

NOVEL REMINISCENCE INSPIRED AND APPROXIMATION BASED MEASUREMENT OF MOUNT KAILASH OPTIMIZATION ALGORITHMS

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Abstract

Reminiscence inspired optimization algorithm (RIA) and Approximation based Measurement of Mount Kailash optimization (MMK) algorithm are applied to solve the true power loss reduction problem. Reminiscence inspired optimization algorithm is scientifically designed based on the reminiscence of human beings around the globe. In the procedure poor solutions are replaced by the present solutions consecutively. In the Approximation Measurement of the Mount Kailash optimization algorithm, the measurement of Mount Kailash is done by approximation of comparison with triangles in the four faces of the Mount Kailash. The first measurements on the east face of Mount Kailash are done through the approximation of the triangle and from this population created in the search space. The key objectives of the paper are true power loss reduction, voltage deviation minimization, and voltage stability enhancement. Validity RIA and MMK are verified in 23 Benchmarking functions and IEEE 30, 354 systems.

Keywords: Mount Kailash, reminiscence; triangle

Introduction

Reminiscence inspired optimization algorithm (RIA) and Approximation based Measurement of Mount Kailash optimization (MMK) algorithm is applied to solve the true power loss reduction problem. Reminiscence inspired optimization algorithm is scientifically designed based on the Reminiscence of the people around the globe. Remembering the past happenings and recollection of certain aspects are used by the people to attain optimized solutions for the present day problems

and also for future decision making. It is common all the people around the world own the collections of memories about the past happenings. Many things or aspects are forgotten by people but few important things they can recollect and analyze with the present situation to take an optimized decision for the problem or matter in the day to day life. This Reminiscence helps the general people to take crucial decisions for the future happenings. Life of the people intermingled with good and bad things

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rendering to their conditions of life. Each individual will analyze the past happenings and carve out the future road of travel in the life. Many times people decisions are reversible or in oscillation conditions, because their past experiences made the people to be in the state of variation. It may not be the basic nature or quality of the individual but the past experiences make them to be in the state of oscillation without being in the stable decision. But at one stage they are bound to take a stable decision through reminiscence effectively. These aspects are scientifically designed to formulate the algorithm. People are storing the important happenings in their reminiscence. Disappointments and achievements are particularly reminisced, and people will endure to remember those occasions. Disappointments and achievements give pain and pleasure for them. Yet all happenings in their life can't be remembered the people. Certain things are remembered and many things may be forgotten. Reminiscence is remembering or recollecting the past happenings by the people. The reminiscing attitude in the people is common. Remembering the disappointments and achievements are particularly reminisced and people will endure to remember those occasions. Through these action people may take a decision in times their on-going life. Poor solutions are erased in the stages and that positions are occupied by the present solutions sequentially. Reminiscence of achievements will give more happiness to the people. Certain times people may suffer short term or long term of loss of reminiscence. They may not even remember the much recently happened aspects and this factor is scientifically designed. Approximation based Measurement of Mount Kailash optimization algorithm is designed based on the triangles found in the four faces (East, West, North and South) of the Mount Kailash. In all the four faces of the Mount Kailash triangles are found and similarly this triangle shape found in other mountains, hills and even in human built pyramids. The measurement is found by approximation of comparing with triangles among the four faces of the Mount Kailash. In general at initial point the comparison between the triangles may be elaborated mode (exploration segment) and the comparison narrow down (exploitation segment) in precise mode in order to obtain the approximated magnitude of other faces of the Mount Kailash. Validity RIA and MMK is verified in 23 Benchmarking functions and IEEE 30, 354 systems.

