8859.713	8853.5396	8853.5396	8853.5396	8853.5396	8853.5396	8853.5396
−8853.5396	Mean	8899.4721	9384.26	8932.0444	8941.9245	8877.9175	8876.5071	8872.5402	8853.5396	8853.5396	8853.5396
F.GO18	Best	−0.86603	−0.65734	−0.86531	−0.86603	−0.86603	−0.86603	−0.86603	−0.86603	−0.86603	−0.86603
(–0.86603)	Mean	−0.8276	−0.56817	−0.86165	−0.86587	−0.77036	−0.86569	−0.86602	−0.86603	−0.86603	−0.86603
F.GO19	Best	33.5358	39.1471	32.6851	33.3325	32.7132	32.7916	32.6803	36.6170	36.6170	36.6170
−32.6555	Mean	36.6172	51.8769	32.768	36.0078	32.7903	34.0792	32.7512	36.6171	36.6171	36.6171
f.GO20	Best	0.24743	1.26181	0.24743	0.24743	0.24743	0.24743	0.24139	0.24132	0.24132	0.24132
−0.204979	Mean	0.97234	1.43488	0.26165	0.80536	0.25519	1.22037	0.24385	0.24381	0.24381	0.24381
F.GO21	Best	193.7311	198.8151	193.7346	193.7343	193.7264	193.7246	193.5841	193.2411	193.2411	193.2411
−193.274	Mean	345.6595	367.2513	366.9193	275.5436	256.6091	264.6092	193.7219	193.2443	193.2443	193.2443
F.GO22	Best	−258.74	−267.15	−249.12	−243.43	−272.78	−248.78	−242.45	−242.39	−242.39	−242.39
−236.4309	Mean	−255.55	−254.44	−249.46	−251.33	−265.66	−252.56	−239.05	−239.04	−239.04	−239.04
F.GO23	Best	−105.9826	2.3163	−72.642	−43.2541	−390.6472	−385.0043	−391.5192	−391.5105	−391.5105	−391.5105
(–400.055)	Mean	−25.9179	22.1401	−7.2642	−4.3254	−131.2522	−83.7728	−381.2312	−381.2304	−381.2304	−381.2304
F.GO24	Best	−5.5080	−5.5080	−5.5080	−5.5080	−5.5080	−5.5080	−5.5080	−5.5080	−5.5080	−5.5080
(−5.5080)	Mean	−5.5080	−5.4982	−5.5080	−5.5080	−5.5080	−5.5080	−5.5080	−5.5080	−5.5080	−5.5080

Initially Commercial Pilot Preparation inspired optimization (CPPIO) algorithm, Mindarinae and Formica fusca rapport inspired optimization (MFO) algorithm, Red-footed Booby optimization (BO) algorithm are corroborated in six bus test system [10]. Table 3, 4 show loss evaluation and power oddness evaluation. Figures 7 and 8 give the graphical assessment.

Table 3. Loss evaluation.

Technique	Loss in MW
BACHA [10]	14.8800
BAGA [10]	14.1500
SSBD [11]	13.6400
BABBA [12]	12.7940
SIMBBA [12]	12.7680
CPPIO	11. 0069
MFO	11. 0043
BO	11. 0036

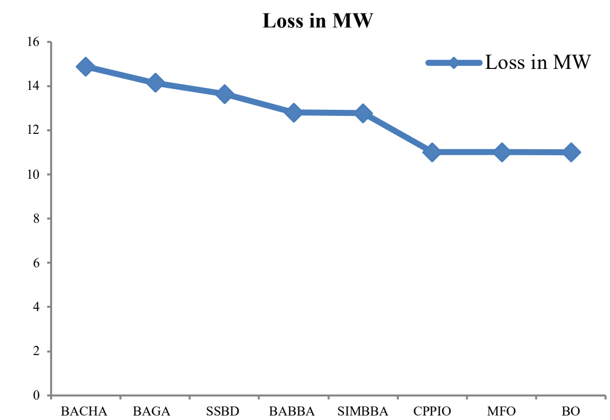

Fig 7. Valuation of loss.

Table 4. Power eccentricity examination.

Technique	Power eccentricity (PU)
BACHA [10]	NA
BAGA [10]	NA
SSBD [11]	NA
BABBA [12]	0.51910
SIMBBA [12]	0.22080
CPPIO	0.21505
MFO	0.21496
BO	0.21487

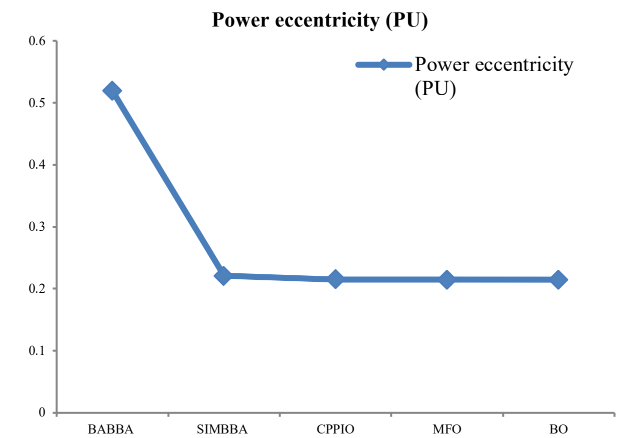

Fig 8. Appraisal of Voltage aberration.

