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Novel Enriched Indus River Flow Dynamics Optimization Algorithm to solve the Electrical Energy -Active Power Loss Reduction and Voltage Stability Enhancement

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Abstract

In this paper Periodic Knowledge acquisition and Replication inspired optimization algorithm, Enriched Indus River flow dynamics Optimization Algorithm, Trade union chief selection optimization, algorithm and Population based optimization, algorithm are designed to solve the Power loss Engineering problem. In Periodic Knowledge acquisition and Replication inspired optimization algorithm, Learning and adapting to the situations are more important in the human being life. Teaching and sequential learning, Solution to Contradictory Opinions, Ikigai and Kaizen, Understanding cosmos and Indus river flow watercourse flow dynamics algorithm are integrated to form the Enriched Indus River flow dynamics Optimization Algorithm. Trade union chief selection optimization is designed by imitating the elective procedure of the trade union to select the leader. Population is channelled by the examination region under the leadership of the chosen chief. In Population based optimization algorithm every optimal problem has an appetizing region which defined as Exploration region and it envisaged as a synchronize structure with a numeral of hatchets equivalent to the problem resolution parameters. Proposed Periodic Knowledge acquisition and Replication inspired optimization algorithm, Enriched Indus River flow dynamics Optimization Algorithm, Trade union chief selection optimization algorithm and Population based optimization algorithm are verified in G01–G24 benchmark functions, Six and IEEE 30, 57, 118 bus test systems.

Keywords: Knowledge, Acquisition, Replication, Teaching, Learning, Cosmos, Indus, Trade union, Population

1. Introduction

Many decades power loss reduction problem plays a challenging task in the transmission and distribution of electrical power. Many researchers [1-10] around the world have been constantly working on this topic in order to improve the quality of the power. Recently Dynamic reactive power optimization [11], Reactive Power Optimization of AC-DC Hybrid Distribution Network [12], Influence of Reactive Power Optimization [13], new Second-order Cone Programming [14], Improved Imperialist Competitive Algorithm [15], and Power Adjustment Based on Jacobi Matrix Decomposition [16] are designed and applied to solve the problem. Many nature inspired algorithms are used to solve the engineering problems [17-29].

In this work Periodic Knowledge acquisition and Replication inspired optimization (PRO) algorithm is applied to solve the problem. Any individual has to continuously acquire knowledge in the life span. Learning and adapting to the situations are more important in the human being life. Knowledge acquisition by an individual plays important role in his / her life to do any actions in efficient mode and to take decisions. This work emulates how an individual acquire knowledge and reproduce learned things to solve the problems in day to day life. Every individual possess cavities in their accrued knowledge. Any individual will try to learn from the elders and other extraordinary people. It's a form of continuous learning in their life span. The individual will analyse himself how far his obtained knowledge will guide in their life span. Many times the individual will try to learn fast and move forward along with others in the society. In this aspect two segments are created; Knowledge acquisition and replication.

Teaching and sequential learning, Solution to Contradictory Opinions, Ikigai and Kaizen, Understanding cosmos and Indus river flow Watercourse flow dynamicsalgorithm are integrated to form the Enriched Indus River flow dynamics Optimization Algorithm (SINDHU) to enhance the search and attaining better solutions. Teaching and sequential learning process is imitated how scholars are learnt from the educators. In the formulation the solution is randomly distributed in the search space.

Group discussion will occur to find the right solution when contradictory opinion occurs. In the general brain storm sessions will be conducted among thegroups to find solution for contradictory opinions. The discussion and analysis of each group will be led by the Group head.After all discussion and analysis completed, a common solution will be obtained.

Cluster of Groups had put forth a detailed discussion about Ikigai and Kaizen. Each adherent has unique perception or meaning about Ikigai and Kaizen. All the Groups conduct a Brain storm session and finally attain the real knowledge about Ikigai and Kaizen rendering to their conditions. Naturally society will have different opinions on Ikigai and Kaizen. It's vital to understand the real meaning of Ikigai and kaizen for the self and development of the nation.

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Time is inestimable with a cyclical universe, where the existing cosmos was heralded and will be trailed by an endless sum of cosmoses. The single, divine personified soul is the lifespan power or mindfulness inside an existing individual. Contemporary physical science has revealed that the tempo of formation and annihilation is not only obvious in the shot of the periods and in the natal and demise of all existing individuals, but then again is likewise the identical spirit of inert substance. Rendering to quantum field concept, dance of formation and annihilation is the foundation of the very presence of substance. Contemporary physical science has thus discovered that each subatomic unit not only does a dynamism dance, but also an energetic procedure of formation and annihilation.

Watercourse flow optimization algorithm is initiated with the conjecture of sprinkle of rain. Indus River drains into Arabian Sea. Rendering to Indus River, Arabian Sea is picked as the premium entity, and quantity of sprinkled rain droplets in the region are selected to designate as watercourse and as river stream it drains into Arabian Sea.

Teaching and sequential learning, Solution to Contradictory Opinions, Ikigai and Kaizen, Understanding cosmos and Indus river flow Watercourse flow dynamics algorithm are integrated to form the Enriched Indus River flow dynamics Optimization Algorithm(SINDHU) to enhance the search and attaining better solutions.

Then in this paper Trade union chief selection optimization (TUCSO) algorithm is applied to solve the problem. TUCSO is designed by imitating the elective procedure of the trade union to select the leader. Vital motivation of TUCSO was the elective procedure, the picking the chief, and the influence of the workers alertness level on the electing their own chief for the trade union. TUCSO population is channelled by the examination region under the leadership of the chosen chief. TUCSO procedure is scientifically designed and it is grounded on exploration and exploitation.

In Population based optimization (PBO) algorithm every optimal problem has an appetizing region which defined as Exploration region and it envisaged as a synchronize structure with a numeral of hatchets equivalent to the problem resolution parameters. Populace associates passage in the Exploration region, targeting to touch the suitable optima. The standards of the problem resolution factors are defined by the location of the PBO associates in the Exploration region. Every associate of the populace delivers info to other associates of the populace about the condition in which they discover themselves. In PBO, iteration grounded procedure, associates of the populace passage to the optimal areas.

2. Engineering problem formulation

Active Power Loss Reduction and Voltage Stability Enhancement is an important problem in power system operation and control. Objective function of Electrical Power Loss Reduction Problem is demarcated as,

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

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

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

Control $(\bar{g})$and dependent $(\bar{h})$vectors are defined as,

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

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

where,
$Q_c \rightarrow reactive\ power\ compensator$
$T \rightarrow Transformer\ tap$
$V_g \rightarrow Generator\ voltage$
$PG_{slack} \rightarrow Slack\ generator$
$V_L \rightarrow Voltage\ in\ transmission\ lines$
$Q_G \rightarrow Reactive\ power\ generator$

Fitness functions are defined as follows,

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

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

where,
$F_3 = Minimize\ L_{MaxImum}$
$S_L \rightarrow Apparent\ power$

$$L_{Max} = Max[L_j] \quad (8)$$

$$j = 1; N_{LB} \quad (9)$$

$$L_j = 1 - \sum_{i=1}^{NPV} F_{ji}\frac{V_i}{V_j} \quad (10)$$

$$F_{ji} = -[Y_1]^1[Y_2] \quad (11)$$

$$L_{Max} = Max\left[1 - [Y_1]^{-1}[Y_2] \times \frac{V_i}{V_j}\right] \quad (12)$$

Parity constraints

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

$$0 = QG_i - QD_i - V_i\sum_{j\in N_B} V_j\left[G_{ij}sin[\emptyset_i - \emptyset_j] + B_{ij}cos[\emptyset_i - \emptyset_j]\right] \quad (14)$$

where,
NB is the number of buses
PG , QG → real and reactive power
Gij , Bij → mutual conductance and susceptance
PD, QD → real and reactive load

Disparity constraints

$$P_{gsl}^{min} \leq P_{gsl} \leq P_{gsl}^{max} \quad (15)$$

Reactive power generation (QGi)

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max}, i \in N_g \quad (16)$$

Load bus voltage (VLi)

$$VL_i^{min} \leq VL_i \leq VL_i^{max}, i \in NL \quad (17)$$

Transformers tap setting (Ti)

$$T_i^{min} \le T_i \le T_i^{max}, i \in N_T \tag{18}$$

Switchable reactive power compensations (QCi)

$$Q_c^{min} \le Q_c \le Q_C^{max}, i \in N_C \tag{19}$$

$$|SL_i| \le S_{L_i}^{max}, i \in N_{TL} \tag{20}$$

Generator bus voltage (VGi)

$$VG_i^{min} \le VG_i \le VG_i^{max}, i \in N_g \tag{21}$$

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

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

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

3. Periodic Knowledge Acquisition and Replication Inspired Optimization Algorithm

In this work Periodic Knowledge acquisition and Replication inspired optimization (PRO) algorithm is applied to solve the problem.Any individual must continuously acquire knowledge in the life span. Learning and adapting to the situations are more important in the human being life. Knowledge acquisition by an individual play's important role in his / her life to do any actions in efficient mode and to take decisions. This work emulates how an individual acquire knowledge and reproduce learned things to solve the problems in day-to-day life.Every individual possess cavities in their accrued knowledge. Any individual will try to learn from the elders and other extraordinary people. It's a form of continuous learning in their life span. The individual will analyse himself how far his obtained knowledge will guide in their life span. Many times the individual will try to learn fast and move forward along with others in the society.In this aspect two segments are created; Knowledge acquisition and replication. In the knowledge acquisition any individual will try to acquire the knowledge as continuous process and in the replication segment the individual will use the acquired knowledge to perform various actions, through this reflection the individual will understand about level and quality of learning.

In the Knowledge acquisition segment the individual are categorized as top level, middle and lower level rendering to the knowledge attained by the individual. There will be fissure between this level of individuals and it defined as,

$$\begin{cases} \overrightarrow{F_A} = \overrightarrow{Z_{Top}} - \overrightarrow{Z_{Middle}} \\ \overrightarrow{F_B} = \overrightarrow{Z_{Top}} - \overrightarrow{Z_{Lower}} \\ \overrightarrow{F_C} = \overrightarrow{Z_{Middle}} - \overrightarrow{Z_{Lower}} \\ \overrightarrow{F_D} = \overrightarrow{Z_{R1}} - \overrightarrow{Z_{R2}} \end{cases} \tag{24}$$

$where\ F\ is\ fissure$
$\overrightarrow{Z_{R1}}\ and\ \overrightarrow{Z_{R2}}\ are\ the\ randomly\ selected\ individuals$

The Knowledge acquisition parameter is defined as,

$$Ka_k = \frac{\|\overrightarrow{Fissure_k}\|}{\sum_{k=1}^{D}\|\overrightarrow{Fissure_k}\|} \tag{25}$$

$Ka_k \rightarrow$
$kth\ fissure\ of\ normalized\ ratio\ \ Euclidean\ distance$
$Ka_k \in [0,1]$
$Ka_k \rightarrow$
$value\ high\ then\ individual\ acquire\ more\ knowledge$
$k = A, B, C, D$

Individuals at diverse ranks in the progression procedure observe themselves differently. Any individual will assess the level of learnt knowledge by himself and sequentially try to acquire more knowledge.

$$L_i = \frac{Knowledge\ acquisition\ disinclination_i}{Maximum\ Knowledge\ acquisition\ disinclination_i} \tag{26}$$

$L_i \rightarrow$
$smaller\ value\ then\ individualperform\ local\ exploitation$

The transformation of Knowledge between the Top, Middle and lower level is defined as,

$$Knowledge\ acquisition_i = L_i \cdot Ka_k \cdot \overrightarrow{Fissure_k} \tag{27}$$

$k = A, B, C, D$

The individual will augment the knowledge through acquisition from others and it defined as,

$$\overrightarrow{Z_i^{Iter+1}} = \overrightarrow{Z_i^{Iter}} + \overrightarrow{Knowledge\ acquisition_1} + \overrightarrow{Knowledge\ acquisition_2} + \overrightarrow{Knowledge\ acquisition_3} + \overrightarrow{Knowledge\ acquisition_4} \tag{28}$$

$iter \rightarrow iterations$

Process of knowledge acquisition will take time for any individual and it may progress continuously and few times some lag will occurred rendering to conditions,

$$\overrightarrow{Z_i^{Iter+1}} = \begin{cases} \overrightarrow{Z_i^{Iter+1}}\ if\ f\left(\overrightarrow{Z_i^{Iter+1}}\right) < f\left(\overrightarrow{Z_i^{Iter}}\right) \\ \begin{cases} \overrightarrow{Z_i^{Iter+1}}\ if\ o_1 < Q_i \\ \overrightarrow{Z_i^{Iter}}\ otherwise \end{cases} otherwise \end{cases} \tag{29}$$

$o_1 \in [0,1]$
$Q_i = 0.001$

In the replication segment the individual will verify about the quantity and quality of learning. Knowledge acquisition will be self analyzed by the individuals.

$$Z_{i,j}^{iter+1} = \begin{cases} \begin{cases} \min + o_4 * (max - min) \; if \; o_3 < attenuation\,factor \\ Z_{i,j}^{iter} + o_5 * \left(U_j - Z_{i,j}^{iter}\right) else \end{cases} & if \; o_2 < V_i \\ Z_{i,j}^{iter} \; Otherwise \end{cases} \tag{30}$$