Problem Formulation

Objective function of Electrical Power Loss Reduction Problem is demarcated as,

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

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

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

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

$$g = [VLG_1, \dots, VLG_{Ng}; QC_1, \dots, QC_{Nc}; T_1, \dots, T_{Nt}] \quad (2)$$

$$h =$$

$$[PG_{slack}; VL_1, \dots, VL_{Nload}; QG_1, \dots, QG_{Ng}; SL_1, \dots, SL_{Nt}] \quad (3)$$

$Q_c \rightarrow$ 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,

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

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

$$F_3 = \text{Minimize } L_{Maximum}$$

$S_L \rightarrow$ Apparent power

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

$$\begin{cases} L_j = 1 - \sum_{i=1}^{NPV} F_{ji} \frac{V_i}{V_j} \\ F_{ji} = -[Y_1]^{-1} [Y_2] \end{cases} \quad (4)$$

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

Parity constraints

$$0 = PG_i - PD_i - V_i \sum_{j \in N_B} V_j [G_{ij} \cos[\theta_i - \theta_j] + B_{ij} \sin[\theta_i - \theta_j]] \quad (5)$$

$$0 = QG_i - QD_i - V_i \sum_{j \in N_B} V_j [G_{ij} \sin[\theta_i - \theta_j] + B_{ij} \cos[\theta_i - \theta_j]] \quad (6)$$

NB is the number of buses

PG, QG $\rightarrow$ real and reactive power

Gij, Bij $\rightarrow$ mutual conductance and susceptance

PD, QD → real and reactive load

$$Z_i(t + 1) = \tilde{Z} + \Delta * (max - min) * R \quad (16)$$

Disparity constraints

$$\Delta = a * \sin\left(\frac{1}{a}\right) * g \quad (17)$$

$$P_{gsi}^{min} \leq P_{gsi} \leq P_{gsi}^{max} \quad (7)$$

$$g = 2 * \left(1 - \frac{t}{T}\right) \quad (18)$$

Reactive power generation (QGi)

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max}, i \in N_g \quad (8)$$

$$\begin{aligned} a &\in [0.1, 1.3] \\ R &\in [0, 1] \\ \tilde{Z} &\rightarrow \text{mean location (reminiscence)} \\ \Delta &\rightarrow \text{people mind state} \end{aligned}$$

Load bus voltage (VLi)

$$VL_i^{min} \leq VL_i \leq VL_i^{max}, i \in NL \quad (9)$$

Transformers tap setting (Ti)

$$T_i^{min} \leq T_i \leq T_i^{max}, i \in N_T \quad (10)$$

Switchable reactive power compensations (QCi)

$$Q_c^{min} \leq Q_c \leq Q_c^{max}, i \in N_C \quad (11)$$

$$|SL_i| \leq S_{L_i}^{max}, i \in N_{TL} \quad (12)$$

Generator bus voltage (VGi)

$$VG_i^{min} \leq VG_i \leq VG_i^{max}, i \in N_g \quad (13)$$

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

$$VL_i^{minimum} = \begin{cases} VL_i^{max}, & VL_i > VL_i^{max} \\ VL_i^{min}, & VL_i < VL_i^{min} \end{cases} \quad (14)$$

$$QG_i^{minimum} = \begin{cases} QG_i^{max}, & QG_i > QG_i^{max} \\ QG_i^{min}, & QG_i < QG_i^{min} \end{cases} \quad (15)$$

Many times people decisions are reversible or in oscillation conditions, because their past experiences made the people to be in the state of variation. It may not be the basic nature or quality of the individual but the past experiences make them to be in the state of oscillation without being in the stable decision. But at one stage they are bound to take a stable decision through reminiscence effectively. These aspects are scientifically designed to formulate the algorithm. In general people will stockpile the happenings in their reminiscence and in times few may be replaced by another one happening. Many times the reminiscence may be erased and filled again with other important happenings in the day to day life. But no people in the world can stockpile all the happenings and recollect. These factors are scientifically defined as follows,

- a. Start
- b. $RM = 1$; %RM → reminiscence
- c. $B = \text{Mod}(RM, N)$
- d. if $B == 0$, then
- e. $Poor(N, :) = P_{poor}$
- f. $Good(N, :) = P_{Good}$
- g. otherwise
- h. $Poor(B, :) = P_{poor}$
- i. $Good(B, :) = P_{Good}$
- j. End