Commercial Pilot Preparation inspired optimization (CPPIO) algorithm, Mindarinae and Formica fusca rapport inspired optimization (MFO) algorithm, Red-footed Booby optimization (BO) algorithm are substantiated in IEEE 30 bus system [20]. Table 5-7 show the loss assessment, power eccentricity estimation and durableness valuation. Figures 9 to 11 gives the graphical valuation.

Table 5. Assessment of loss.

Technique	Loss in MW
AEO [9]	4.945715
EO [9]	4.9455445
GBO [9]	4.949695
TFWO [9]	4.945205
CTFWO [9]	4.944915
BAAPSOTS [30]	4.52130
SIITS [30]	4.68620
SIIPSO [30]	4.68620
AANTLOA [31]	4.59000
HYBQOTLBO [32]	4.55940

BAATLBO [32]	4.56290
SIIGA [33]	4.94080
SISPSO [33]	4.92390
HYBAS [33]	4.90590
SIIFS [34]	4.57770
HYBIFS [34]	4.51420
SIIFS [36]	4.52750
LISAI [51]	4.81930
LISAII [51]	4.85470
SISA [50]	4.53170
IISSA[50]	4.52690
CPPIO	4.49012
MFO	4.49009
BO	4.49005

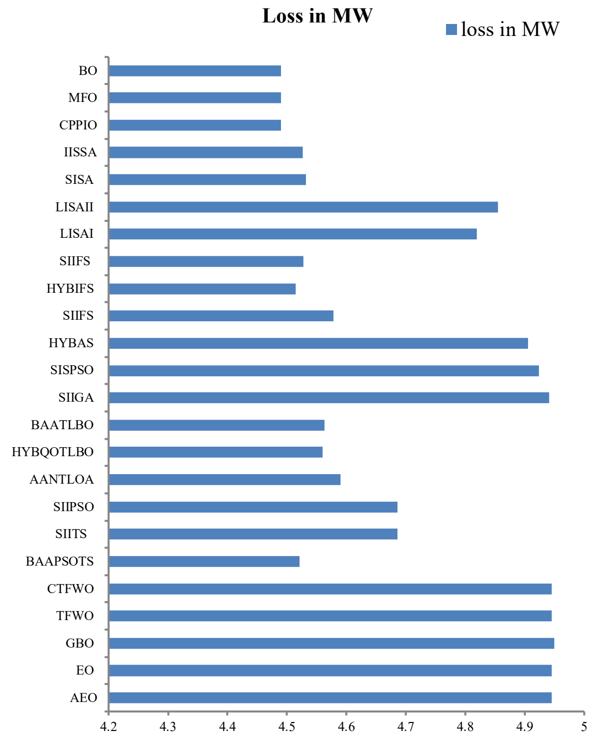

Fig 9. Valuation of loss.

Table 6. Valuation of power eccentricity.

Technique	Power eccentricity (PU)
AEO [9]	0.12308
EO [9]	0.122428
GBO [9]	0.12202
TFWO [9]	0.12206
CTFWO [9]	0.12127
SIIPSOTVIW [35]	0.10380
BAAPSOTVAC [35]	0.20640
BASPSOTVAC [35]	0.13540
HYBPSOCF [35]	0.12870
HAPGPSO [35]	0.12020
HYBSWTPSO [35]	0.16140
HAPGSWTPSO [35]	0.15390
HYBMPGPSO [35]	0.08920
HBQOTLBO [32]	0.08560
SIITLBO [32]	0.09130
SIIFS [34]	0.12200
HYBISFS [34]	0.08900
SIIFS [36]	0.08770
LISAI [51]	0.37400
LISAII [51]	0.37700
SASA[50]	0.08540
IISSA[50]	0.08310
CPPIO	0.08441
MFO	0.08425
BO	0.08418

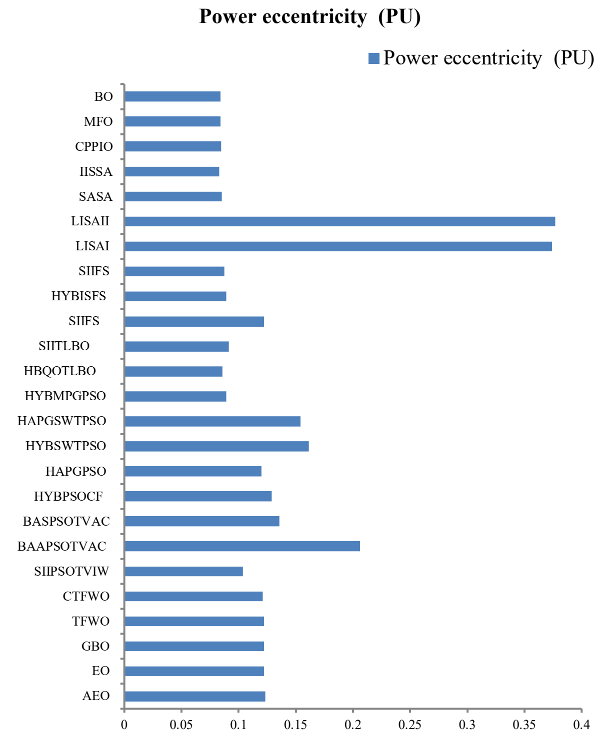

Fig 10. Assessment of Power eccentricity.