Where,
$o_1, o_2, o_3, o_4 \in [0,1]$
$V_i = 0.50$
$U_j \rightarrow Knowledge\ acquisition\ of\ the\ jth\ aspect$

$$attenuation\,factor = 0.01 + 0.99 * \left(1 - \frac{iter}{max.iter}\right) \tag{31}$$

a. Start
b. Set the parameters
c. Engender the population
d. Apply Knowledge acquisition segment
e. $For\ i = N: do$
f. Compute $\overrightarrow{Fissure_k}$
g. $\begin{cases} \overrightarrow{F_A} = \overrightarrow{Z_{Top}} - \overrightarrow{Z_{Middle}} \\ \overrightarrow{F_B} = \overrightarrow{Z_{Top}} - \overrightarrow{Z_{Lower}} \\ \overrightarrow{F_C} = \overrightarrow{Z_{Middle}} - \overrightarrow{Z_{Lower}} \\ \overrightarrow{F_D} = \overrightarrow{Z_{R1}} - \overrightarrow{Z_{R2}} \end{cases}$
h. Calculate Ka_k
i. $Ka_k = \frac{\|\overrightarrow{Fissure_k}\|}{\sum_{k=1}^{D}\|\overrightarrow{Fissure_k}\|}$
j. Compute L_i
k. $L_i = \frac{Knowledge\ acquisition\ disinclination_i}{Maximum\ Knowledge\ acquisition\ disinclination\ _i}$
l. $Calculate\ Knowledge\ acquisition_i$
m. $Knowledge\ acquisition_i = L_i \cdot Ka_k \cdot \overrightarrow{Fissure_k}$
n. Accomplish the Knowledge acquisition process for ith individual
o. $\overrightarrow{Z_i^{Iter+1}} = \overrightarrow{Z_i^{Iter}} + \overrightarrow{Knowledge\ acquisition_1} + \overrightarrow{Knowledge\ acquisition_2} + \overrightarrow{Knowledge\ acquisition_3} + \overrightarrow{Knowledge\ acquisition_4}$
p. Update the ith individual
q. $\overrightarrow{Z_i^{Iter+1}} = \begin{cases} \overrightarrow{Z_i^{Iter+1}}\ if\ f\left(\overrightarrow{Z_i^{Iter+1}}\right) < f\left(\overrightarrow{Z_i^{Iter}}\right) \\ \begin{cases} \overrightarrow{Z_i^{Iter+1}}\ if\ o_1 < Q_i \\ \overrightarrow{Z_i^{Iter}}\ otherwise \end{cases} otherwise \end{cases}$
r. Apply the replication segment
s. $For\ i = N: do$
t. Accomplish the replication process for ith individual
u. $Z_{i,j}^{iter+1} = \begin{cases} \begin{cases} \min + o_4 * (max - min)\ if\ o_3 < attenuation\,factor \\ Z_{i,j}^{iter} + o_5 * \left(U_j - Z_{i,j}^{iter}\right) else \end{cases} & if\ o_2 < V_i \\ Z_{i,j}^{iter}\ Otherwise \end{cases}$
v. $attenuation\,factor = 0.01 + 0.99 * \left(1 - \frac{iter}{max.iter}\right)$
w. Update the ith individual
x. $\overrightarrow{Z_i^{Iter+1}} = \begin{cases} \overrightarrow{Z_i^{Iter+1}}\ if\ f\left(\overrightarrow{Z_i^{Iter+1}}\right) < f\left(\overrightarrow{Z_i^{Iter}}\right) \\ \begin{cases} \overrightarrow{Z_i^{Iter+1}}\ if\ o_1 < Q_i \\ \overrightarrow{Z_i^{Iter}}\ otherwise \end{cases} otherwise \end{cases}$
y. end for
z. $t = t + 1$
aa. Output the best solution
bb. End

4. Enriched Indus River flow dynamics Optimization Algorithm

Teaching and sequential learning, Solution to Contradictory Opinions, Ikigai and Kaizen, Understanding cosmos and Indus river flow Watercourse flow dynamics algorithm are integrated to form the Enriched Indus River flow dynamics Optimization Algorithm (SINDHU) to enhance the search and attaining better solutions.

- Teaching and sequential learning algorithm
- Solution to Contradictory Opinions algorithm
- Ikigai and Kaizen algorithm
- Teaching on cosmos algorithm
- Indus river watercourse flow dynamics algorithm

Teaching and sequential learning algorithm

Teaching and sequential learning process is imitated how scholars are learnt from the educators. In the formulation the solution is randomly distributed in the search space. The position is represented as,

$Z_i = \{z_{i,1}, z_{i,2}, \ldots, z_{i,d}\}$
$d \rightarrow dimension$

The matrix of the mutation [33-37] is defined as,

$$A = Z_{gbest} + variation\ constant\ parameter * (Z_{r1} - Z_{r2}) \tag{32}$$

$Z_{r1}\ and\ Z_{r2} \rightarrow different\ matrixes\ to\ update\ the\ pontiff\ location\ variation\ constant\ parameter = 0.70$

Evolution is generated [28, 32] as follows,

$$Z = O \times Z + \bar{O} \times A \tag{33}$$

$O \rightarrow transformation\ matrix$
$\bar{O} \rightarrow\ binary\ inverse\ of\ O$

a. Start
b. Initialization of the process
c. Position in the search space defined
d. Calculation of fitness value
e. $Fix\ Z_{gbest}$
f. $While\ t < maximum\ generation$
g. Engendering the mutilation factor
h. $A = Z_{gbest} + variation\ constant\ parameter * (Z_{r1} - Z_{r2})$
i. Create the evolution
j. $Z = O \times Z + \bar{O} \times A$
k. Calculation of fitness value
l. $t = t + 1$
m. End while
n. Output the Z_{gbest}
o. End

In the procedure Trial vector creators (TC), recognized TC (RTC), preeminent antiquity trial vector creator (PATC), and arbitrary trial vector creator (ATC) are utilized to enhance the solution by maintain the equilibrium between exploration and exploitation [38, 39].

Engendering the solutions randomly in the exploration space as follows,

$$z_{ij} = min_j + \left(max_j - min_j\right) \times R \quad (34)$$

$R \in [0,1]$
$z_{ij} \rightarrow define\ the\ location$

The complete generation is alienated into k segments comprising "n" generations. The principal phase of every segment is to pick the preeminent Trial vector creators (TC), with the uppermost degree of enhancement over the preceding "n" generations.

$$ID_{X-TC} = \neq Enhanced\ solution / \neq function\ evaluations \quad (35)$$

$ID \rightarrow improved\ degree$
$X \rightarrow one\ of\ the\ TC$

The magnitude of the Trial vector creators (TC) sub population is defined as,

$$N_{X-TC} = \begin{cases} 2 * \tau * N, for\ TC\ (improved\ degree) \\ \tau * N, for\ other\ TC \end{cases} \quad (36)$$

$\tau = 0.250$
$N \rightarrow number$

Recognized TC (RTC) enhance the exploitation capability, preeminent antiquity trial vector creator (PATC) will evade the trapping into local optima, arbitrary trial vector creator (ATC) will balance the exploration and exploitation. When every Trial vector creators (TC) transforms its devoted sub-population the progressed vector of the mind is defined through $O\ and\ \bar{O}$ as follows,

$$Y_i^{Rpop}(t+1) = O_i \times O_i^{Rpop} + \bar{O}_\iota \times M_i^{Rpop} \quad (37)$$

$Y_i^{Rpop} \rightarrow create\ candidate\ solution$
$M_i^{Rpop} \rightarrow mutated\ vector$
$Rpop \rightarrow\ Recognized\ TC\ (RTC)\ population$
$O \rightarrow transformation\ matrix$
$\bar{O} \rightarrow\ binary\ inverse\ of\ O$

$$Y_i^{Ppop}(t+1) = O_i \times O_i^{Ppop} + \bar{O}_\iota \times M_i^{Ppop} \quad (38)$$

$Y_i^{Ppop} \rightarrow create\ candidate\ solution$
$M_i^{Ppop} \rightarrow mutated\ vector$
$Ppop \rightarrow\ preeminent\ antiquity\ trial\ vector\ creator\ (PATC) population$
$O \rightarrow transformation\ matrix$
$\bar{O} \rightarrow\ binary\ inverse\ of\ O$

$$Y_i^{Apop}(t+1) = O_i \times O_i^{Apop} + \bar{O}_\iota \times M_i^{Apop} \quad (39)$$

$Y_i^{Apop} \rightarrow create\ candidate\ solution$
$M_i^{Apop} \rightarrow mutated\ vector$
$Apop \rightarrow arbitrary\ trial\ vector\ creator\ (ATC)\ population$
$O \rightarrow transformation\ matrix$
$\bar{O} \rightarrow\ binary\ inverse\ of\ O$

Recognized TC (RTC) engender the mutated vector as follows,

$$M_i^{Rpop}(t+1) = gbest_t^{pop} + Vcp * \left(Z_{r1}^{Rpop}(t) - Z_{r2}^{Rpop}(t)\right) \quad (40)$$

$Vcp \rightarrow\ variation\ constant\ parameter$
$Vcp = 0.70$

Procedure for Recognized TC (RTC)

a. Start
b. $for\ i = 1 to N_{RTC}$
c. $M_i^{Rpop}(t+1) = gbest_t^{pop} + Vcp * \left(Z_{r1}^{Rpop}(t) - Z_{r2}^{Rpop}(t)\right)$
d. $Y_i^{Rpop}(t+1) = O_i \times O_i^{Rpop} + \bar{O}_\iota \times M_i^{Rpop}$
e. $End\ for$
f. Output the produced vectors in Y^{Rpop}
g. End

Preeminent antiquity trial vector creator (PATC) engender the mutated vector as follows,

$$M_i^{Ppop}(t+1) = Z_t^{Papop} + G * \left(Z_{r1}^{Ppop}(t) - Z_{r2}^{Ppop}(t)\right) \quad (41)$$

$G \rightarrow reduction\ factor$
$Z_t^{Papop} \rightarrow\ Preeminent\ antiquity\ trial\ vector\ creator\ population$

$$G = \gamma - (\gamma - \delta) * \left(\frac{\max gen - gen}{\max gen}\right) \rho \quad (42)$$

$\gamma\ and\ \delta\ \rightarrow primary\ and\ final\ values$
$\rho \rightarrow value\ by\ dimension$

Procedure for Preeminent antiquity trial vector creator (PATC)

a. Start
b. $for\ i = 1 to N_{PTC}$
c. $M_i^{Ppop}(t+1) = Z_t^{Papop} + G * \left(Z_{r1}^{Ppop}(t) - Z_{r2}^{Ppop}(t)\right)$
d. $Y_i^{Ppop}(t+1) = O_i \times O_i^{Ppop} + \bar{O}_\iota \times M_i^{Ppop} End\ for$
e. Output the produced vectors in Y^{Ppop}
f. End

Arbitrary trial vector creator (ATC) engender the mutated vector as follows,

$$M_i^{Apop}(t+1) = Z_t^{Apop} + H * \left(Z_{r1}^{Apop}(t) - Z_{r2}^{Apop}(t)\right) + H * \left(Z_{r2}^{Apop}(t) - Z_j^{Cpop}(t)\right)$$

$M_i^{Apop}(t+1) \rightarrow Arbitrary\ trial\ vector\ creator\ (ATC)\ population$
$H \rightarrow Vcp\ enegnedered\ by\ cauchy\ distribution$
$Vcp \rightarrow\ variation\ constant\ parameter$
$Z_j^{Cpop}(t) \rightarrow complete\ population$

$$H = R_c(\rho f \varphi) \quad (43)$$

$\rho f = 0.50$
$\varphi = 0.20$

$$\rho f = \frac{\sum_{f_i \in Q_f} U_{f_i} * f_i^2}{\sum_{f_i \in Q_f} U_{f_i} * f_i} \quad (44)$$

$U_{f_i} \rightarrow weight$
$Q_f \rightarrow scale\ factor$

$$U_{f_i} = \frac{\Delta f_i}{\sum_{f_i \in Q_f} \Delta f_i} \quad (45)$$

Procedure for Arbitrary trial vector creator (ATC)

a. Start
b. $for\ i = 1 to N_{ATC}$
c. $M_i^{Apop}(t+1) = Z_t^{Apop} + H * \left(Z_{r1}^{Apop}(t) - Z_{r2}^{Apop}(t)\right) + H * \left(Z_{r2}^{Apop}(t) - Z_j^{Cpop}(t)\right)$
d. $Y_i^{Apop}(t+1) = O_i \times O_i^{Apop} + \overline{O_i} \times M_i^{Apop}$
e. Output the produced vectors in Y^{Apop}
f. End

Istiompax Indica algorithm is integrated into the procedure to enhance the search.Istiompax indica is rapacious and hunt Amblygaster sirm in cluster mode. Regular performances of Istiompax indica have been used to design the algorithm. A contestant elucidation in the proposed procedure is Istiompax indica and populace in the investigation zone is indiscriminately prompted.

In the penetrating zone,

$$Z_{i,k} \in \mathcal{B}(i = 1,2,..,m) \quad (46)$$

$where\ \ Z_{i,k}\ specify\ the\ Istiompax\ indica\ \ location$

$$Z_p = \begin{bmatrix} Z_{1,1} & Z_{1,2} \cdots Z_{1,d} \\ Z_{2,1} & Z_{2,2} \cdots Z_{2,d} \\ \vdots & \vdots \ \ \dots \ \vdots \\ Z_{m,1} & Z_{m,2} \cdots Z_{m,d} \end{bmatrix} \quad (47)$$

Solution appropriateness rate designed as,

$$Z_p = \begin{bmatrix} f(Z_{1,1} & Z_{1,2} \cdots Z_{1,d}) \\ f(Z_{2,1} & Z_{2,2} \cdots Z_{2,d}) \\ \vdots & \vdots \ \ \dots \ \vdots \\ f(Z_{m,1} & Z_{m,2} \cdots Z_{m,d}) \end{bmatrix} = \begin{bmatrix} F_{Z1} \\ F_{Z2} \\ \vdots \\ F_{Zm} \end{bmatrix} \quad (48)$$

Amblygaster Sirm School is intermingled in the procedure and in the examination space it also swimming. Then the Amblygaster sirm location and appropriateness is obtained by,

$$D_p = \begin{bmatrix} D_{1,1} & D_{1,2} \cdots D_{1,d} \\ D_{2,1} & D_{2,2} \cdots D_{2,d} \\ \vdots & \vdots \ \ \dots \ \vdots \\ D_{m,1} & D_{m,2} \cdots D_{m,d} \end{bmatrix} \quad (49)$$

$$D_p = \begin{bmatrix} f(Z_{1,1} & Z_{1,2} \cdots Z_{1,d}) \\ f(Z_{2,1} & Z_{2,2} \cdots Z_{2,d}) \\ \vdots & \vdots \ \ \dots \ \vdots \\ f(Z_{m,1} & Z_{m,2} \cdots Z_{m,d}) \end{bmatrix} = \begin{bmatrix} F_{Z1} \\ F_{Z2} \\ \vdots \\ F_{Zm} \end{bmatrix} \quad (50)$$

The location of the greater Istiompax indica and the incapacitated Amblygaster sirm which own the superlative appropriateness rate in the ith iteration is indicated as $Q_{s\_Z}^i$ and $Q_{in\_D}^i$. Fresh location of Istiompax indica designated as,

$$Q_{fresh_Z}^i = Q_{s\_Z}^i - \lambda_i \times \left(r(0,1) \times \left(\frac{Q_{s\_Z}^i + Q_{in\_D}^i}{2}\right) - Q_{pre\ \_Z}^i\right) \quad (51)$$