Reminiscence Inspired Optimization Algorithm

In this paper Reminiscence inspired optimization algorithm (RIA) is scientifically designed based on the Reminiscence actions of the people around the world (Reisinho *et al.*, 2022; Shikha *et al.*, 2022; Strawn, 2023). In general people will remember pleasant incidents, experiences which happened previously. Each individual will analyze the past happenings and carve out the future road of travel in the life. General people will stockpile the important happenings in their reminiscence and it will be remembered or recollected in times. This aspect scientifically defined as,

People are storing the important happenings in their reminiscence. Disappointments and achievements are particularly reminisced, and people will endure to remember those occasions. Disappointments and achievements give pain and pleasure for them. Yet all happenings in their life can't be remembered the people. Certain things are remembered and many things may be forgotten. Reminiscence is remembering or recollecting the past happenings by the people.

The reminiscing attitude in the people is common. Remembering the disappointments and achievements are particularly reminisced and people will endure to remember those occasions.

A good example is shown in the Figure 1; Pontiff SGS is in the phase of Reminiscence; Pontiff SGS in Antarctica and his holiness time in the segment of Reminiscence.

Through these action people may take a decision in times their on-going life. This aspect scientifically defined as,

$$Z_i(t+1) = Z_{good} + \alpha * (R_1 * poor_{c1} - R_2 * \tilde{Z}) \quad (19)$$

$$\alpha = -\frac{1}{\gamma} * \log(1 - \varphi) \quad (20)$$

$C1 \rightarrow$ arbitrarily picked reminiscence

$Z_{good} \rightarrow$ best history of reminiscence

$R_1, R_2 \in [0,1]$

$\gamma = 4.0$

$\varphi \in [1, dimension]$

Poor solutions are erased in the stages and that positions are occupied by the present solutions sequentially. Reminiscence of achievements will give more happiness to the people and it defined as,

$$Z_i(t+1) = Z_{good} + \alpha * (R_1 * Good_{c2} - R_2 * \tilde{Z}) \quad (21)$$

Certain times people may suffer short term or long term of loss of reminiscence. They may not even remember the much recently happened aspects and this factor is scientifically designed as,

$$Z_i(t+1) = Z_r(t) + \rho * (R_1 * \tilde{Z} - P poor) \quad (22)$$

$Z_r(t) \rightarrow$ arbitrarily picked individual

Few people may forget the past happenings but they can remember well the present happenings and this aspect is defined as,

$$Z_i(t+1) = Z_{good} + R_2 * (Z_L - Z_i(t)) \quad (23)$$

$Z_L \rightarrow$ present optimal solution

$Z_{good} \rightarrow$ best history of reminiscence

$R_1, R_2 \in [0,1]$

- a. Start
- b. Fix the parameters
- c. Create the population
- d. Initialization of the entities
- e. *while* ($t \leq T_{max}$) *do*
- f. *for* $i \leftarrow 1$ *to* N *do*
- g. Streamline the reminiscence
- h. $Z_i(t+1) = \tilde{Z} + \Delta * (max - min) * R$
- i. $\Delta = a * \sin\left(\frac{1}{a}\right) * g$