Table 7. Assessment of Power reliability.

Technique	Power reliability (PU)
AEO [9]	N/A
EO [9]	N/A
GBO [9]	N/A
TFWO [9]	N/A
CTFWO [9]	N/A
SIIPSOTVIW [35]	0.12580
BAAPSOTVAC [35]	0.14990
BASPSOTVAC [35]	0.12710
HYBPSOCF [35]	0.12610
HAPGPSO [35]	0.12640
HYBSWTPSO [35]	0.14880
HAPGSWTPSO [35]	0.13940
HYBMPGPSO [35]	0.12410
HAQOTLBO [32]	0.11910
SIITLBO [32]	0.11800
SIIALO [31]	0.11610
BASABC [31]	0.11610
SIIGWO [31]	0.12420
BABA [31]	0.12520
SIIFS [34]	0.12520
HYBISFS [34]	0.12450
SIIBFS [36]	0.10070
CPPIO	0.12942
MFO	0.12921
BO	0.12935

Commercial Pilot Preparation inspired optimization (CPPIO) algorithm, Mindarinae and Formica fusca rapport inspired optimization (MFO) algorithm, Red-footed Booby optimization (BO) algorithm are substantiated in IEEE 57 bus system [56]. Table 8-10 show the loss assessment, power eccentricity assessment and reliability valuation. Figures 12 to 14 gives the graphical valuation.

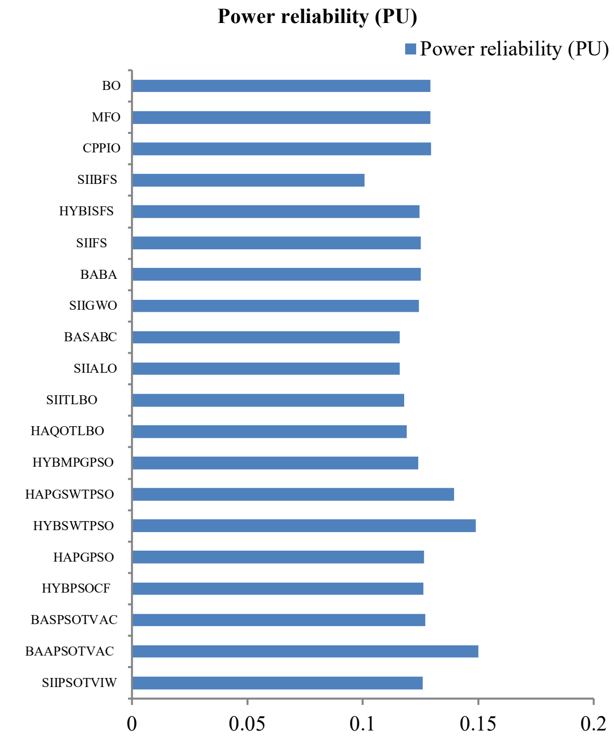

Fig 11. Assessment of voltage constancy.

Table 8. Assessment of power loss.

Technique	Loss in MW
AEO [9]	23.4554
EO [9]	23.68991
GBO [9]	23.4998
TFWO [9]	23.3654
CTFWO [9]	23.3235
IICOA [38]	22.37600
IICOA1[38]	22.38300
WACA [38]	26.04020
SISA [38]	25.38540
SIFOA [38]	26.65410
CUOA [38]	24.53580
LISAI [41]	26.88000
LISAII [41]	26.92000
IISA [41]	26.97000
MAOPSO [39]	27.83000
MAOEPSO [39]	27.42000
MAFO [52]	24.25000
MAOGWA [53]	21.17100
SIGA [54]	25.64000
PASO [54]	25.03000
HYAS [54]	24.90000
CPPIO	21.67901
MFO	21.67893
BO	21.67889

Table 9. Power eccentricity assessment.

Technique	Power eccentricity (PU)
AEO [9]	0.60495
EO [9]	0.596804
GBO [9]	0.60383
TFWO [9]	0.58588
CTFWO [9]	0.58553
IICOA [38]	0.60510
IICOA1[38]	0.61550
WACA [38]	0.73090
SISA [38]	0.94000
SIFOA [38]	0.79130
CUOA [38]	0.67110
LISAI [41]	1.06420
LISAII [41]	1.07200
IISA [41]	1.09120
MAOPSO [39]	1.10000
MAOEPSO [39]	0.89600