$\lambda_i = 2 \times r(0,1) \times p.d - p.d$
$p.d = 1 - \left(\frac{Z}{Z+D}\right)$

Fresh position of Amblygaster sirm is,

$$Q_{fresh\_D}^i = r \times \left(Q_{s\_Z}^i - Q_{pre\ \_Z}^i + Z.P\right) \quad (52)$$

$$Z.P = l \times (2 \times iter \times \varepsilon) \quad (53)$$

Through $Z.P$ number of Amblygaster sirm will revolutionize the location (α) and parameter (β),

$\alpha = D \times Z.P$
$\beta = Pa \times Z.P$

$$Q_Z^i = Q_P^i\ if\ f(D_i) < f(Z_i) \quad (54)$$

a. Start
b. Fix the parameter values
c. Compute the fitness rate
d. Pick superlative Istiompax indica and incapacitated Amblygaster sirm
e. $while\ (end\ condition\ is\ not\ met) do$
f. Istiompax indica location is rationalised
g. End for
a. Location ofselected Amblygaster sirmis rationalized
b. End if
c. Calculate appropriateness rate of Amblygaster sirm
d. Exclude the startled Amblygaster sirm
e. Streamline the optimum Istiompax indica and Amblygaster sirm
f. End if
g. End while
h. Reoccurrence of finest Istiompax indica
i. End

<u>Teaching and sequential learning</u>

a. Start
b. $generation = 1$
c. Arbitrarily engender the solution in the search space
p. Calculation of fitness value
q. $Fix\ Z_{gbest}$
r. $While\ t < maximum\ generation$
d. $If\ mod(gen, ngen) == 0$
e. Determine the alienated k segments
f. End if
g. Apply Istiompax indica procedure
h. Determine the magnitude Trial vector creators (TC) sub population
i. $N_{X-TC} = \begin{cases} 2 * \tau * N\ , for\ TC\ posses \\ \quad improved\ degree \\ \quad \tau * N, for\ other\ TC \end{cases}$
j. $Do\ for\ each\ Trial\ vector\ creators\ (TC)$
k. $for\ i = 1 to N_{X-TC}$
l. $for\ i = 1 to N_{RTC}$

m. $M_i^{Rpop}(t+1) = gbest_t^{pop} + Vcp * \left(Z_{r1}^{Rpop}(t) - Z_{r2}^{Rpop}(t)\right)$
n. $Y_i^{Rpop}(t+1) = O_i \times O_i^{Rpop} + \overline{O_i} \times M_i^{Rpop}$
o. $End\ for$
p. $for\ i = 1 to N_{PTC}$
q. $M_i^{Ppop}(t+1) = Z_t^{Papop} + G * \left(Z_{r1}^{Ppop}(t) - Z_{r2}^{Ppop}(t)\right)$
r. $Y_i^{Ppop}(t+1) = O_i \times O_i^{Ppop} + \overline{O_i} \times M_i^{Ppop} End\ for$
s. End for
t. $for\ i = 1 to N_{ATC}$
u. $M_i^{Apop}(t+1) = Z_t^{Apop} + H * \left(Z_{r1}^{Apop}(t) - Z_{r2}^{Apop}(t)\right) + H * \left(Z_{r2}^{Apop}(t) - Z_j^{Cpop}(t)\right)$
v. $Y_i^{Apop}(t+1) = O_i \times O_i^{Apop} + \overline{O_i} \times M_i^{Apop}$
w. End for
x. $generation = Gneration + 1$
y. Output the Z_{gbest}
z. End

Solution to Contradictory Opinions algorithm

Group discussion will occur to find the right solution when contradictory opinion occurs. In the general brain storm sessions will be conducted among thegroups to find solution for contradictory opinions. The discussion and analysis of each group will be led by the Group head.After all discussion and analysis completed, a common solution will be obtained.

The following steps are followed in the discussion and analysis,

a. Groups will be formed
b. Each learner should deliver his/her observation
c. A brain storm session will be conducted
d. Contradictions of opinionanalyzed
e. Optimal solution found

Contradictory Opinions Inspired Optimization Algorithm

a. Start
b. Randomly create “n” probable solutions (entities)
c. Clump “n” entities into “m” bunches
d. Compute “n” entities
e. Evaluate the entities in each bunch
f. Record the finest entity as bunch hub in every collection
g. Randomly produce rate among 0 and 1
h. If the rate is minor than a preordained probability then,
i. Randomly pick a bunch hub
j. Randomly engender an entity to standby the designated bunch hub
k. Generate fresh entities
l. $0_{\mathrm{fresh}}^{\mathrm{d}} = 0_{\mathrm{picked}}^{\mathrm{d}} + \xi * \mathrm{n}(\mu, \sigma)$ (55)
m. $0_{\mathrm{picked}}^{\mathrm{d}} \rightarrow$ magnitude of the entity
n. $0_{\mathrm{fresh}}^{\mathrm{d}} \rightarrow$ magnitude of the entity
o. $\mathrm{n}(\mu, \sigma) \rightarrow$ Gaussian random function
p. $\xi \rightarrow$ coefficient that weights
q. $\xi = \mathrm{l.sig}\left((0.5 * \mathrm{maximum\_iter} - \mathrm{present\_iteration})/k\right) * \mathrm{R}(0,1)$ (56)
r. Pick the bunch hub and comprise arbitrary rate to it to generate fresh entity
s. Otherwise randomly pick an entity from this bunch and comprise arbitrary rate to the entity to form fresh entity
t. Otherwise randomly pick double bunches to generate fresh entity
u. Effervescent function is introduced in the procedure to convergence rate
v. $\xi = \mathrm{R}^* \exp\left(1 - \frac{\mathrm{max\_iter}}{\mathrm{max_{iter}} - \mathrm{Present_{iter}} + 1}\right)$ (57)
w. Produce an arbitrary rate
x. If it is a smaller amount than a preordained probability , then the twofold bunch centres are assembled in composed mode and then included with arbitrary rate to generate fresh entity
y. Otherwise, twofold entities from each picked bunch are randomly designate and pooled with arbitrary rate to generate fresh entity
z. Freshly produced entity is associated with the dynamic entity with the similar entity directory
aa. The grander one is reserved and logged as the fresh entity
bb. If “n” fresh entities have been produced, then go to next step or else go to step k
cc. Complete if preordained maximum number of iterations has been touched or else go to step c
dd. End

Ikigai and Kaizen inspired Optimization Algorithm

Ikigai and Kaizen inspired Optimization Algorithm is designed based on the humanity actions of happy living and continuous improvement [30, 31]. The term Ikigai means reason to live and kaizen meaning is continuous improvement. Even though the conception of Ikigai has long been existent in Japanese principles, it was mainly promoted by Japanese psychoanalyst and academician Mieko Kamiya in her book titled -On the Meaning of Life in 1966. In Ikigai causes or substances that fetch worth or importance to lifespan and a sensation that one's lifespan has worth or importance for the reason that of the presence of its cause or entity. Societal Ikigai mentions; that are acknowledged by humanity by means of helping actions and loop happenings. Non - Societal Ikigai is not openly connected to humanity, such as confidence and self-control. Anti-social Ikigai mentions the uncomplicated inspiration for existing from end to end murky sentiments, such as the wish to disgust somebody or craving for vengeance. Kaizen is the concept of continuous improvement. Enhancement may be single time or unceasing, big or minor, that will improve the productivity of the work.

Cluster of Groups had put forth a detailed discussion about Ikigai and Kaizen. Each adherent has unique perception or meaning about Ikigai and Kaizen. All the Groups conduct a Brain storm session and finally attain the real knowledge about Ikigai and Kaizen rendering to their conditions. Naturally society will have different opinions on Ikigai and Kaizen. It’s vital to understand the real meaning of Ikigai and kaizen for the self and development of the nation.Osborn [32] given innovative guidelines for Notion engendering in Brainstorming procedure and solutions are attained by the following rules,

i. Defer the decision
ii. Entirety Drives in its way
iii. Synthesizethe outcome
iv. Drive for capability

a. Each adherent will deliver the own perception on Ikigai and Kaizen
b. Many perception and meaning will outflow in the brain storm session

c. Kaizen. Cluster will be formed among the Groups and each cluster will be headed by an individual who possesses better perceptions
d. Groups will compare the perceptions of the Groups and finally deliver the best
e. An optimal perception will be generated

Every corner of the perceptions delivered by all Groups will be analysed in the brainstorm session and each adherent difficulties, then deliver final meaning of Ikigai and Kaizen. Cluster will be formed among the Groups and each cluster [33, 34] will be headed by an individual who possesses better perceptions. The cluster will be formed after initial observations of all perceptions.Through this actions all Groups confusion and opposite perceptions will be erased and it will make them to live happily and enhance their lifestyle through high productivity in their working atmosphere. Engendering the fresh Groups as follows,

$$A^{e}_{fresh} = A^{e}_{Pick} + \varphi * g(\rho,\tau) \quad (58)$$

$A^{e}_{Pick} \rightarrow to\ pick\ fresh\ entity$
$g(\rho,\tau) \rightarrow\ Gaussian\ rate$

Calculation the Gaussian rate [46] is done as follows,

$$\varphi = logsig\big((0.50 * max.iter\ - cur.iter)/k\big) * Z \quad (59)$$

$Z \in [0,1]$
$max, cur.iter \rightarrow maximum\ and\ current\ iteraion$
Effervescent functional value [35] included to enhance the solution

$$\varphi = Z^{*}exp\left(1 - \frac{max\ iter}{max\ iter - current\ iter + 1}\right) \quad (60)$$

Algorithm Ikigai and Kaizen
a. Start
b. Create the probable solutions
c. The Groups in the Brain storm session
d. Compute the individual rate
e. Rank the and identify the best adherent
f. Produce an arbitrary assessment between 0 and 1
g. If the probability value is minor than a foreordained prospect then,
h. Select the cluster core and take account of arbitrary standards to it in order to generate fresh entity
i. Or else capriciously pick a specific from cluster and take account of arbitrary assessment to the specific to produce fresh entity.
j. Or else capriciously pick double clusters to produce fresh entity
k. Produce an arbitrary assessment
l. If it is below a foreordained probability , at that juncture the dual clusters are joined together and sequentially included with arbitrary standards to produce fresh entity
m. Or else, dual entities from each cluster are capriciously joined together and included with arbitrary standards to produce fresh entity
n. Freshly produced entities are equalled with the sprightly entity and documented as the fresh entity
o. $t = t + 1$
p. output the best solution
q. end

Teaching on cosmos inspired optimization algorithm
Time is inestimable with a cyclical universe, where the existing cosmos was heralded and will be trailed by an endless sum of cosmoses. The single, divine personified soul is the lifespan power or mindfulness inside an existing individual. Contemporary physical science has revealed that the tempo of formation and annihilation is not only obvious in the shot of the periods and in the natal and demise of all existing individuals, but then again is likewise the identical spirit of inert substance. Rendering to quantum field concept, dance of formation and annihilation is the foundation of the very presence of substance. Contemporary physical science has thus discovered that each subatomic unit not only does a dynamism dance, but also an energetic procedure of formation and annihilation. In exploration region circumscribed the population "Q" is capriciously initialized.

$$Q^{0}_{(i,j)} = Q^{min}_{j} + R \times \left(Q^{max}_{j} - Q^{min}_{j}\right) \quad (61)$$

$R \in [0,1]$
$Q^{max}_{j}\ and\ Q^{min}_{j} \rightarrow limits$

The ith student rendering generation is defined as,

$$Q^{g}_{(i)} = \left[Q^{g}_{(i,1)}, Q^{g}_{(i,2)}, Q^{g}_{(i,3)}, .., Q^{g}_{(i,j)}, .., Q^{g}_{(i,D)}\right] \quad (62)$$

$g \rightarrow generation$

In the teaching segment, the students will learn about Cosmos, Cosmic dance and Music sequentially,

$$U^{g} = \left[u^{g}_{1}, u^{g}_{2}, .., u^{g}_{j}, \ldots, u^{g}_{D}\right] \quad (63)$$

The teacher Q^{g}_{T} with the least goal functional rate of the student is measured as for individual iteration. Attention of the students in the direction of Teacher is accomplished in teaching segment of teacher. An illogical prejudiced disparity vector is designed to attain a fresh set of enhanced students from the existing mean, preferred mean factors is included to the present population of students.

$$Qfresh^{g}_{(i)} = Q^{g}_{(i)} + R \times (Q^{g}_{T} - TH_{P} \cdot U^{g}) \quad (64)$$

$R \in [0,1]$
$TH_{P} \rightarrow teaching\ parameter\ \in [1,2]$

$$TH_{P} = \mathrm{Rotund}[1 + R\ (0.01)\ \{2 - 1\}] \quad (65)$$

$R \in [0,1]$

In the generation if $Qfresh^{g}_{(i)}$ is higher student in the learning process than $Q^{g}_{(i)}$, then exchange the mediocre student learner $Q^{g}_{(i)}$. In the student learning segment the reciprocated communication inclines to enlarge the knowledge of the student. The illogical communication amongst students progresses the knowledge. For student $Q^{g}_{(i)}$ additional student $Q^{g}_{(r)}$ is illogically nominated $(i \neq r)$. In student learning segment the ith factor, $Q_{fresh^{\mathrm{new}}}$ is defined as,

$$Q_{(i)}^{g} = \begin{cases} Q_{(i)}^{g} + R \times \left(Q_{(i)}^{g} - Q_{(r)}^{g}\right) \\ if\ f\left(Q_{(i)}^{g}\right) < f\left(Q_{(r)}^{g}\right) \\ Q_{(i)}^{g} + R \times \left(Q_{(r)}^{g} - Q_{(i)}^{g}\right)\ else \end{cases} \quad (66)$$

Initial levels of the exploration individuals are reinvigorated to trial miscellaneous sectors of the exploration region. Movements of probationary solutions magnificently tuned and it will discover the inner areas of regions in advanced stages. Rate of the weight parameter “A” condensed linearly with period from extreme to a least rate.

$$A = A_{max} - \left(\frac{A_{max} - A_{min}}{\max iter}\right) * i \quad (67)$$

where,
$A_{max} and\ A_{min} \rightarrow limits\ of\ weight\ values$
$A_{max} and\ A_{min} \in [0,1]$