Figure 1. Pontiff in the phase of Reminiscence

- j. $g = 2 * \left(1 - \frac{t}{T}\right)$
- k. End for
- l. $RM = 1; \%RM \rightarrow$ reminiscence
- m. $B = Mod(RM, N)$
- n. *if* $B == 0$, *then*
- o. $Poor(N, :) = P poor$
- p. $Good(N, :) = P Good$
- q. otherwise
- r. $Poor(B, :) = P poor$
- s. $Good(B, :) = P Good$
- t. *for* $j \leftarrow 1$ *to* N *do*
- u. $R = Random(1)$
- v. $R \leq 0.50$, *then*
- w. Streamline the Reminiscence of disappointments
- x. $Z_i(t+1) = Z_{good} + \alpha * (R_1 * poor_{c1} - R_2 * \tilde{Z})$
- y. $\alpha = -\frac{1}{\gamma} * \log(1 - \varphi)$
- z. $Z_i(t+1) = Z_r(t) + \rho * (R_1 * \tilde{Z} - P poor)$
- aa. $Z_i(t+1) = Z_{good} + R_2 * (Z_L - Z_i(t))$
- bb. *else then*
- cc. Streamline the Reminiscence of achievements
- dd. $Z_i(t+1) = Z_{good} + \alpha * (R_1 * Good_{c2} - R_2 * \tilde{Z})$
- ee. $RM = 1; \%RM \rightarrow$ reminiscence
- ff. $B = Mod(RM, N)$
- gg. *if* $B == 0$, *then*
- hh. $Poor(N, :) = P poor$
- ii. $Good(N, :) = P Good$
- jj. otherwise
- kk. $Poor(B, :) = P poor$
- ll. $Good(B, :) = P Good$
- mm. $t = t + 1$
- nn. Output the best solution
- oo. End



Figure 2. East face of the Mount Kailash and Triangle approximation



Figure 4. North face of the Mount Kailash and Triangle approximation



Figure 3. West face of the Mount Kailash and Triangle approximation



Figure 5. South face of the Mount Kailash and Triangle approximation

Approximation based Measurement of Mount Kailash Optimization algorithm

Approximation based Measurement of Mount Kailash optimization (MMK) algorithm is designed based on the triangles found in the four faces (East, West, North and South) of the Mount Kailash (Chakrabarty and Sadhukhan, 2020). In all the four faces of the Mount Kailash triangles are found and similarly this triangle shape found in other mountains, hills and even in human built pyramids. It's natural and difficult to measure directly the triangles found in the Mount Kailash in all the four faces (Figures 2-6). The measurement is found by approximation of comparing with triangles among the four faces of the Mount Kailash. At first east face of the Mount Kailash is considered and the approximation of the three sides triangle found in that face is measured and this condition is used

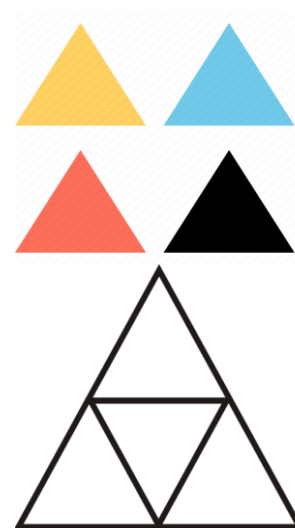


Figure 6. Approximations of four triangles

to engender the population in the search space as follows,

$$Z_{i1} = R * (max - min) + min \quad (24)$$

$Z_{i1} \rightarrow$ approximation and measuring the triangle in the east face

$R \in [0,1]$

$max, min \rightarrow limits$

Vertex of the triangle (Dettling *et al.*, 2023; Yuan *et al.*, 2023) is computed as follows,

$$Z_{i2} = Z_{i1} + U * f(\theta) \quad (25)$$

$U \rightarrow$ magnitude of the triangle in the east face

$$Z_{i3} = Z_{i1} + U * f\left(\theta + \frac{\pi}{3}\right) \quad (26)$$

$$U = 9.0 * e^{-\frac{t}{T}}$$

The value of “U” decreases as the iterations increases.

Accumulation of approximation in the measurement of the triangle in the East face is done as follows,

$$Z_{i4} = R_1 * Z_{i1} + R_2 * Z_{i2} + R_3 * Z_{i3} \quad (27)$$

$$R_1, R_2, R_3 \in [0,1]$$

The vertex comparison between the four faces (Figure 6) of the Mount Kailash is mathematically formulated as follows,

$$Z_{i,n1}^{t+1} = R_4 * Z_{i,b}^t + (1 - R_4) * Z_{R,b} \quad (28)$$

$$R_4 \in [0,1]$$

$Z_{i,b}^t, Z_{R,b} \rightarrow$ best comparison of approximation between the faces