CPPIO	0.60330
MFO	0.60317
BO	0.60310

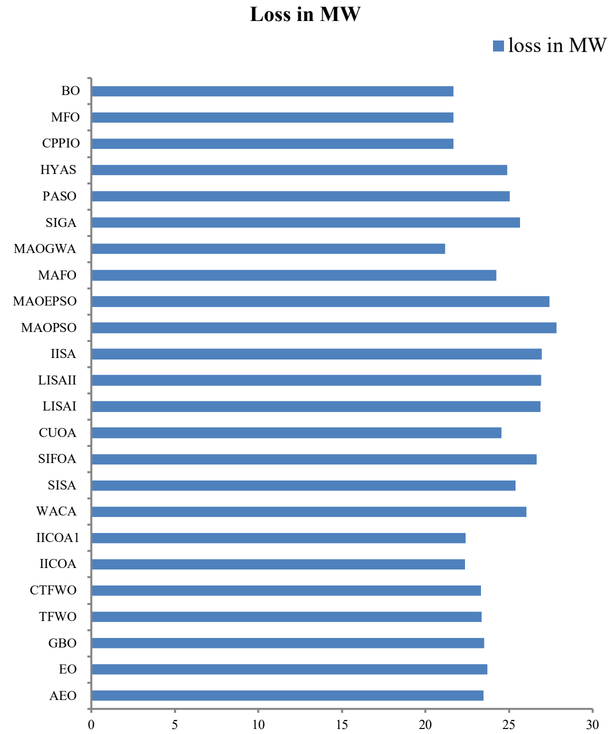

Fig 12. Assessment of loss.

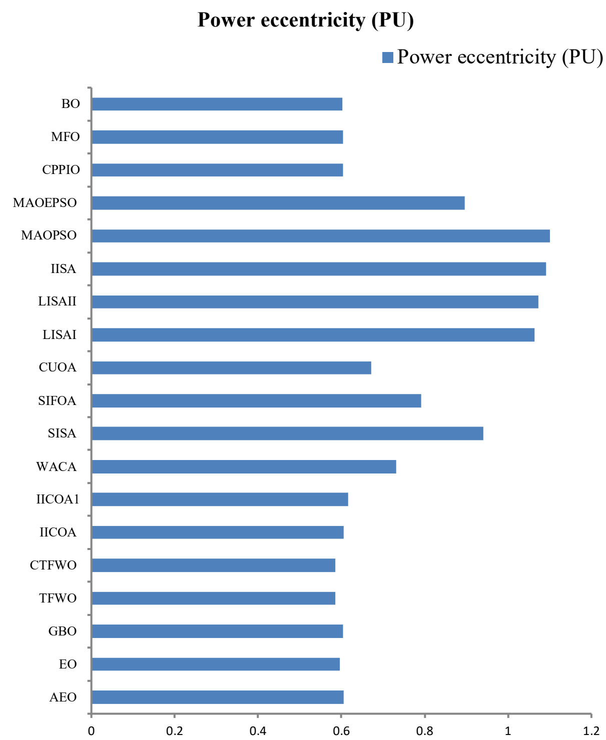

Fig 13. Assessment of power eccentricity.

Table 10. Power reliability valuation.

Technique	Power permanence
AEO [9]	N/A
EO [9]	N/A
GBO [9]	N/A
TFWO [9]	N/A
CTFWO [9]	N/A

IICOA [38]	0.251690
IICOA1[38]	0.258300
WACA [38]	0.278900
SISA [38]	0.290000
SAFOA [38]	0.283100
CUOA [38]	0.275700
CPPIO	0.289898
MFO	0.289901
BO	0.289912

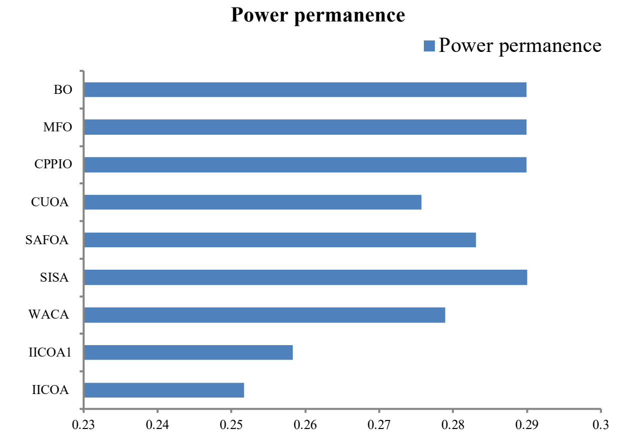

Fig 14. Assessment of power solidity.

Commercial Pilot Preparation inspired optimization (CPPIO) algorithm, Mindarinae and Formica fusca rapport inspired optimization (MFO) algorithm, Red-footed Booby optimization (BO) algorithm are substantiated in IEEE 118 bus system [58]. Table 11 -13 shows the loss evaluation, power eccentricity assessment and reliability valuation. Figures 15 to 17 give the graphical evaluation.

Table 11. Loss appraisal.

Technique	Loss in MW
GBBBA [8]	174.3956
DeGBBBA [8]	183.4976
IICOA [38]	114.80360
IICOA1[38]	114.86230
WACA [38]	118.32070
SISA [38]	125.72880
SAFOA [38]	125.68010
CUOA [38]	132.33410
CUOAI[38]	123.68670
CUOAII[38]	126.04260
LISAI [41]	119.79000
LISAII [41]	120.15000
IISA [41]	120.67000
AALCPSO [55]	121.53000
CLEPSO[55]	130.96000
CPPIO	113.54321
MFO	113.54305
BO	113.54298

Table 12. Power eccentricity valuation.