With weight parameter the enhanced students in the teaching segment is defined as,

$$Qfresh_{(i)}^{g} = A * Q_{(i)}^{g} + R * \left(Q_{Guru}^{g} - TH_{P} \cdot U^{g}\right) \quad (68)$$

In students learning segment a set of enhanced learners are defined as,

$$Qfresh_{(i)}^{g} = \begin{cases} A * Q_{(i)}^{g} + R \times \left(Q_{(i)}^{g} - Q_{(r)}^{g}\right) \\ if\ f\left(Q_{(i)}^{g}\right) < f\left(Q_{(r)}^{g}\right) \\ A * Q_{(i)}^{g} + R \times \left(Q_{(r)}^{g} - Q_{(i)}^{g}\right) Else \end{cases} \quad (69)$$

a. Start
b. Set the parameters
c. Initialize the entities
d. Define the Teacher
e. $For\ i = 1\ toNP$
f. Compute the rate of updated student
g. End for
h. $Qfresh_{(i)}^{g}$ is higher student in the learning process than $Q_{(i)}^{g}$
i. Exchange the mediocre student learner $Q_{(i)}^{g}$
j. Define the student learning segment
k. $Q_{(i)}^{g} = \begin{cases} Q_{(i)}^{g} + R \times \left(Q_{(i)}^{g} - Q_{(r)}^{g}\right) \\ if\ f\left(Q_{(i)}^{g}\right) \\ < f\left(Q_{(r)}^{g}\right) \\ Q_{(i)}^{g} + R \times \left(Q_{(r)}^{g} - Q_{(i)}^{g}\right)\ else \end{cases}$
l. Include the weight parameter
m. With weight parameter the enhanced students in the teaching segment are defined
n. $Qfresh_{(i)}^{g} = A * Q_{(i)}^{g} + R * (Q_{T}^{g} - TH_{P} \cdot U^{g})$
o. In Students learning segment a set of enhanced learners are defined
p. $t = t + 1$
q. Output the best solution
r. End

<u>Indus river watercourse flow optimization algorithm</u>

Indus river watercourse flow optimization algorithm is deigned based on the flow of Watercourse in the river Indus [36, 37]. Watercourse flow optimization algorithm is initiated with the conjecture of sprinkle of rain. Indus River drains into Arabian Sea. Fig 1. Shows the Indus and Pontiff SGS in the river

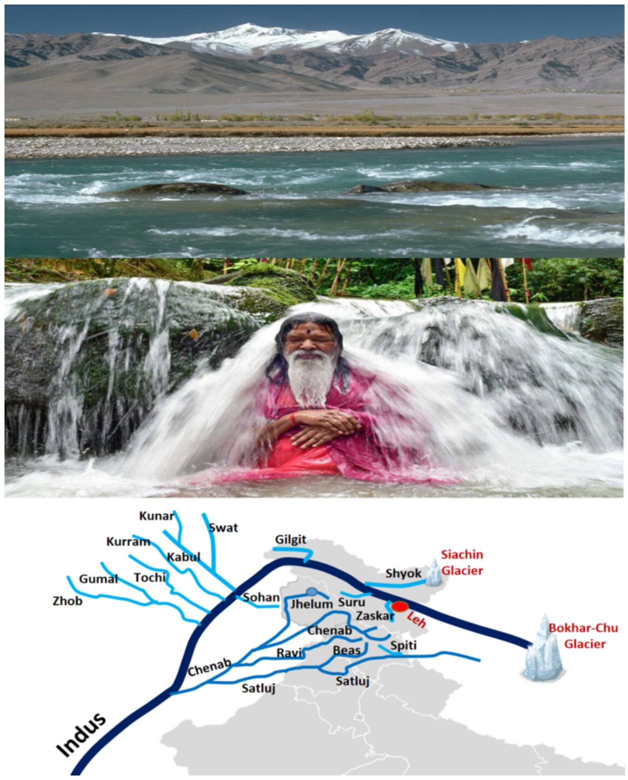

Fig. 1. Indus river flow and map

The Indus is a Trans boundary of Asia and a trans-Himalayan river of South and Central Asia. The 3,120 km (1,940 mi)river rises in mountain springs northeast of Mount Kailash in Western Tibet, flows northwest through the disputed region of Kashmir, bends sharply to the left after the Nanga Parbat massif, and flows south-by-southwest through Pakistan, before emptying into the Arabian Sea near the port city of KarachiRendering to Indus River, Arabian Sea is picked as the premium entity, and quantity of sprinkled rain droplets in the region are selected to designate as watercourse and as river stream it drains into Arabian Sea. Sprinkled rain droplets is described as,

$$SRD = [Z_1, Z_2, Z_3, .., Z_n] \quad (70)$$

$SRD \rightarrow Sprinkled\ rain\ droplets$

Rate of Sprinkled rain droplets is premeditated through cost function,

$$o_i = \int\left(Z_1^i, Z_2^i, .., Z_{N_v}^i\right) \quad (71)$$

where,
$i = 1,2, .., N_p$
$o_i = cost\ funtion_i$
$N_v\ and\ N_p \rightarrow quantity\ of\ sprinkled\ rain\ droplets$
$N_s \rightarrow river\ drain\ into\ Arabian\ Sea$

$$N_s = quantity\ of\ rivers + 1 \quad (72)$$

$$N_{SRD} = N_p - N_s \quad (73)$$

Forte of river torrent which drain into the Arabian Sea is defined as,

$$N_F = r\left\{\left|\frac{o_n}{\sum_{i=1}^{N_s} o_i}\right| \times N_{SRD}\right\} \quad (74)$$

$r \rightarrow round$
$F = 1,2,..,N_s$
$N_F \rightarrow Forte\ of\ river\ torrent$
$SRD \rightarrow\ Sprinkled\ rain\ droplets$
$o_i = cost\ funtion_i$
$N_v\ and\ N_p \rightarrow\ quantity\ of\ sprinkled\ rain\ droplets$
$N_s \rightarrow\ river\ drain\ into\ Arabian\ Sea$

Update the location of the river torrent

$$G_i^e(t+1) = R_i \times G_i^e(t) + Q_i^e(t) \quad (75)$$

$$Z_i^e(t+1) = Z_i^e(t) + G_i^d(t+1) \quad (76)$$

$G \rightarrow velocity\ of\ river\ torrent\ during\ flow$

Indus River will drains into Arabian Sea and the fresh spot of the river torrent is defined as

$$Z_T^{i+} = Z_T^i + R \times o \times (Z_R^i - Z_T^i) \quad (77)$$

$$Z_R^{i+} = Z_R^i + R \times o \times (Z_B^i - Z_R^i) \quad (78)$$

$R \in [0,1]$
$R \rightarrow river$
$T \rightarrow\ torrent$
$B \rightarrow Arabian\ Sea$

Vaporization process (e) which occurs in the Indus river torrent is defined as,

$$e_{max}^{i+1} = e_{max}^i - \frac{e_{max}^i}{max\ no.\ of\ iter} \quad (79)$$

Fresh spots of the recently formed Indus river torrents is demarcated as,

$$Z_T^n = min + R \times (max - min) \quad (80)$$

$$Z_T^n = Z_B + \sqrt{\mu} \times R \cdot n(1, N_v) \quad (81)$$

$\mu \rightarrow\ coefficient\ \ of\ exploration\ region\ near\ to\ ocean$

$R \in [0,1]$
$R \rightarrow river$
$T \rightarrow\ torrent$
$B \rightarrow Arabian\ Sea$
$N_v\ and\ N_p \rightarrow\ quantity\ of\ sprinkled\ rain\ droplets$

Updating the river torrent is done by,

$$Z_T^{t+1} = Z_T^t + (1 + a_i) \times (Z_R^i - \vec{Z}_T^i) \quad (82)$$

$$Z_T^{t+1} = X_T^t + (1 + a_i) \times (Z_B^i - \vec{Z}_T^i) \quad (83)$$

$$Z_R^{t+1} = X_R^t + (1 + a_i) \times (X_B^i - \vec{Z}_R^i) \quad (84)$$

where,
$R \rightarrow river$
$T \rightarrow\ torrent$
$B \rightarrow bay\ of\ bengal$

a. Start
b. Set the initial values
c. Determine the quantity of Indus river torrent flow into ocean
d. $N_s = quantity\ of\ river + 1$
e. $N_{SRD} = N_p - N_s$
f. Engender the initial population
g. Calculate the deliberation forte of Indus river torrent flow
h. $N_F = r\left\{\left|\frac{o_n}{\sum_{i=1}^{N_s} o_i}\right| \times N_{SRD}\right\}$
i. $while\ FE < max.FE\ do$
j. Update the location of the Indus river torrent
k. $G_i^e(t+1) = R_i \times G_i^e(t) + Q_i^e(t)$
l. $Z_i^e(t+1) = Z_i^e(t) + G_i^d(t+1)$
m. $Streamline\ the\ flow\ of\ Indus\ river\ torrent$
n. $Z_T^{t+1} = Z_T^t + (1 + a_i) \times (Z_R^i - \vec{Z}_T^i)$
o. $Z_T^{t+1} = X_T^t + (1 + a_i) \times (Z_B^i - \vec{Z}_T^i)$
p. $Z_R^{t+1} = X_R^t + (1 + a_i) \times (X_B^i - \vec{Z}_R^i)$
q. Calculate the fitness value
r. River will drain into $Arabian\ Sea$
s. $Z_T^{i+} = Z_T^i + R \times o \times (Z_R^i - Z_T^i)$
t. $Z_R^{i+} = Z_R^i + R \times o \times (Z_B^i - Z_R^i)$
u. Verify the Vaporization process
v. $e_{max}^{i+1} = e_{max}^i - \frac{e_{max}^i}{max\ no.\ of\ iter}$
w. Identify the Fresh spots of the nelwy formed Indus river torrents
x. $Z_T^n = min + R \times (max - min)$
y. $Z_T^n = Z_B + \sqrt{\mu} \times R \cdot n(1, N_v)$
z. $t = t + 1$
aa. Obtain the best value
bb. End

Teaching and sequential learning, Solution to Contradictory Opinions, Ikigai and Kaizen, Understanding cosmos and Indus river flow Watercourse flow dynamics algorithm are integrated to form the Enriched Indus River flow dynamics Optimization Algorithm (SINDHU), to enhance the search and attaining better solutions.

Enriched Indus River flow dynamics Optimization Algorithm (SINDHU)

a. Start
b. Set the parameters
c. Fix the points
//
Teaching and sequential learning//
d. $M_i^{Rpop}(t+1) = gbest_t^{pop} + Vcp * (Z_{r1}^{Rpop}(t) - Z_{r2}^{Rpop}(t))$
e. $Y_i^{Rpop}(t+1) = O_i \times O_i^{Rpop} + \overline{O}_\iota \times M_i^{Rpop}$
f. $End\ for$
g. $for\ i = 1 to N_{PTC}$
h. $M_i^{Ppop}(t+1) = Z_t^{Papop} + G * (Z_{r1}^{Ppop}(t) - Z_{r2}^{Ppop}(t))$
i. $Y_i^{Ppop}(t+1) = O_i \times O_i^{Ppop} + \overline{O}_\iota \times M_i^{Ppop} End\ for$
j. End for
k. $for\ i = 1 to N_{ATC}$
l. $M_i^{Apop}(t+1) = Z_t^{Apop} + H * \left(Z_{r1}^{Apop}(t) - Z_{r2}^{Apop}(t)\right) + H * \left(Z_{r2}^{Apop}(t) - Z_j^{Cpop}(t)\right)$
m. $Y_i^{Apop}(t+1) = O_i \times O_i^{Apop} + \overline{O}_\iota \times M_i^{Apop}$

// Solution to Contradictory Opinions//

n. Randomly pick a bunch hub
o. Randomly engender an entity to standby the designated bunch hub
p. Generate fresh entities
q. $O^d_{fresh} = O^d_{picked} + \xi * n(\mu, \sigma)$
  a. $O^d_{picked} \rightarrow$ magnitude of the entity
  b. $O^d_{fresh} \rightarrow$ magnitude of the entity
  c. $n(\mu, \sigma) \rightarrow$ Gaussian random function
  d. $\xi \rightarrow$ coefficient that weights
r. $\xi = l.\,sig\big((0.5 * maximum\_iter - present\_iteration)/k\big) * R(0,1)$

// Understanding Ikigai and Kaizen//

s. Pick the bunch hub and comprise arbitrary rate to it to generate fresh entity
t. Otherwise randomly pick an entity from this bunch and comprise arbitrary rate to the entity to form fresh entity
u. Otherwise randomly pick double bunches to generate fresh entity
v. Effervescent function is introduced in the procedure to convergence rate
w. $\xi = R^{*}\exp\left(1 - \frac{max\_iter}{max_{iter} - Present_{iter} + 1}\right)$
x. Select the cluster core and take account of arbitrary standards to it in order to generate fresh entity
y. Or else capriciously pick a specific from cluster and take account of arbitrary assessment to the specific to produce fresh entity.
z. Or else capriciously pick double clusters to produce fresh entity

//Teaching on cosmos //

s. Define the Teacher
t. $For\ i = 1\ to NP$
u. Compute the rate of updated student
v. End for
w. $Qfresh^g_{(i)}$ is higher student in the learning process than $Q^g_{(i)}$
x. Exchange the mediocre student learner $Q^g_{(i)}$
y. Define the student learning segment
z. $Q^g_{(i)} = \begin{cases} Q^g_{(i)} + R \times \left(Q^g_{(i)} - Q^g_{(r)}\right) \\ \quad if\ f\left(Q^g_{(i)}\right) < f\left(Q^g_{(r)}\right) \\ Q^g_{(i)} + R \times \left(Q^g_{(r)} - Q^g_{(i)}\right)\ else \end{cases}$
aa. Include the weight parameter
bb. With weight parameter the enhanced students in the teaching segment are defined
cc. $Qfresh^g_{(i)} = A * Q^g_{(i)} + R * (Q^g_T - TH_P \cdot U^g)$
dd. In Students learning segment a set of enhanced learners are defined

// Indus river watercourse flow optimization //

cc. Determine the quantity of Indus river torrent flow into ocean
dd. $N_s = quantity\ of\ river + 1$
ee. $N_{SRD} = N_p - N_s$
ff. Engender the initial population
gg. Calculate the deliberation forte of Indus river torrent flow
hh. $N_F = r\left\{\left|\frac{o_n}{\sum_{i=1}^{N_s} o_i}\right| \times N_{SRD}\right\}$
ii. while FE < max. FE do
jj. Update the location of the Indus river torrent
kk. $G^e_i(t+1) = R_i \times G^e_i(t) + Q^e_i(t)$
ll. $Z^e_i(t+1) = Z^e_i(t) + G^d_i(t+1)$
mm. Streamline the flow of Indus river torrent
nn. $Z^{t+1}_T = Z^t_T + (1 + a_i) \times \left(Z^i_R - \vec{Z}^i_T\right)$
oo. $Z^{t+1}_T = X^t_T + (1 + a_i) \times \left(Z^i_B - \vec{Z}^i_T\right)$
pp. $Z^{t+1}_R = X^t_R + (1 + a_i) \times \left(X^i_B - \vec{Z}^i_R\right)$
qq. Calculate the fitness value
rr. River will drain into Arabian Sea
ss. $Z^{i+}_T = Z^i_T + R \times o \times \left(Z^i_R - Z^i_T\right)$
tt. $Z^{i+}_R = Z^i_R + R \times o \times \left(Z^i_B - Z^i_R\right)$
uu. Verify the Vaporization process
vv. $e^{i+1}_{max} = e^i_{max} - \frac{e^i_{max}}{max\ no.\ of\ iter}$
ww. Identify the Fresh spots of the
xx. nelwy formed Indus river torrents
yy. $Z^n_T = \min + R \times (\max - \min)$
zz. $Z^n_T = Z_B + \sqrt{\mu} \times R \cdot n(1, N_v)$
aaa. $t = t + 1$
bbb. Output the solution
ccc. End

In order to analyse the competency of the proposed algorithms (Periodic Knowledge acquisition and Replication inspired optimization (PRO) algorithm, SINDHU algorithm are compared with two populations algorithms; Trade union chief selection optimization (TUCSO) algorithm and Population based optimization (PBO) algorithm in section 5 and 6 sequentially.