$Z_{i,n1}^{t+1} \rightarrow$ comparison of east face with another face

Rendering to the problem of minimization, the limit factor are defined as follows,

$$\begin{cases} Z_{i,b}^{t+1} = Z_{i,n1}^{t+1}, f_{Z_{i,n1}^{t+1}} < f_{Z_{i,b}^{t+1}} \\ Z_{i,sb}^{t+1} = Z_{i,n1}^{t+1}, f_{Z_{i,n1}^{t+1}} < f_{Z_{i,sb}^{t+1}} \end{cases} \quad (29)$$

$Z_{i,sb}^{t+1} \rightarrow$ sub-optimal condition in comparison of approximation between the faces

Once the magnitude of the triangle in the east face of the mount kailash is found and the comparison of approximation of the other triangles found in west, north and south face are accomplished.

In general at initial point the comparison between the triangles may be elaborated mode (exploration segment) and the comparison narrow down (exploitation segment) in precise mode in order to obtain the approximated magnitude of other faces of the Mount Kailash.

The approximation of comparison is done with triangles found in the four faces (East, West, North and South) of the Mount Kailash. The comparison narrow down (exploitation segment) in precise mode is mathematically defined as,

$$Z_{i,n2}^{t+1} = Z_{i,b}^t + \delta * (Z_{i,b}^t - Z_{i,sb}^{t+1}) \quad (30)$$

$\delta \rightarrow$ decreasing factor

$$\delta = in \left(\frac{a-a^3}{T-1} t + e^3 - \frac{a-a^3}{T-1} \right) \quad (31)$$

Sub-optimal conditions are utilized to evade the trapping of the solution in local conditions. Then the updating conditions are defined as follows,

$$Z_{i,b}^{t+1} = \begin{cases} Z_{i,n2}^{t+1}, f_{Z_{i,n2}^{t+1}} < f_{Z_{i,b}^{t+1}} \\ Z_{i,b}^{t+1} \text{ else} \end{cases} \quad (32)$$

- a. Start
- b. Set the parameters
- c. Create the population
- d. $Z_{i1} = R * (max - min) + min$
- e. Measurement approximation of vertex of the triangle
- f. $Z_{i2} = Z_{i1} + U * f(\theta)$
- g. $Z_{i3} = Z_{i1} + U * f\left(\theta + \frac{\pi}{3}\right)$
- h. Accumulation of approximation in the measurement
- i. $Z_{i4} = R_1 * Z_{i1} + R_2 * Z_{i2} + R_3 * Z_{i3}$
- j. Vertex comparison between the four faces
- k. $Z_{i,n1}^{t+1} = R_4 * Z_{i,b}^t + (1 - R_4) * Z_{R,b}$
- l. *Verify the limit factor*
- m. $\begin{cases} Z_{i,b}^{t+1} = Z_{i,n1}^{t+1}, f_{Z_{i,n1}^{t+1}} < f_{Z_{i,b}^{t+1}} \\ Z_{i,sb}^{t+1} = Z_{i,n1}^{t+1}, f_{Z_{i,n1}^{t+1}} < f_{Z_{i,sb}^{t+1}} \end{cases}$
- n. *Apply the Exploitation segment*
- o. $Z_{i,n2}^{t+1} = Z_{i,b}^t + \delta * (Z_{i,b}^t - Z_{i,sb}^{t+1})$
- p. *Update the values*
- q. $Z_{i,b}^{t+1} = \begin{cases} Z_{i,n2}^{t+1}, f_{Z_{i,n2}^{t+1}} < f_{Z_{i,b}^{t+1}} \\ Z_{i,b}^{t+1} \text{ else} \end{cases}$
- r. $t = t + 1$
- s. End

Results

Reminiscence inspired optimization algorithm (RIA) and Approximation based Measurement of