Method	VD (PU)
GBBBA [8]	1.5966
DeGBBBA [8]	1.6668
IICOA [38]	0.1605
IICOA1[38]	0.1608
WACA [38]	0.2315
SISA [38]	0.4883
SAFOA [38]	0.6061
CUOA [38]	0.2034
CUOAI[38]	0.1928
CUOAII[38]	0.1936
LISAI [41]	0.2819
LISAII [41]	0.2876
IISA [41]	0.2948

CPPIO	0.1535
MFO	0.1519
BO	0.1509

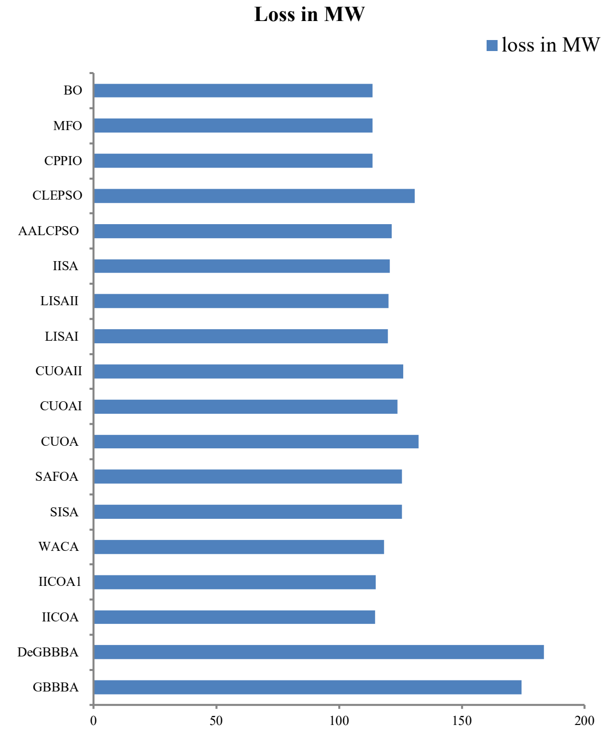

Fig 15. Assessment of loss.

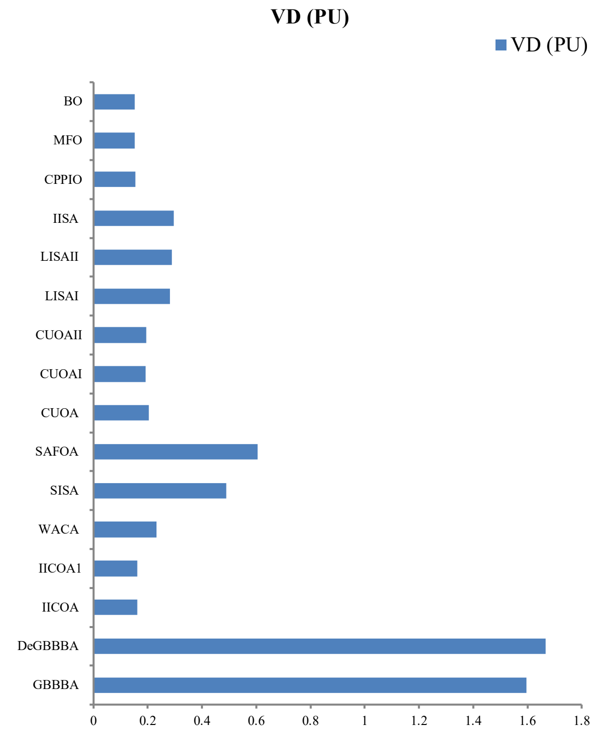

Fig 16. Assessment of power eccentricity.

Table 13. Power reliability valuation.

Technique	Power permanence
GBBBA [8]	0.0558
DeGBBBA [8]	0.0543
IICOA [38]	0.060610
IICOA1[38]	0.060640
WACA [38]	0.060731
SISA [38]	0.063900
SAFOA [38]	0.061900

CUOA [38]	0.061230
CUOAI[38]	0.060720
CUOAII[38]	0.060770
CPPIO	0.066233
MFO	0.066242
BO	0.066251

Commercial Pilot Preparation inspired optimization (CPPIO) algorithm, Mindarinae and Formica fusca rapport inspired optimization (MFO) algorithm, Red-footed Booby optimization (BO) algorithm are substantiated in IEEE 300 bus system [57]. Table 14 , 15shows the loss valuation and voltage eccentricity valuation. Figures 18 and 19 give the graphical evaluation.