5. Trade Union Chief Selection Optimization Algorithm

Then in this paper Trade union chief selection optimization (TUCSO) algorithm is applied to solve the problem. TUCSO is designed by imitating the elective procedure of the trade union to select the leader. Vital motivation of TUCSO was the elective procedure, the picking the chief, and the influence of the workers alertness level on the electing their own chief for the trade union. TUCSO population is channelled by the examination region under the leadership of the chosen chief. TUCSO procedure is scientifically designed and it is grounded on exploration and exploitation.
In Trade union chief selection optimization (TUCSO) algorithm, each worker indicates the solution for the problem and in matrix the population defined as,

$$T = \begin{bmatrix} T_1 \\ \vdots \\ T_i \\ \vdots \\ T_N \end{bmatrix}_{N \times D} = \begin{bmatrix} t_{1,1} & \cdots & t_{1,d} \\ \vdots & \ddots & \vdots \\ t_{N,1} & \cdots & t_{N,d} \end{bmatrix}_{N \times d} \tag{85}$$

$T \rightarrow$
Trade union chief selection optimization algorithm population

$$t_{i,j} = min_j + R_{i,j} \cdot \left(max_j - min_j\right) \tag{86}$$

where,
$R_{i,j} \in [0,1]$
$max_j and min_j\ are\ the\ limits$
$i = 1,2,3,4, \ldots, N$
$j = 1,2,3,4, \ldots, d$

$$Y = \begin{bmatrix} Y_1 \\ \vdots \\ Y_i \\ \vdots \\ Y_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} Y(O_1) \\ \vdots \\ Y(O_i) \\ \vdots \\ Y(O_N) \end{bmatrix}_{N\times 1} \quad (87)$$

where,
$Y \rightarrow\ objective\ functional\ value$

In the first segment electing procedure and conducting the secret balloting process is accounted for the exploration. TUCSO associates, grounded on their alertness and partake in the balloting process. Workers alertness is measured as reliant on the excellence and blimey of the charge of the objective functional value. Consequently, the alertness of entities is imitated and mathematically formulated. In this alertness reproduction procedure, entities with improved standards of the objective functional value are additional alert.

$$X_i = \begin{cases} \frac{Y_i - Y_{poor}}{Y_{good} - Y_{poor}}, Y_{good} \neq Y_{poor} \\ 1, otherwise \end{cases} \quad (88)$$

where,
$Y_{good}\ and\ Y_{poor} \rightarrow$
$bood\ and\ poor\ objective\ functional\ values$

From all workers around nine to ten percentages are considered as contenders in the secret balloting process and they possess extreme alertness. Then the minimum quantity of the contenders will be two,

$B_c \geq 2$
$B_c \rightarrow\ contenders\ in\ the\ balloting\ process$

Execution of the secret balloting process in TUCSO algorithm is grounded on the level of alertness of every worker and is equated to an arbitrary number, if the level of alertness of a worker is upper than that arbitrary number, then the worker is capable to ballot for the finest contender. Or else, that worker arbitrarily ballots for one of the other contenders. This secret balloting process is scientifically defined as,

$$SBP_i = \begin{cases} Z_1, X_i < r \\ Z_k, otherwise \end{cases} \quad (89)$$

where,
$SBP_i \rightarrow secret\ balloting\ process$
$Z_1 \rightarrow best\ contender$
$Z_k \rightarrow kth\ contender$
$k \in \{2,3,..B_c\}$
$B_c \geq 2$
$r \in [0,1]$
$i = 1,2,3,4,..,N$
$j = 1,2,3,4,..,d$

At the conclusion of the secret balloting process, grounded on the sum total of polled ballots, the contender who obtained the uppermost quantity of ballots in his/ her name is designated as chosen chief. The location of entities in the TUCSO algorithm is rationalized beneath the impact and direction of the designated chief. This chief leads the procedure population to dissimilar zones in the examination region and upsurges the TUCSO exploration capability in the global examination. The procedure of apprising the TUCSO populace is led by the chief in such a system that primarily a fresh location is produced for each worker. The recently engendered location is adequate for apprising if it progresses the rate of the objective functional value. Or else, the parallel workers will remain in the preceding location. This modernization procedure in the TUCSO is designed as,

$$g_{i,j}^{new,p1} = \begin{cases} g_{i,j} + r_{i,j} \cdot (H_j - M \cdot g_{i,j}), Y_H < Y_i \\ g_{i,j} + r_{i,j} \cdot (g_{i,j} - H_j), Else \end{cases} \quad (90)$$

$$G_i = \begin{cases} G_i^{new,P1}, Y_i^{P1} < Y_i \\ Y_i, Else \end{cases} \quad (91)$$

where,
$r_{i,j} \in [0,1]$
$i = 1,2,3,4,..,N$
$j = 1,2,3,4,..,d$
$g_{i,j}^{new,p1} \rightarrow freshly\ created\ position$
$H \rightarrow elected\ chief$
$M \in \{1,2\}$

In the exploitation segment alertness of the workers has a prodigious influence on their accurate choices in the balloting procedure. Furthermore to the chief's inspiration on workers alertness, each workers opinions and actions can upsurge that individual's alertness. An enhanced solution may be recognized, which grounded on a local examination neighbouring to any projected solution. Consequently, the actions of workers to upsurge their alertness, tip to a rise in the TUCSO exploitation capability in the local examination and discover improved solutions. To pretend this local examination procedure, an arbitrary location is measured in the area of each worker in the search region. Objective functional value is assessed grounded on this fresh condition to define if this fresh condition is improved than the present condition of that worker. If the fresh location has an improved rate for the objective functional value, the local examination is efficacious and the location of the parallel worker is rationalised. Refining the rate of the objective functional value will upsurge that individual's alertness for superior decision making in the subsequent balloting (following iteration). This modernization procedure is to upsurge workers alertness in TUCSO procedure.

$$g_{i,j}^{new,p2} = g_{i,j} + (1 - 2r) * O * \left(1 - \frac{t}{T}\right) * g_{i,j} \quad (92)$$

$$G_i = \begin{cases} G_i^{new,P2}, Y_i^{P2} < Y_i \\ Y_i, Else \end{cases} \quad (93)$$

where,
$r_{i,j} \in [0,1]$
$i = 1,2,3,4,..,N$
$j = 1,2,3,4,..,d$
$g_{i,j}^{new,p2} \rightarrow newly\ created\ position$
$O = 0.02$
$t, T \rightarrow\ present\ and\ maximum\ iterations$

a. Start
b. Set the parameters
c. Create the population
d. Compute the objective functional value
e. $For\ i = 1toT$
f. Update the good and poor population associates

g. Execute secret balloting process (exploration segment)
h. Compute X_i
i. $X_i = \begin{cases} \frac{Y_i - Y_{poor}}{Y_{good} - Y_{poor}}, Y_{good} \neq Y_{poor} \\ 1, otherwise \end{cases}$
j. Define the contenders (based on alertness)
k. $SBP_i = \begin{cases} Z_1, X_i < r \\ Z_k, otherwise \end{cases}$
l. Ballot papers are counted and winner will be declared
m. $For\ i = 1 to\ N$
n. Compute the new position
o. $g_{i,j}^{new,p1} = \begin{cases} g_{i,j} + r_{i,j} \cdot (H_j - M \cdot g_{i,j}), Y_H < Y_i \\ g_{i,j} + r_{i,j} \cdot (g_{i,j} - H_j), Else \end{cases}$
p. Update G_i
q. $G_i = \begin{cases} G_i^{new,P1}, Y_i^{P1} < Y_i \\ Y_i, Else \end{cases}$
r. Alertness of the workers prior to balloting (Exploitation segment)
s. Calculate the fresh location
t. $g_{i,j}^{new,p2} = g_{i,j} + (1 - 2r) * O * \left(1 - \frac{t}{T}\right) * g_{i,j}$
u. Update G_i
v. $G_i = \begin{cases} G_i^{new,P2}, Y_i^{P2} < Y_i \\ Y_i, Else \end{cases}$
w. End for
x. $t = t + 1$
y. Output the best solution
z. End

6. Population based Optimization Algorithm

In Population based optimization (PBO) algorithm every optimal problem has an appetizing region which defined as Exploration region and it envisaged as a synchronize structure with a numeral of hatchets equivalent to the problem resolution parameters. Populace associates passage in the Exploration region, targeting to touch the suitable optima. The standards of the problem resolution factors are defined by the location of the PBO associates in the Exploration region. Every associate of the populace delivers info to other associates of the populace about the condition in which they discover themselves. In PBO, iteration grounded procedure, associates of the populace passage to the optimal areas. The chief notion in planning of the proposed PBO is to appraise the location of the populace associates of the procedure grounded on the middling info, and deduction of the vilest and preeminent associates of the populace.
The populace associates are demarcated as,

$$P = \begin{bmatrix} P_1 \\ \vdots \\ P_i \\ \vdots \\ P_N \end{bmatrix}_{N \times M} = \begin{bmatrix} p_{1,1} & \cdots & p_{1,M} \\ \vdots & \ddots & \vdots \\ p_{N,1} & \cdots & p_{N,M} \end{bmatrix} \quad (94)$$

where,
$P\ define\ the\ candidate\ solutions$
$P_i\ specify\ the\ ith\ candidate\ solutions$
$N, m\ are\ the\ decision\ variables\ and\ amount\ of\ PBO\ associates$
Then the vector rate is defined as,

$$VF = \begin{bmatrix} VF_1 \\ \vdots \\ VF_i \\ \vdots \\ VF_N \end{bmatrix}_{N \times 1} = \begin{bmatrix} VF(P_1) \\ \vdots \\ VF(P_i) \\ \vdots \\ VF(P_N) \end{bmatrix}_{N \times 1} \quad (95)$$

$VF \rightarrow vector\ function\ of\ the\ objectivefunction$
$VF_i \rightarrow ith\ objective\ functional\ value$

In the principal segment of Population based optimization (PBO) algorithm, an associate poised of the middling of the preeminent and vilest associates of the populace is tasked with modernizing the PBO populace. This part is scientifically defined as,

$$Q^{s_1} = P_{\text{preeminent}} + P_{\text{vilest}}/2 \quad (96)$$

$Q^{s_1}\ is\ middling\ of\ the\ preeminent\ and\ vilest\ associates\ of\ the\ populace$
$P_{\text{preeminent}}, P_{\text{vilest}}\ is\ preeminent\ and\ vilest\ associates\ of\ the\ populace$

$$P_{i,d}^{new,s_1} = \begin{cases} p_{i,d} + random \cdot (Q_d^{s_1} - U \cdot p_{i,d}), VF_i^{s_1} < VF_i \\ p_{i,d} + random \cdot (p_{i,d} - Q_d^{s_1}), Else \end{cases} \quad (97)$$

$$P_i = \begin{cases} P_{i,d}^{new,s_1}, VF_i^{new,s_1} < VF_i \\ P_i, Else \end{cases} \quad (98)$$

$P_{i,d}^{new,s_1}\ define\ the\ new\ position\ of\ the\ ith\ populace\ associate$
$VF_i^{new,s_1}\ is\ the\ new\ objective\ functional\ value$
$U \in [1,2]$

In the subsequent segment, the location of the populace associates is rationalized, which grounded on the deduction info of the preeminent and vilest populace associates and it defined as,

$$Q^{s_2} = P_{\text{preeminent}} - P_{\text{vilest}} \quad (99)$$

$$P_{i,d}^{new,s_2} = p_{i,d} + random \cdot Q_d^{s_2} \quad (100)$$

$Q^{s_2}\ is\ the\ deduction\ info\ of\ the\ preeminent\ and\ vilest\ populace\ associates$
$P_{i,d}^{new,s_2}\ define\ the\ new\ position\ of\ the\ ith\ populace\ associate$

$$P_i = \begin{cases} P_{i,d}^{new,s_2}, VF_i^{new,s_2} < VF_i \\ P_i, Else \end{cases} \quad (101)$$

$VF_i^{new,s_2}\ is\ the\ new\ objective\ functional\ value$

In the next segment the preeminent associate is engaged to lead the PBO population to attain the enhanced solutions.

$$P_{i,d}^{new,s_3} = p_{i,d} + random \cdot (p_{i,d} - U \cdot p_{\text{preeminent},d}) \quad (102)$$

$P_{i,d}^{new,s_3}\ define\ the\ new\ position\ of\ the\ ith\ populace\ associate$

$$P_i = \begin{cases} P_{i,d}^{new,s_3}, VF_i^{new,s_3} < VF_i \\ P_i, Else \end{cases} \quad (103)$$