Table 1. Outcome of ria in 23 benchmark functions

Benchmark Function	IORSSA (Tudose <i>et al.</i> , 2021)	BCSSSA (Tudose <i>et al.</i> , 2021)	RIA	MMK
1	6.38×10^{-12}	6.96×10^{-9}	6.33×10^{-12}	6.33×10^{-12}
2	3.08×10^{-7}	5.48×10^{-6}	3.02×10^{-7}	3.02×10^{-7}
3	2.53×10^{-1}	4.35×10^{-10}	2.50×10^{-1}	2.50×10^{-1}
4	6.71×10^{-7}	1.19×10^{-5}	6.59×10^{-7}	6.59×10^{-7}
5	4.110208	4.11726	4.11101	4.11101
6	3.19×10^{-10}	4.50×10^{-10}	3.01×10^{-10}	3.01×10^{-10}
7	2.23×10^{-5}	0.002002	2.20×10^{-5}	2.20×10^{-5}
8	-2,877.61	-3052.87	-2869.01	-2869.01
9	1.01×10^{-12}	22.85084	1.00×10^{-12}	1.00×10^{-12}
10	4.79×10^{-7}	0.810233	4.6×10^{-7}	4.6×10^{-7}
11	5.91×10^{-12}	0.33718	5.8×10^{-12}	5.8×10^{-12}
12	2.56×10^{-12}	0.051897	2.3×10^{-12}	2.3×10^{-12}
13	0.000366	0.001099	0.000336	0.000336
14	0.998004	0.998004	0.998000	0.998000
15	0.000307	0.000829	0.000210	0.000210
16	-1.03163	-1.03163	-1.03108	-1.03108
17	0.397887	0.397887	0.397861	0.397861
18	3	3	3	3
19	-3.86278	-3.86278	-3.86225	-3.86225
20	-3.23084	-3.21497	-3.23035	-3.23035
21	-10.1532	-8.80506	-10.1523	-10.1523
22	-10.0486	-8.46635	-10.0428	-10.0428
23	-10.5364	-9.28557	-10.5358	-10.5358

Table 2. Assessment of results (IEEE30 Bus)

Procedure	TPS (MW)	VOD (PU)	VFS (PU)
PDVC (Mandal and Roy, 2013)	4.6862	0.1354	0.1271
BCTLBO (Mouassa <i>et al.</i> , 2017)	4.5777	0.0913	0.1180
TIFS (Tran <i>et al.</i> , 2019)	4.5135	0.0896	0.1252
IMFS (Duong <i>et al.</i> , 2020)	4.5284	0.0891	0.1245
BCDE (Anil Kumar <i>et al.</i> , 2022)	4.6482	0.0802	0.1004
CTFWO (Abd-El Wahab <i>et al.</i> , 2022)	4.9448	0.1212	0.1232
IMPA (Khan <i>et al.</i> , 2022)	4.5677	0.1250	0.1135
PD (Ali <i>et al.</i> , 2023)	4.8395	1.2663	0.1259
RS (Ali <i>et al.</i> , 2023)	5.1328	1.0240	0.1287
AV (Ali <i>et al.</i> , 2023)	4.5464	1.9889	0.1294
RIA	4.4911	0.0839	0.1330
MMK	4.4508	0.0813	0.1353

Mount Kailash optimization (MMK) algorithm validated in 23 benchmark functions (Unimodal-7, Multimodal-6, fixed- dimension multimodal- 10) (Tudose *et al.*, 2021), Table 1 exhibit the outcome of RIA and MMK in 23 benchmark functions.

Reminiscence inspired optimization algorithm (RIA) and Approximation based Measurement of Mount Kailash optimization (MMK) validated in IEEE 30 bus system.

Table 2 shows the True power loss (TPS (MW)), Voltage oddness (VOD (PU)) and Firmness (VFS (PU)). Figures 7-9 show the evaluation.

Reminiscence inspired optimization algorithm (RIA) and Approximation based Measurement of

Table 3. Assessment of outcome (IEEE354 Bus)

Procedure	TPS (MW)	VOD (PU)
PEISAI (Mouassa and Bouktir, 2018)	337.374	0.4978
IMPSTAI (Mouassa and Bouktir, 2018)	338.715	0.5117
BCSA (Mouassa and Bouktir, 2018)	339.325	0.5216
PECLS (Nagarajan <i>et al.</i> , 2020)	341.001	0.5354
QOBT (Lenink, 2023)	341.123	0.6395
RIA	336.098	0.4378
MMK	334.336	0.4309

Mount Kailash optimization (MMK) verified in IEEE 354 bus test system.