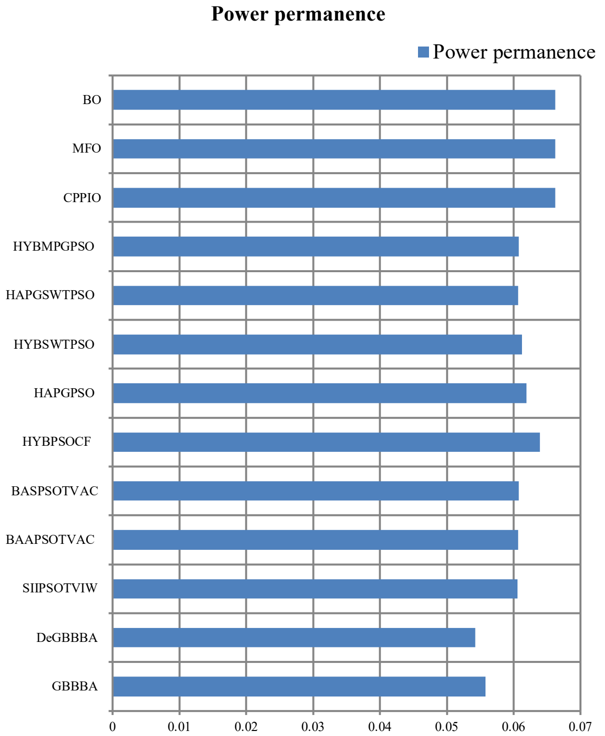

Fig 17. Appraisal of power solidity.

Table 14. Loss appraisal.

Technique	Loss in MW
SMA [7]	392.6028
ISMA[7]	377.2697
LISAI [41]	396.9830
LISAII [41]	397.2360
IISA [41]	397.9020
MAOALO [39]	398.8530
CPPIO	360.0601
MFO	360.0589
BO	360.0581

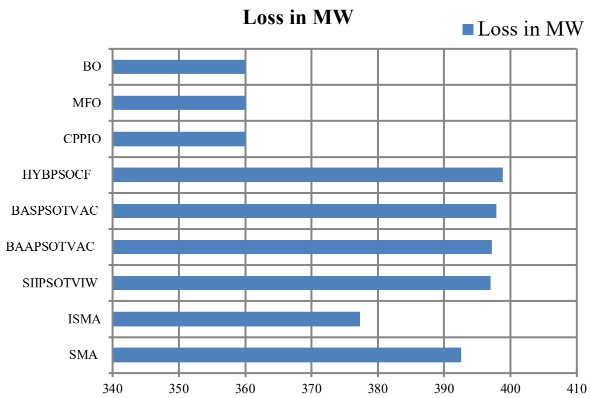

Fig 18. Assessment of power loss.

Table 15. Power eccentricity appraisal.

Technique	Power eccentricity (PU)
SMA [7]	N/A
ISMA[7]	N/A
LISAI [41]	5.9324
LISAII [41]	5.9416
IISA [41]	5.9613
MAOALO [39]	6.0169
CPPIO	5.8925
MFO	5.8916
BO	5.8911

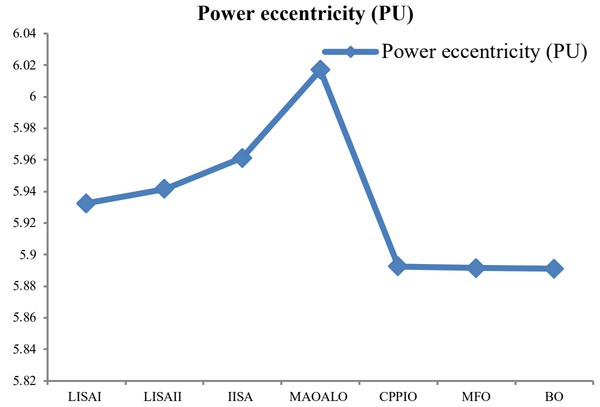

Fig 19. Appraisal of power deviance.

Projected Commercial Pilot Preparation inspired optimization (CPPIO) algorithm, Mindarinae and Formica fusca rapport inspired optimization (MFO) algorithm, Red-footed Booby optimization (BO) algorithm corroborated in IEEE 354 bus system [57]. In Table 16, 17 show the loss assessment and power eccentricity valuation. Figures 20 and 21 give the graphical evaluation.

Table 16. Loss evaluation.

Technique	Loss in MW
LISAI [41]	337.3740
LISAII [41]	338.7150
IISA [41]	339.3250
FAAHCLSO [39]	341.0010
PASO [39]	341.1230
CPPIO	336.5153
MFO	336.5133
BO	336.5129

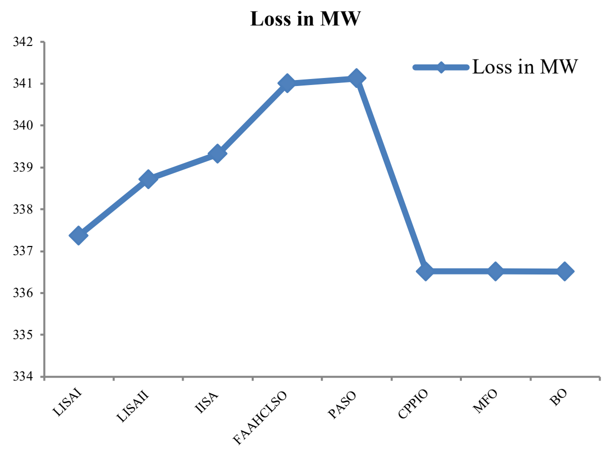

Fig 20. Assessment of power loss.

Table 17. Power eccentricity.