VF_i^{new,s_3} *is the new objective functional value*

By applying the three segments in the projected Population based optimization (PBO) algorithm, every populace associate is positioned in a new-fangled location in the Exploration region. The fresh position of PBO associates means new-fangled candidate standards for resolution variables, tip to the assessment of fresh rates of objective function.

a. Start
b. Fix the parameters
c. Create the preliminary population randomly
d. Compute the objective function
e. $For\ t = 1\ to\ T$
f. Modernize the preeminent and vilest populace associates
g. $For\ i = 1\ to\ N$
h. Apply principal segment of Population based optimization algorithm
i. Compute Q^{s_1}
j. $Q^{s_1} = P_{\text{preeminent}} + P_{\text{vilest}}/2$
k. Modernize P_i
l. $P_{i,d}^{new,s_1} = \begin{cases} p_{i,d} + random \cdot \left(Q_d^{s_1} - U \cdot p_{i,d}\right), VF_i^{s_1} < VF_i \\ p_{i,d} + random \cdot \left(p_{i,d} - Q_d^{s_1}\right), Else \end{cases}$
m. $P_i = \begin{cases} P_{i,d}^{new,s_1}, VF_i^{new,s_1} < VF_i \\ P_i, Else \end{cases}$
n. Execute the segment two of Population based optimization algorithm
o. Compute Q^{s_2}
p. $Q^{s_2} = P_{\text{preeminent}} - P_{\text{vilest}}$
q. Modernize P_i
r. $P_{i,d}^{new,s_2} = p_{i,d} + random \cdot Q_d^{s_2}$
s. $P_i = \begin{cases} P_{i,d}^{new,s_2}, VF_i^{new,s_2} < VF_i \\ P_i, Else \end{cases}$
t. Employ the third segment of the Population based optimization algorithm
u. Modernize P_i
v. $P_{i,d}^{new,s_3} = p_{i,d} + random \cdot \left(p_{i,d} - U \cdot p_{\text{preeminent},d}\right)$
w. $P_i = \begin{cases} P_{i,d}^{new,s_3}, VF_i^{new,s_3} < VF_i \\ P_i, Else \end{cases}$
x. End for
y. $t = t + 1$
z. Output the best solution
aa. End

Computation complexity

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

$O(1)$

$O(n * d)$

$O(K * f * n)$

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

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

7. Simulation study

Proposed Trade union chief selection optimization (TUCSO) algorithm, Population based optimization (PBO) algorithm, Periodic Knowledge acquisition and Replication inspired optimization (PRO) algorithm, Enriched Indus River flow dynamics Optimization Algorithm (SINDHU) competences are corroborated in G01–G24 benchmark functions [21, 22]. Table 1 shows the comparative results.

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

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

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

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

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

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

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

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

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

$$F(x) = x_1 + x_2 + x_3$$

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

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

$$F(x) = e^{x_1x_2x_3x_4x_5}$$

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

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

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

$$F(x) = f_1(x_1) + f_2(x_2)$$

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

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

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

$$F(x) = x_1$$

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

$$F(x) = -x_1 - x_2$$

Table 1. Outcome of G01–G24 benchmark functions

B. Fun		SPSO[22]	BJAYA[22]	TUCSO	PBO	PRO	SINDHU
Fn.GO1 (-15.00)	Best Mean	-15 -14.71	-15 -15	-15 -15	-15 -15	-15 -15	-15 -15
Fn.GO2 (−0.803619)	Best Mean	−0.669158 −0.41996	−0.803605 −0.7968	−0.803619 −0.7978	−0.803619 −0.7978	−0.803619 −0.7978	−0.803619 −0.7978
Fn.GO3 (−1.0005)	Best mean	-1 0.764813	-1.0005 -1	-1.0005 -1	-1.0005 -1	-1.0005 -1	-1.0005 -1
Fn.GO4 (−30,665.539)	Best mean	−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	−30,665.539 −30,665.539
Fn.GO5 −5126.486	Best Mean	5126.484 5135.973	5126.486 5126.5060	5126.486 5126.5061	5126.486 5126.5061	5126.486 5126.5061	5126.486 5126.5061
Fn.GO6 (−6961.814)	Best Mean	−6961.814 −6961.814	−6961.814 −6961.814	−6961.814 −6961.814	−6961.814 −6961.814	−6961.814 −6961.814	−6961.814 −6961.814
Fn.GO7 −24.3062	Best Mean	24.37 32.407	24.3062 24.3092	24.3062 24.3095	24.3062 24.3095	24.3062 24.3095	24.3062 24.3095
Fn.GO8 (−0.095825)	Best Mean	−0.095825 −0.095825	−0.095825 −0.095825	−0.095825 −0.095825	−0.095825 −0.095825	−0.095825 −0.095825	−0.095825 −0.095825
Fn.GO9 −680.6301	Best Mean	680.630 680.630	680.6301 680.6301	680.6301 680.6301	680.6301 680.6301	680.6301 680.6301	680.6301 680.6301
Fn.GO10 −7049.28	Best Mean	7049.481 7205.5	7049.312 7052.7841	7049.310 7052.7840	7049.310 7052.7840	7049.310 7052.7840	7049.310 7052.7840
Fn.GO11 −0.7499	Best Mean	0.749 0.749	0.7499 0.7499	0.7499 0.7499	0.7499 0.7499	0.7499 0.7499	0.7499 0.7499
Fn.GO12 (−1)	Best Mean	−1 −0.998875	−1 −1	−1 −1	−1 −1	−1 −1	−1 −1
Fn.GO13 (−0.05394)	Best Mean	0.085655 0.569358	0.003625 0.003627	0.003621 0.003620	0.003621 0.003620	0.003621 0.003620	0.003621 0.003620
Fn.GO14 (–47.764)	Best Mean	−44.9343 −40.871	−47.7322 −46.6912	−47.7324 −46.6910	−47.7324 −46.6910	−47.7324 −46.6910	−47.7324 −46.6910
Fn.GO15 −961.715	Best Mean	961.715 965.5154	961.715 961.715	961.715 961.715	961.715 961.715	961.715 961.715	961.715 961.715
Fn.GO16 (–1.9052)	Best Mean	−1.9052 −1.9052	−1.9052 −1.9052	−1.9052 −1.9052	−1.9052 −1.9052	−1.9052 −1.9052	−1.9052 −1.9052
Fn.GO17 −8853.5396	Best Mean	8857.514 8899.4721	8853.5396 8872.5402	8853.5396 8853.5396	8853.5396 8853.5396	8853.5396 8853.5396	8853.5396 8853.5396
Fn.GO18 (−0.86603)	Best Mean	−0.86603 −0.8276	−0.86603 −0.86602	−0.86603 −0.86603	−0.86603 −0.86603	−0.86603 −0.86603	−0.86603 −0.86603
Fn.GO19 −32.6555	Best Mean	33.5358 36.6172	32.6803 32.7512	36.6170 36.6171	36.6170 36.6171	36.6170 36.6171	36.6170 36.6171
Fn.GO20 −0.204979	Best Mean	0.24743 0.97234	0.24139 0.24385	0.24132 0.24381	0.24132 0.24381	0.24132 0.24381	0.24132 0.24381
Fn.GO21 −193.274	Best Mean	193.7311 345.6595	193.5841 193.7219	193.2411 193.2443	193.2411 193.2443	193.2411 193.2443	193.2411 193.2443
Fn.GO22 −236.430	Best Mean	−258.74 −255.55	−242.45 −239.05	−242.39 −239.04	−242.39 −239.04	−242.39 −239.04	−242.39 −239.04
Fn.GO23 (–400.055)	Best Mean	−105.9826 −25.9179	−391.5192 −381.2312	−391.5105 −381.2304	−391.5105 −381.2304	−391.5105 −381.2304	−391.5105 −381.2304
Fn.GO24 (−5.5080)	Best Mean	−5.5080 −5.5080	−5.5080 −5.5080	−5.5080 −5.5080	−5.5080 −5.5080	−5.5080 −5.5080	−5.5080 −5.5080

Proposed Trade union chief selection optimization (TUCSO) algorithm, Population based optimization (PBO) algorithm, Periodic Knowledge acquisition and Replication inspired optimization (PRO) algorithm, Enriched Indus River flow dynamics Optimization Algorithm (SINDHU) validated in Six, IEEE bus test systems. Initially proposed algorithms are corroborated in Garver's six bus test system [38]. Table 2, 3 show loss evaluation and power oddness evaluation. Figs 2 and 3 give the assessment.

Table 2. Loss evaluation (Garver's six bus test system)

Technique	Loss in MW
BICHA [15]	14.8800
BIGA [16]	14.1500
SRSBD [17]	13.6400
BICBBA [18]	12.7940
IRBBA [19]	12.7680
TUCSO	11. 0096
PBO	11. 0095
PRO	11. 0059
SINDHU	11. 0002

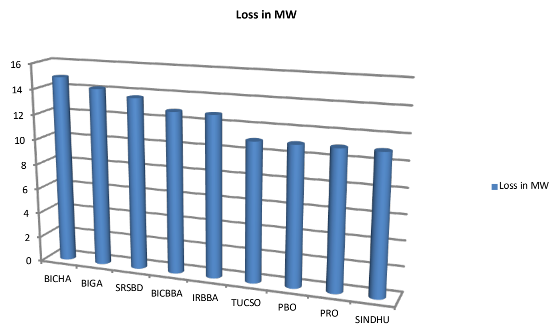

Fig. 2. Valuation of loss (Garver's six bus test system)

Table 3. Power eccentricity examination (Garver's six bus test system)

Technique	Power eccentricity (PU)
BICHA [15]	NA
BIGA [16]	NA

SRSBD [17]	NA
BICBBA [18]	0.51910
IRBBA [19]	0.22080
PEIO	0.21515
TUCSO	0.21518
PBO	0.21516
PRO	0.21488
SINDHU	0.21464

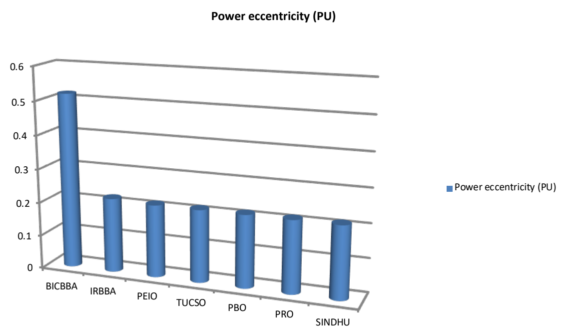

Fig. 3. Appraisal of Voltage aberration (Garver's six bus test system)

Trade union chief selection optimization (TUCSO) algorithm, Population based optimization (PBO) algorithm, Periodic Knowledge acquisition and Replication inspired optimization (PRO) algorithm Enriched Indus River flow dynamics Optimization Algorithm (SINDHU) are substantiated in IEEE 30 bus system [39]. Table 4 show the loss assessment, power eccentricity estimation and durableness valuation. Figures 4 to 6 give the valuation (L- Loss, PD- Power deviation, S- stability)

Table 4. Assessment of loss (IEEE 30 bus system)

Technique	L (MW)	PD(PU)	S(PU)
BAAPSOTS [1]	4.52130	0.10380	0.12580
MSIITS [1]	4.68620	0.20640	0.14990
MSIIPSO [1]	4.68620	0.13540	0.12710
AANTLOA [1]	4.59000	0.12870	0.12610
HDQOTLBO [2]	4.55940	0.12020	0.12640
BCATLBO [2]	4.56290	0.16140	0.14880
MSIIGA [3]	4.94080	0.15390	0.13940
MSISPSO [3]	4.92390	0.08920	0.12410
HBBAS [3]	4.90590	0.08560	0.11910
ROIFS [4]	4.57770	0.09130	0.11800
HDIFS [5]	4.51420	0.12200	0.11610
MSIIFS [6]	4.52750	0.08900	0.11610
MHLISAI [9]	4.81930	0.08770	0.12420
MHLISAII [10]	4.85470	0.37400	0.12520
ROSA [10]	4.53170	0.37700	0.12520
ROSSA[10]	4.52690	0.08540	0.12450
TUCSO	4.49012	0.08318	0.15469
PBO	4.49010	0.08316	0.15471
PRO	4.49001	0.08302	0.15490
SINDHU	4.43000	0.08298	0.15503

Trade union chief selection optimization (TUCSO) algorithm, Population based optimization (PBO) algorithm, Periodic Knowledge acquisition and Replication inspired optimization (PRO) algorithm, Enriched Indus River flow dynamics Optimization Algorithm (SINDHU) substantiated in IEEE 57 bus system [40]. Table 5 show the loss assessment, power eccentricity assessment and reliability valuation. Figs 7 to 9 give the valuation (L- Loss, PD- Power deviation, S- stability)

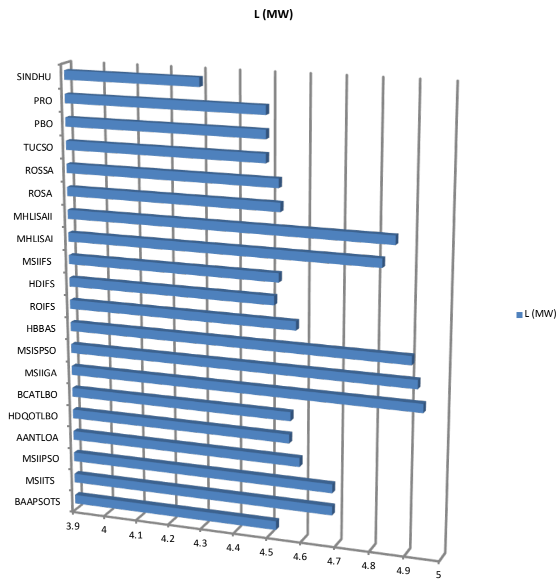

Fig. 4. Valuation of loss (IEEE 30 bus system)

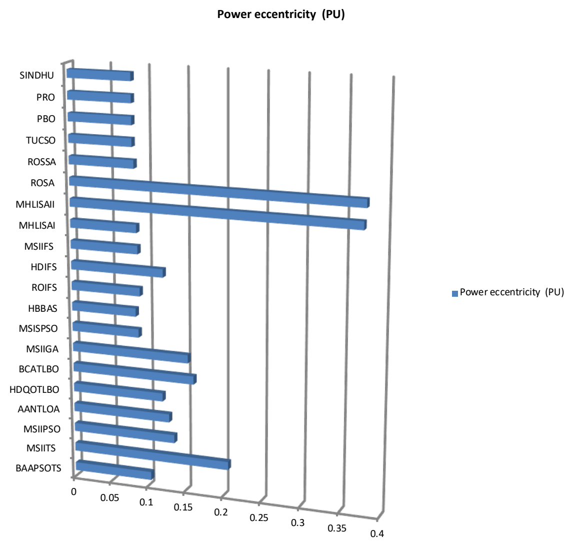

Fig. 5. Assessment of Power eccentricity (IEEE 30 bus system)