Table 3, Figures 10 and 11 give assessment.

Table 2 shows the True power loss (TPS (MW)), Voltage oddness (VOD (PU)) and Firmness (VFS (PU)). Figures 7-9 show the evaluation.

Proposed Reminiscence inspired optimization algorithm (RIA) and Approximation based Measurement of Mount Kailash optimization (MMK) reduced the true power loss effectively. True Power loss (MW) (IEEE 30 bus) obtained by RIA-4.4911, MMK-4.4508. The comparisons had been done with the other standard reported algorithms.

Proposed Reminiscence inspired optimization algorithm (RIA) and Approximation based Measurement of Mount Kailash optimization (MMK) reduced the voltage deviation. The values of voltage deviation (PU) (IEEE 30 bus) obtained are RIA-0.0839, MMK-0.0813 and comparison of values are done with standard algorithms.

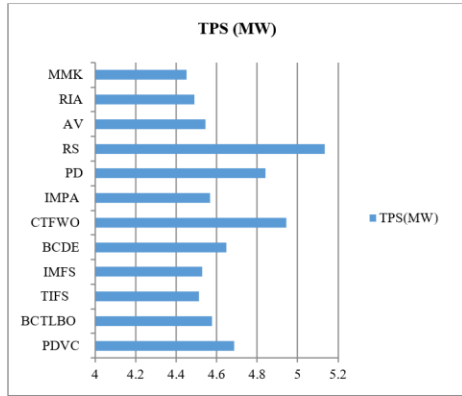


Figure 7. TPS (MW) valuation (IEEE30 BUS)

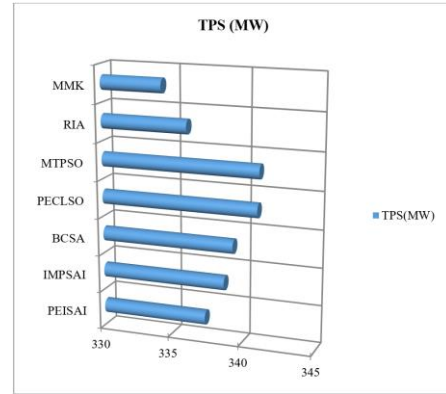


Figure 10. TPS (MW) valuation (IEEE354 BUS)

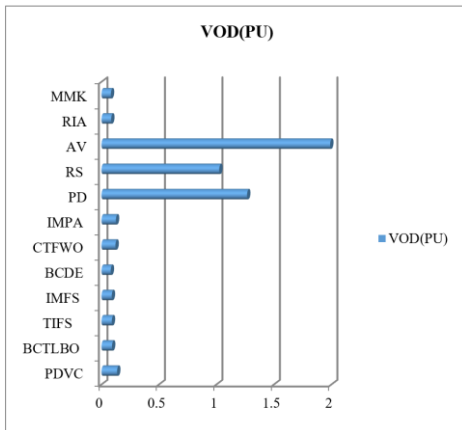


Figure 8. VOD (PU) valuation (IEEE30 BUS)

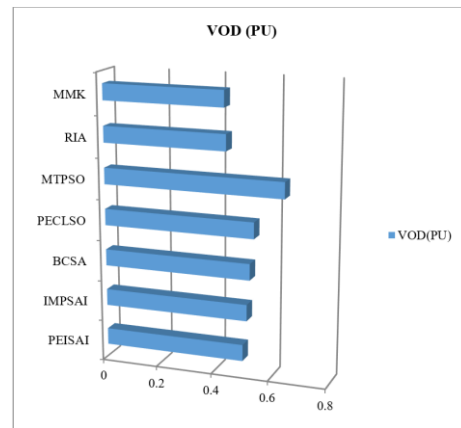


Figure 11. VOD (PU) valuation (IEEE354 BUS)