Technique	Power eccentricity (PU)
LISAI [41]	0.49780
LISAII [41]	0.51170
IISA [41]	0.52160
FAAHCLSO [39]	0.53540
PASO [39]	0.63950
CPPIO	0.47546
MFO	0.47531
BO	0.47526

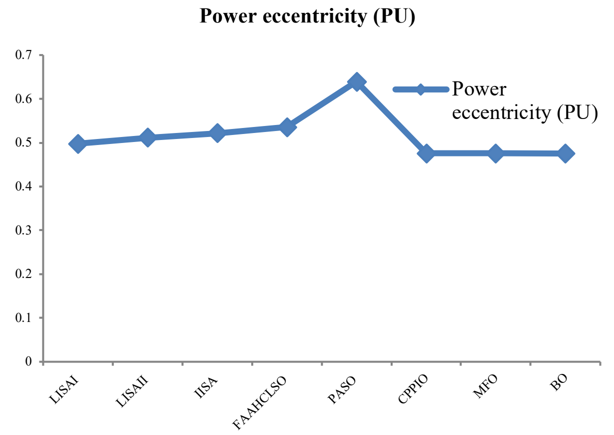

Fig 21. Appraisal of power deviance.

Proposed Commercial Pilot Preparation inspired optimization (CPPIO) algorithm, Mindarinae and Formica fusca rapport inspired optimization (MFO) algorithm, Red-footed Booby optimization (BO) algorithm validated in Unified Egyptian Transmission Network Practical system (WDN 220 KV) [13].Table 18, 19 shows the loss assessment and power eccentricity valuation. Figures 22 and 23 give the graphical evaluation.

Table 18. Loss assessment.

Technique	Loss in MW
BASPSO[12]	32.3140
BABBA [12]	33.8750
IAMBBA [12]	30.7860
CPPIO	29. 0526
MFO	29. 0509
BO	29. 0495

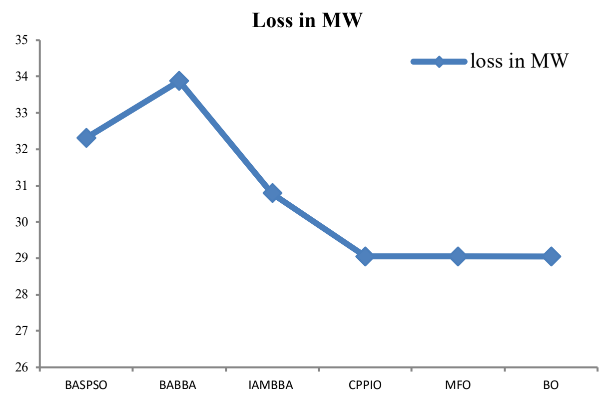

Fig 12. Valuation of loss.

Table 19. Power eccentricity analysis.

Technique	Power eccentricity (PU)
BASPSO[12]	0.58000
BABBA [12]	0.63270
IAMBBA [12]	0.67510
CPPIO	0.58219
MFO	0.58201
BO	0.58196

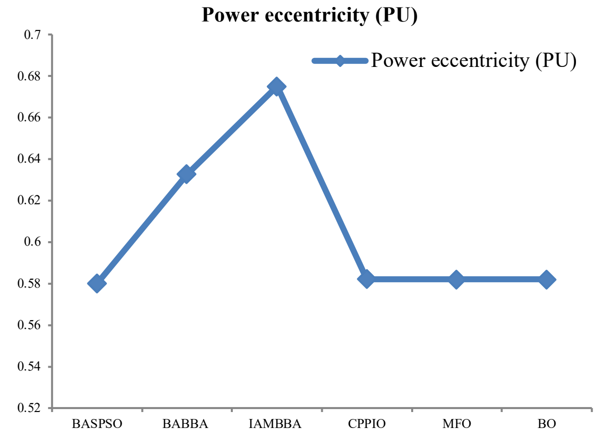

Fig 23. Appraisal of Power eccentricity.

Table 20 and Figure 24 show the time taken for Commercial Pilot Preparation inspired optimization (CPPIO) algorithm, Mindarinae and Formica fusca rapport inspired optimization (MFO) algorithm, Red-footed Booby optimization (BO) algorithm.

Table 20. Time taken for proposed algorithm.

Technique	6-bus T (S)	30 bus T (S)	57 bus T (S)	118 bus T(S)	300 bus T(S)	354 bus T (S)	UETN 220 KV T (S)
CPPIO	7.64	20.43	27.36	37.28	71.16	83.04	22.51
MFO	7.12	20.09	27.14	37.12	71.01	83.00	22.10
BO	7.05	20.01	26.92	36.89	70.89	82.86	21.91

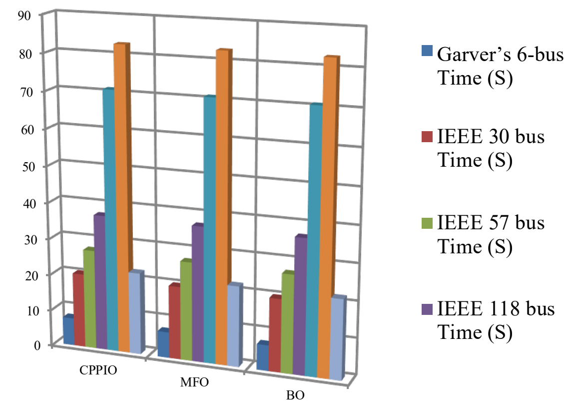

Fig 24. Time taken by Commercial Pilot Preparation inspired optimization (CPPIO) algorithm, Mindarinae and Formica fusca rapport inspired optimization (MFO) algorithm, Red-footed Booby optimization (BO) algorithm.