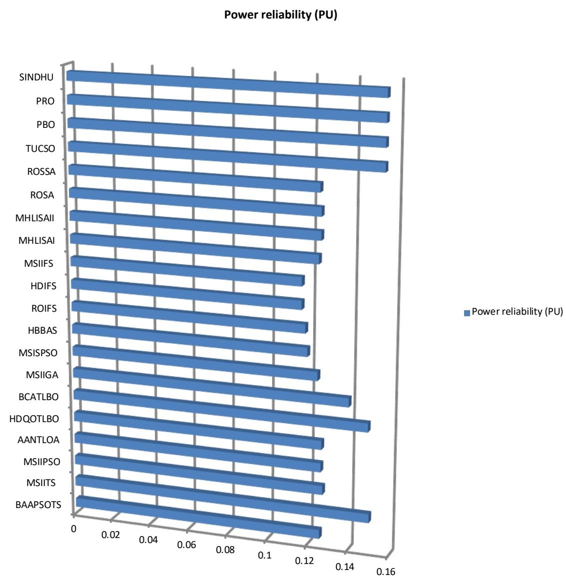

Fig. 6. Assessment of energy reliability (IEEE 30 bus system)

Table 5. Assessment of power loss (IEEE 57 bus system)

Technique	L (MW)	PD(PU)	S(PU)
MHIICOA [7]	22.37600	0.60510	0.251690
MHIICOA1[7]	22.38300	0.61550	0.258300
YRWACA [8]	26.04020	0.73090	0.278900
MHISA [8]	25.38540	0.94000	0.290000
MHIFOA [8]	26.65410	0.79130	0.283100
BICUOA [8]	24.53580	0.67110	0.275700
MHLISAI [10]	26.88000	1.06420	0.261690
MHLISAII [10]	26.92000	1.07200	0.278300
MHIISA [10]	26.97000	1.09120	0.298900
MDOPSO [9]	27.83000	1.10000	0.292000
MDOEPSO [9]	27.42000	0.89600	0.287100
MDFO [11]	24.25000	1.07420	0.278700
MDOGWA [12]	21.17100	1.09200	0.261690
IDGA [13]	25.64000	1.09820	0.288300
MHASO [13]	25.03000	1.12000	0.258900
RDAS [13]	24.90000	1.19600	0.294500
TUCSO	21.07918	0.60342	0.299796
PBO	21.07916	0.60340	0.299797
PRO	21.07894	0.60330	0.299811
SINDHU	21.00012	0.60000	0.299999

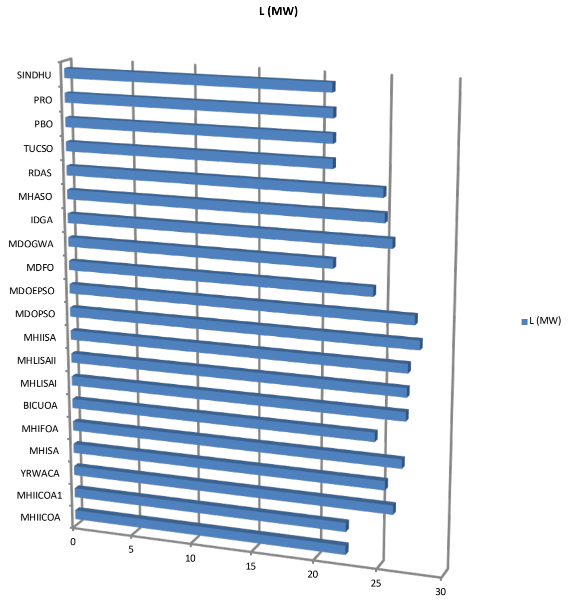

Fig. 7. Assessment of loss (IEEE 57 bus system)

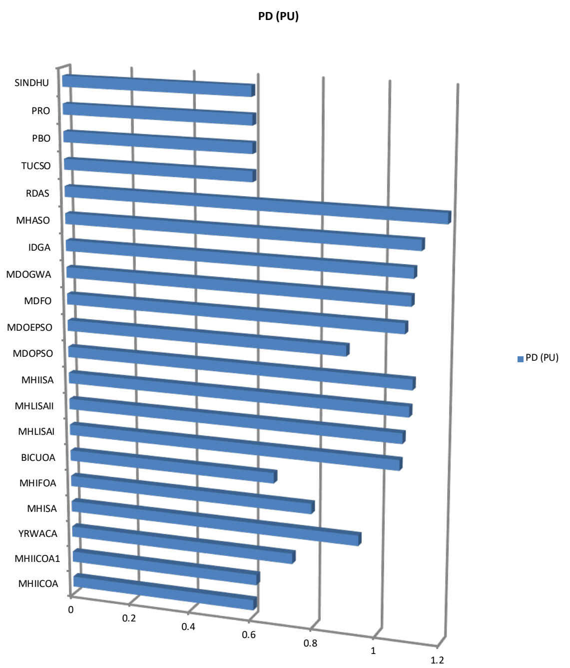

Fig. 8. Assessment of power eccentricity (IEEE 57 bus system)

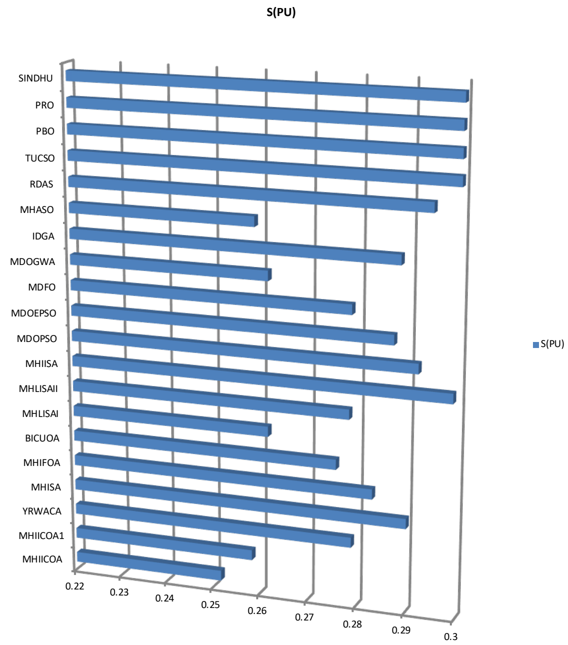

Fig. 9. Assessment of power solidity (IEEE 57 bus system)

Trade union chief selection optimization (TUCSO) algorithm, Population based optimization (PBO) algorithm, Periodic Knowledge acquisition and Replication inspired optimization (PRO) algorithm, Enriched Indus River flow dynamics Optimization Algorithm (SINDHU) are substantiated in IEEE 118 bus system [41]. Table 6 shows the loss evaluation, power eccentricity assessment and reliability valuation. Figs 10 to 12 give the evaluation (L- Loss, PD- Power deviation, S- stability).

Table 6. loss assessment (IEEE 118 bus system)

Technique	L (MW)	PD(PU)	S(PU)
MHIICOA [7]	114.80360	0.1605	0.060610
MHIICOA1[7]	114.86230	0.1608	0.060640
MDWACA [8]	118.32070	0.2315	0.060731
RDSA [8]	125.72880	0.4883	0.063900
IDAFOA [8]	125.68010	0.6061	0.061900
MHCUOA [8]	132.33410	0.2034	0.061230
MHCUOAI[8]	123.68670	0.1928	0.060720
MHCUOAII[8]	126.04260	0.1936	0.060770
PTLISAI [10]	119.79000	0.2819	0.066199
PTLISAII [10]	120.15000	0.2876	0.069230
PTIISA [10]	120.67000	0.2948	0.061720
MHAALCPSO [13]	121.53000	0.2976	0.065770
MHCLEPSO[13]	130.96000	0.2998	0.064199
TUCSO	113.54396	0.1565	0.069898
PBO	113.54393	0.1564	0.069900
PRO	113.54294	0.1536	0.069912
SINDHU	113.43240	0.1501	0.070128

Table 7 and Fig 13 show the time taken by Trade union chief selection optimization (TUCSO) algorithm, Population based optimization (PBO) algorithm, Periodic Knowledge acquisition and Replication inspired optimization (PRO) algorithm, Enriched Indus River flow dynamics Optimization Algorithm (SINDHU)

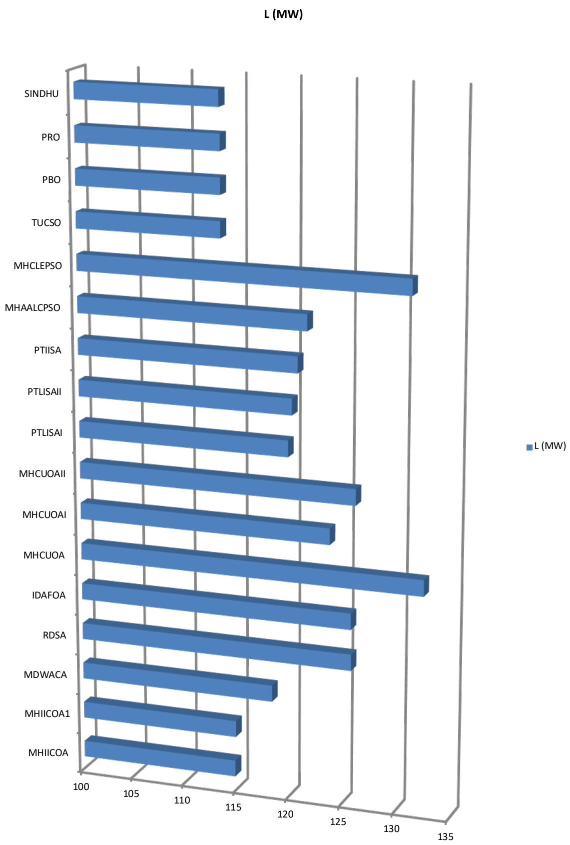

Fig. 10. Assessment of loss (IEEE 118 bus system)

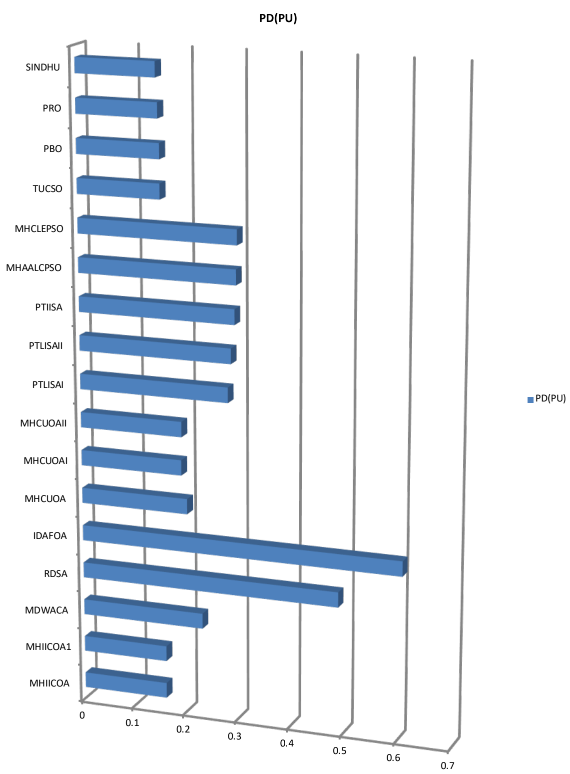

Fig. 11. Assessment of power eccentricity (IEEE 118 bus system)

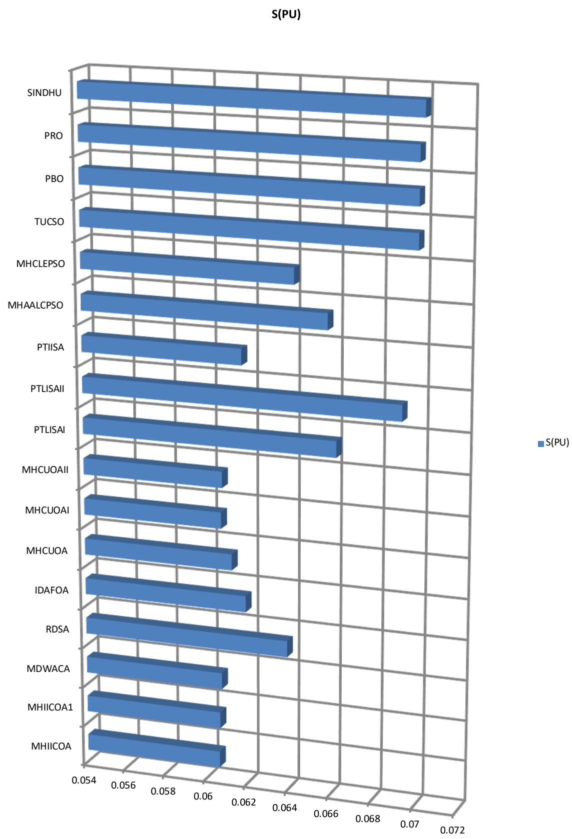

Fig. 12. Appraisal of power solidity (IEEE 118 bus system)

Table 7. Time taken by proposed algorithms

Technique	6-busT (S)	30 bus T (S)	57busT(S)	118 bus T(S)
TUCSO	7.72	20.46	27.88	37.93
PBO	7.71	20.44	27.85	37.91
PRO	7.51	20.12	27.24	37.56
SINDHU	7.48	20.07	27.12	37.39

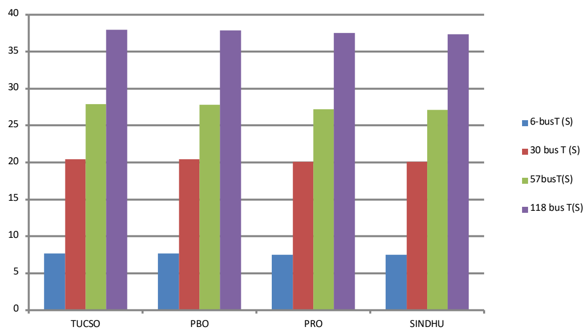

Fig. 13. Time taken by Trade union chief selection optimization (TUCSO) algorithm, Population based optimization (PBO) algorithm, Periodic Knowledge acquisition and Replication inspired optimization (PRO) algorithm, Enriched Indus River flow dynamics Optimization Algorithm (SINDHU)

8. Conclusion

Periodic Knowledge acquisition and Replication inspired optimization (PRO) algorithm, Enriched Indus River flow dynamics Optimization Algorithm (SINDHU) algorithm, Trade union chief selection optimization (TUCSO) algorithm and Population based optimization (PBO) algorithm are solved the Power loss Engineering problem efficiently.