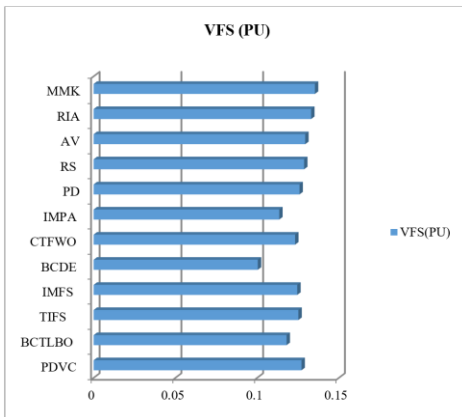


Figure 9. VFS (PU) valuation (IEEE30 BUS)

Proposed Reminiscence inspired optimization algorithm (RIA) and Approximation based Measurement of Mount Kailash optimization

(MMK) enhanced the voltage stability. The values of voltage stability (PU) (IEEE 30 bus) obtained are RIA-0.1330, MMK-0.1353 and comparison of values are done with standard algorithms.

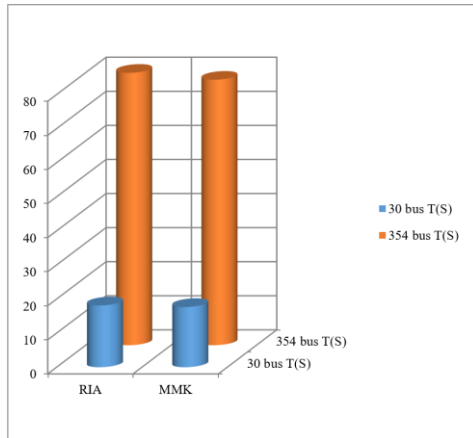
Proposed Reminiscence inspired optimization algorithm (RIA) and Approximation based Measurement of Mount Kailash optimization (MMK) reduced the true power loss effectively. True Power loss (MW) (IEEE 354 bus) obtained by RIA-336.098, MMK-334.336. The comparisons had been done with the other standard reported algorithms.

Proposed Reminiscence inspired optimization algorithm (RIA) and Approximation based Measurement of Mount Kailash optimization (MMK) reduced the voltage deviation. The values of voltage deviation (PU) (IEEE 354 bus) obtained are RIA-0.4378, MMK - 0.4309 and comparison of values are done with standard algorithms

Table 4 and Figure 12 show the time taken by RIA and MMK

Table 4. Time taken by RIA, MMK

Method	30 bus T(S)	354 bus T(S)
RIA	18.13	79.92
MMK	17.67	77.89

**Figure 12. Time taken by RIA and MMK**

Conclusions

Reminiscence inspired optimization algorithm (RIA) and Approximation based Measurement of Mount Kailash optimization (MMK) solved the true power loss reduction problem competently. Reminiscence helps the general people to take crucial decisions for the future happenings. Life of the people intermingled with good and bad things rendering to their conditions of life. Poor solutions are erased in the stages and that positions are occupied by the present solutions sequentially. Reminiscence of achievements will give more happiness to the people. Certain times people may suffer short term or long term of loss of reminiscence. They may not even remember the much recently happened aspects and this factor is scientifically designed. Few people may forget the past happenings but they can remember well the present happenings and this aspect is defined. In MMK, the measurement is found by approximation of comparing with triangles among the four faces of the Mount Kailash. At first east face of the Mount Kailash is considered and the approximation of the three side's triangle found in that face is measured and this condition is used to engender the population in the search space. Once the magnitude of the triangle in the east face of the mount kailash is found and the comparison of approximation of the other triangles found in west, north and south face are accomplished. In general at initial point the comparison between the triangles may be elaborated

mode (exploration segment) and the comparison narrow down (exploitation segment) in precise mode in order to obtain the approximated magnitude of other faces of the Mount Kailash. Validity of RIA and MMK is substantiated in 23 Benchmarking functions and IEEE 30, 354 systems.

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