6. Conclusion

Proposed Commercial Pilot Preparation inspired optimization (CPPIO) algorithm, Mindarinae and Formica fusca rapport inspired optimization (MFO) algorithm, Red-footed Booby optimization (BO) algorithm solved the problem competently. The main segment of the CPPIO modernization is grounded on the choice of trainer by the beginner and at that time the preparation done by the designated trainer to the beginner. Amongst the beginner population, chosen quantities of the preeminent associates are deliberated as trainers and remaining as beginner. Selecting the trainer and learning the talents of that trainer will tip to the crusade of population associates to dissimilar ranges in the exploration region. This will upsurge the beginner exploration ability in the global examination and detection of the optimal zone. CPPIO approach modernization is grounded on the beginner emulating the trainer and talents of the trainer. This procedure passages CPPIO associates to dissimilar locations in the exploration region, thus aggregating the CPPIO exploration ability. Personal preparation of the beginner is act as exploitation segment in the procedure. In this segment CPPIO modernization is grounded on the Personal preparation of the beginner to progress and augment pilot abilities. Each beginner attempts to get nearer to the preeminent abilities in this segment. In Mindarinae and Formica fusca rapport inspired optimization (MFO) algorithm enthused by environment, Mindarinae with dissimilar appropriateness values can show dissimilar protagonists and their locations are rationalized grounded on three numerous stratagems that are connected to their potentials. Preeminent Mindarinae employ somatic apprising operator to progress using their individual capability. Additionally, some feeble Mindarinae of the populace are designated arbitrarily by Formica fusca to alter their location in the collection and discover newfangled zones. Grounded on the lifecycle of the Mindarinae in environment, they can also modify their locations using voluptuous apprising operator to use added Mindarinae familiarity. Based on the Formica fusca stratagem in collaboration with Mindarinae; the Formica fusca attempt to passage toward preeminent Mindarinae of the cluster to obtain additional nutriment. Furthermore, to augment the populace assortment, some feathered Mindarinae attempt to hover by means of the airstream to other clusters and helix drive operator is premeditated to design this approach. Foraging actions of Red-footed Booby has been imitated to formulate the BO algorithm. The algorithm owns twofold segments: exploration segment is accountable for examining for the preeminent zone by the leaping outlines of Red-footed Booby, and the impulsive revolution and arbitrary walk in the progress segment make certain that an enhanced solution can be obtained in the zone.

- Preparation of the beginner to become as commercial pilot by the trainer
- Beginner prefiguring from trainer talents
- Personal preparation of the beginner
- Mindarinae and Formica fusca rapport inspired optimization algorithm envisages double divergent sorts of entities that are Mindarinae and Formica fusca.
- Preeminent Mindarinae which are named as spearhead create clusters comprise of enduring Mindarinae and Formica fusca.
- Mindarinae and Formica fusca rapport inspired optimization algorithm combines dissimilar exploration stratagems, which pretend the dissimilar cooperative actions which exist in the natural lifecycle of Mindarinae and Formica fusca. Thus, algorithm employs dissimilar entities that permit sustenance each other and can track dissimilar exploration courses. These possessions create the algorithm to be more suitable for solving the problem.
- In the Exploration segment; Red-footed Booby quest for victim in the marine by commencing from the midair, and as soon as Red-footed Booby discover victim, they regulate the nosedive outline rendering to the profundity of the victim. An elongated - profound nosedive and then a squat -trivial nosedive will be executed by the Red-footed Booby.
- In the Exploitation segment two additional activities are required to advance exploitation subsequent to the Red-footed Booby flashes into the marine by elongated - profound nosedive and then a squat -trivial nosedive.
- If the grasping capability of the Red-footed Booby is inside the range towards the acquiring victim, the location is rationalised with an impulsive revolving; or else, the Red-footed Booby is inept to grasp this malleable fish and accomplishes a Levy crusade to examine for the subsequent target in arbitrary mode.

Proposed Commercial Pilot Preparation inspired optimization (CPPIO) algorithm, Mindarinae and Formica fusca rapport inspired optimization (MFO) algorithm, Red-footed Booby optimization (BO) algorithm corroborated in G01–G24 benchmark functions, Six, IEEE bus test systems and in Practical Unified Egyptian Transmission Network.

6.1 Scope of future work

In future Commercial Pilot Preparation inspired optimization (CPPIO) algorithm, Mindarinae and Formica fusca rapport inspired optimization (MFO) algorithm, Red-footed Booby optimization (BO) algorithm can be protracted to smear in Science and technology problems. Predominantly in the zone of curative identification it can be smeared for augmenting the empathy and handling the ailment. Consecutively the procedure can be modified more to resolve the big problems in multifaceted schemes. Especially in the other areas of Electrical engineering proposed algorithms can be applied sequentially. To the same problem the projected algorithms can be expanded to apply in real time systems.

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