In PRO Learning and adapting to the situations are more important in the human being life. This work emulates how an individual acquire knowledge and reproduce learned things to solve the problems in day to day life. Teaching and sequential learning, Solution to Contradictory Opinions, Ikigai and Kaizen, Understanding cosmos and Indus river flow Watercourse flow dynamics algorithm are integrated to form the Enriched Indus River flow dynamics Optimization Algorithm (SINDHU), to enhance the search and attaining better solutions.

TUCSO is designed by imitating the elective procedure of the trade union to select the leader. Vital motivation of TUCSO was the elective procedure, the picking the chief, and the influence of the workers alertness level on the electing their own chief for the trade union. TUCSO population is channelled by the examination region under the leadership of the chosen chief. TUCSO procedure is scientifically designed and it is grounded on exploration and exploitation.

In Population based optimization (PBO) algorithm every optimal problem has an appetizing region which defined as Exploration region and it envisaged as a synchronize structure with a numeral of hatchets equivalent to the problem resolution parameters. Populace associates passage in the Exploration region, targeting to touch the suitable optima.

Proposed Periodic Knowledge acquisition and Replication inspired optimization (PRO) algorithm, SINDHU algorithm, Trade union chief selection optimization (TUCSO) algorithm and Population based optimization (PBO) algorithm are verified in G01–G24 benchmark functions, Six and IEEE bus test systems.

In G01–G24 benchmark functions projected Trade union chief selection optimization (TUCSO) algorithm, Population based optimization (PBO) algorithm, Periodic Knowledge acquisition and Replication inspired optimization (PRO) algorithm, Enriched Indus River flow dynamics Optimization Algorithm (SINDHU) performed well and comparison done with Improved Particle swarm optimization algorithm and basic JAYA algorithm.

In Garver's six bus test system, Active power loss (MW) obtained is: TUCSO- 11. 0096, PBO- 11. 0095, PRO- 11. 0059 and SINDHU-11. 0002.Comparison done with other standard reported algorithms.

In IEEE 30 bus system, Active power loss (MW) obtained is: TUCSO- 4.49012, PBO- 4.49010, PRO- 4.49001, and SINDHU- 4.43000. Projected algorithms are compared with other reported algorithms.

In IEEE 57 bus system, Active power loss (MW) obtained is: TUCSO- 21.07918, PBO- 21.07916, PRO- 21.07894, and SINDHU- 21.00012. Proposed algorithms are appraised with other standard algorithms.

In IEEE 118 bus system, Active power loss (MW) obtained is: TUCSO- 113.54396, PBO- 113.54393, PRO- 113.54294, and SINDHU- 113.43240. Designed algorithms are compared with standard procedures.

Over all projected algorithms performed well in reducing the active power loss equally the voltage stability has been enhanced. This show that projected Trade union chief selection optimization (TUCSO) algorithm, Population based optimization (PBO) algorithm, Periodic Knowledge acquisition and Replication inspired optimization (PRO) algorithm, Enriched Indus River flow dynamics Optimization Algorithm (SINDHU) solved the problem efficiently.

Future scope of the work

In future Trade union chief selection optimization (TUCSO) algorithm, Population based optimization (PBO) algorithm, Periodic Knowledge acquisition and Replication inspired optimization (PRO) algorithm, Enriched Indus River flow dynamics Optimization Algorithm (SINDHU)can be applied to the problems inother areas in Engineering and Technology. Mainly algorithms can be used in the medical imaging and diagnostic conditions.

References

[1] A. Nasser Hussain, A. Abdulabbas Abdullah, and O. Muhammed Neda, "Optimal capacitor sizing for reactive power optimization by using a new hybrid algorithm based on merging of chaotic strategy with PSO algorithm", *J. Eng. Appl. Sci.*, vol. 14, no. 7, pp. 2112–2123, Dec. 2019.

[2] S. Mouassa, T. Bouktir, and A. Salhi, "Ant lion optimizer for solving optimal reactive power dispatch problem in power systems", *Eng. Sci. Technol. Int. J.*, vol. 20, no. 3, pp. 885–895, Jun. 2017.

[3] B. Mandal and P. K. Roy, "Optimal reactive power dispatch using quasi-oppositional teaching learning based optimization", *Int. J. Electr. Power Energy Syst.*, vol. 53, pp. 123–134, Dec. 2013.

[4] A. H. Khazali and M. Kalantar, "Optimal reactive power dispatch based on harmony search algorithm", *Int. J. Electr. Power Energy Syst.*, vol. 33, no. 3, pp. 684–692, Mar. 2011.

[5] Z. Li, Y. Cao, L. Van Dai, X. Yang, and T. T. Nguyen, "Finding solutions for optimal reactive power dispatch problem by a novel improved ant lion optimization algorithm," *Energies*, vol. 12, no. 15, p. 2968, Aug. 2019.

[6] J. Polprasert, W. Ongsakul, and V. N. Dieu, "Optimal reactive power dispatch using improved pseudo-gradient search particle swarm optimization", *Electr. Power Compon. Syst.*, vol. 44, no. 5, pp. 518–532, Aug. 2016.

[7] T. L. Duong, M. Q. Duong, V.-D. Phan, and T. T. Nguyen, "Optimal reactive power flow for large-scale power systems using an effective metaheuristic algorithm", *J. Electr. Comput. Eng.*, vol. 2020, pp. 1–11, Mar. 2020.

[8] H. S. Ahirwar and L. Srivastava, "Minimization of real power losses of transmission lines and improvement of voltage stability in power system using recurring MODE algorithm", *J. Inst. Eng. (India) Ser. B*, vol. 103, no. 2, pp. 525–540, Jul. 2022.

[9] P. Singh, R. Arya, L. S. Titare, and L. D. Arya, "Optimal load shedding to avoid risks of voltage collapse using black hole algorithm", *J. Inst. Eng. (India) Ser. B*, vol. 102, no. 2, pp. 261–276, Jan. 2021.

[10] K. Nagarajan, "Multi-objective optimal reactive power dispatch using Levy Interior Search Algorithm", *Int. J. Electr. Eng. Inform.*, vol. 12, no. 3, pp. 547–570, Sep. 2020.

[11] M. Weisberg and J. Duffin, "Evoking the moral imagination: Using stories to teach ethics and professionalism to nursing, medical, and law students", *J. Med. Humanit.*, vol. 16, no. 4, pp. 247–263, Jun. 1995.

[12] Y. Zhang, W. Wei, S. Xie, and Z. Wang, "Brain storm optimization algorithm with an adaptive parameter control strategy for finding multiple optimal solutions", *Int. J. Comput. Intell. Syst.*, vol. 16, no. 160, pp. 1 - 17, Sep. 2023.

[13] L. Chang and A. Mantooth, “Brainstorming for game-changing ideas”, *IEEE Power Electron. Mag.*, vol. 9, no. 4, pp. 35–37, Dec. 2022.

[14] Y. Hou, H. Wang, Y. Fu, K. Gao, and H. Zhang, “Multi-Objective brain storm optimization for integrated scheduling of distributed flow shop and distribution with maximal processing quality and minimal total weighted earliness and tardiness”, *Comput. Ind. Eng.*, vol. 179, Art. No. 109217, May 2023.

[15] W. Li, H. Luo, and L. Wang, “Multifactorial brain storm optimization algorithm based on direct search transfer mechanism and concave lens imaging learning strategy”, *J. Supercomput.*, vol. 79, no. 6, pp. 6168–6202, Oct. 2023.

[16] B. W. Carroll and D. A. Ostlie, *An introduction to modern astrophysics*. Cambridge University Press, 2017.

[17] S. Das, A. Verma, and P. R. Bijwe, “Transmission network expansion planning using a modified artificial bee colony algorithm”, *Int. Trans. Electr. Energy Syst.*, vol. 27, no. 9, Art No..e2372, May 2017.

[18] M. J. Rider, A. V. Garcia, and R. Romero, “Power system transmission network expansion planning using AC model”, *IET Gener. Transm. Distrib.*, vol. 1, no. 5, pp. 731 - 742, Sep. 2007.

[19] A. Mahmoudabadi, M. Rashidinejad, and M. Zeinaddini-Maymand, “A new model for transmission network expansion and reactive power planning in a deregulated environment”, *Engineering*, vol. 04, no. 02, pp. 119–125, Feb. 2012.

[20] S. Asadamongkol and B. Eua-arporn, “Transmission expansion planning with AC model based on generalized Benders decomposition”, *Int. J. Electr. Power Energy Syst.*, vol. 47, pp. 402–407, May 2013.

[21] M. T. Mouwafi, A. A. A. El-Ela, R. A. El-Sehiemy, and W. K. Al-Zahar, “Techno-economic based static and dynamic transmission network expansion planning using improved binary bat algorithm”, *Alex. Eng. J.*, vol. 61, no. 2, pp. 1383–1401, Feb. 2022.

[22] A. A. El-Ela, M. Mouwafi, and W. Al-Zahar, “Optimal transmission system expansion planning via binary bat algorithm,” in *2019 21st Int. Mid. East Power Sys. Conf, (MEPCON)*, Aug. 2019.

[23] J. Derrac, S. García, D. Molina, and F. Herrera, “A practical tutorial on the use of nonparametric statistical tests as a methodology for comparing evolutionary and swarm intelligence algorithms”, *Swarm Evol. Comput.*, vol. 1, no. 1, pp. 3–18, Mar. 2011.

[24] A. S. Alghamdi, “Optimal power flow of renewable-integrated power systems using a Gaussian bare-bones Levy-flight firefly algorithm”, *Front. Energy Res.*, vol. 10, May 2022.

[25] S. Sreejith, V. Suresh, and P. Ponnambalam, “Static economic dispatch incorporating UPFC using artificial bee colony algorithm”, in *Adv. in Intelligent Sys. and Comp.*, Singapore: Springer Singapore, pp. 757–769, Mar. 2016.

[26] C. Venkaiah and D. M. Vinod Kumar, “Fuzzy adaptive bacterial foraging congestion management using sensitivity based optimal active power re-scheduling of generators”, *Appl. Soft Comput.*, vol. 11, no. 8, pp. 4921–4930, Dec. 2011.

[27] D. T. Phan, “Lagrangian duality and branch-and-bound algorithms for optimal power flow”, *Oper. Res.*, vol. 60, no. 2, pp. 275–285, Apr. 2012.

[28] E. Anitha and J. Aravindhar D, “Efficient retinal detachment classification using hybrid machine learning with levy flight-based optimization,” *Expert Syst. Appl.*, vol. 239, Art. No. 122311, Apr. 2024.

[29] S. Ngeh., “Travel-associated SARS-CoV-2 transmission documented with whole genome sequencing following a long-haul international flight”, *J. Travel Med.*, vol. 29, no. 6, pp. 1 – 7, May 2022.

[30] M. Kumano, “On the concept of well-being in japan: Feeling shiawase as hedonic well-being and feeling ikigai as eudaimonic well-being”, *Appl. Res. Qual. Life*, vol. 13, no. 2, pp. 419–433, May 2018.

[31] A. C. Zeferino, G. N. Santos, T. L. Queiroz, and J. R. S. Ramos, “Evaluation of the application of continuous improvement based on the Kaizen concept in Emergency Healthcare Units,” *Rev. Meta Aval.*, Vol. 3, pp. 1 - 22, Jun. 2023.

[32] M. Weisberg and J. Duffin, “Evoking the moral imagination: Using stories to teach ethics and professionalism to nursing, medical, and law students”, *J. Med. Humanit.*, vol. 16, no. 4, pp. 247–263, Jun. 1995.

[33] Y. Zhang, W. Wei, S. Xie, and Z. Wang, “Brain storm optimization algorithm with an adaptive parameter control strategy for finding multiple optimal solutions”, *Int. J. Comput. Intell. Syst.*, vol. 16, no. 160, pp. 1 - 17, Sep. 2023.

[34] L. Chang and A. Mantooth, “Brainstorming for game-changing ideas”, *IEEE Power Electron. Mag.*, vol. 9, no. 4, pp. 35–37, Dec. 2022.

[35] W. Li, H. Luo, and L. Wang, “Multifactorial brain storm optimization algorithm based on direct search transfer mechanism and concave lens imaging learning strategy”, *J. Supercomput.*, vol. 79, no. 6, pp. 6168–6202, Oct. 2023.

[36] W. Hernandez, A. Viviescas, and C. A. Riveros-Jerez, “Water–structure interaction analysis of a segmental bridge using ambient vibration testing at different water levels”, *J. Civ. Struct. Health Monit.*, Vol. 13, pp. 1483 – 1497, Sep. 2022.

[37] N. Iqbal, F. Hossain, H. Lee, and G. Akhter, “Satellite gravimetric estimation of groundwater storage variations over Indus basin in Pakistan”, *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, vol. 9, no. 8, pp. 3524–3534, Jun. 2016.

[38] A. A. El-Ela, M. Mouwafi, and W. Al-Zahar, “Optimal transmission system expansion planning via binary bat algorithm,” in *2019 21st Int. Mid. East Power Sys. Conf, (MEPCON)*, Aug. 2019.

[39] S. Sreejith, V. Suresh, and P. Ponnambalam, “Static economic dispatch incorporating UPFC using artificial bee colony algorithm”, in *Adv. in Intelligent Sys. and Comp.*, Singapore: Springer Singapore, pp. 757–769, Mar. 2016.

[40] C. Venkaiah and D. M. Vinod Kumar, “Fuzzy adaptive bacterial foraging congestion management using sensitivity based optimal active power re-scheduling of generators”, *Appl. Soft Comput.*, vol. 11, no. 8, pp. 4921–4930, Dec. 2011.

[41] D. T. Phan, “Lagrangian duality and branch-and-bound algorithms for optimal power flow”, *Oper. Res.*, vol. 60, no. 2, pp. 275–285, Apr. 2012.