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True power loss reduction by mountain zebra, augmented bat, and improved kidney search algorithms

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Article Info	ABSTRACT
	In this paper optimal reactive power problem is solved by mountain zebra algorithm (MZA), augmented bat algorithm (AB), and improved kidney search (IKS) algorithm. In the proposed algorithm, an intermediate state has been established at first, and then explores the intermediate state in order to obtain the global optima. Iterative local search implemented in this proposed algorithm. This technique enhances the search procedure in rapid mode. Then in this work, IKS algorithm has been proposed for solving optimal reactive power problem. In initial phase, a random population of probable solutions is created and re-absorption, secretion, excretion are imitated in the search process to check various conditions entrenched to the algorithm. The algorithm has been built to advance the search even a potential solution moved to waste (W) and it will be brought back to the filtered blood (FB). Glomerular filtration rate (GFR) test is utilized to verify the fitness of kidneys. Better efficiency of the proposed MZA, AB, and IKS algorithm confirmed by successful evaluation in standard IEEE 14-bus, 118-bus, and 300-bus test systems. The results show that active power loss has been reduced.

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1. INTRODUCTION

To minimize the true power loss is key aim in this reactive power optimization problem. Various techniques [1]-[6] have been applied to solve the reactive power optimization problem. Yet many difficulties are found while solving problem due to various types of constraints. After that many evolutionary techniques [7]-[16] applied to solve the reactive power problem, but many algorithms stuck in local optimal solution also failed to balance the exploration and exploitation during the search of global solution. In this work mountain zebra algorithm (MZA), augmented bat algorithm (AB), and improved kidney search (IKS) algorithm is applied for solving reactive power optimization problem. MZA emulates the searching techniques of the mountain zebra behaviour. Mainly mountain zebra utilize its special logical, cooperative and self-determining approach in its search to find the grassland. This technique enhances the search procedure in rapid mode. Then this paper proposes AB algorithm to solve optimal reactive power problem. Bat algorithm is mimicked from the actions of the bat and it fly randomly to look for the prey. Wavelength can be adjusted regularly and can control the rate of pulse emission r ∈ [0; 1], depend on the propinquity of the target. Standard bat algorithm often falls into the local optima when applied to many optimization problems. In the proposed AB algorithm local an intermediate state has been established at first, and then

explore the intermediate state in order to obtain the global optima. In the proposed algorithm, balance between local and global search has been maintained. Movements of the bats by toggle between local search and global search is controlled by the pulse rate r and receipt or refusal of a new-fangled engendered solution is controlled by loudness A.

Then in this work, IKS algorithm is proposed to solve the optimal reactive power problem. It imitates assorted progression of a biological kidney. Four main activities: filtration, re-absorption, secretion, and excretion play major role in the operation of kidneys. Kidneys function plays major role in urine formation and blood filtration in the human body. Fundamentally, the kidneys supervise the quantity of ions in the blood and also decrease the presence of surplus water and waste. In initial phase, a random population of probable solutions is created and re-absorption, secretion, and excretion are imitated in the search process to check various conditions entrenched to the algorithm. The algorithm is built to improve the search even a potential solution moved to waste (W) and it will be brought back to the filtered blood (FB). Glomerular filtration rate (GFR) test is utilized to verify the fitness of kidneys. Proposed MZA, AB, and IKS algorithm efficiency is verified by testing it in standard IEEE 14-bus, 118-bus, and 300-bus test systems.

2. OBJECTIVE FUNCTION

Objective of the problem is to reduce the true power loss as (1).

$$F = P_L = \sum_{k \in Nbr} g_k \left(V_i^2 + V_j^2 - 2V_i V_j \cos\theta_{ij} \right) \tag{1}$$

Voltage deviation is given as (2).

$$F = P_L + \omega_v \times \text{Voltage Deviation} \tag{2}$$

Voltage deviation is given by (3).

$$\text{Voltage Deviation} = \sum_{i=1}^{Npq} |V_i - 1| \tag{3}$$

In equality constraint is given by (4).

$$P_G = P_D + P_L \tag{4}$$

In inequality constraints are given by (5)-(9).

$$P_{gslack}^{min} \leq P_{gslack} \leq P_{gslack}^{max} \tag{5}$$

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max}, i \in N_g \tag{6}$$

$$V_i^{min} \leq V_i \leq V_i^{max}, i \in N \tag{7}$$

$$T_i^{min} \leq T_i \leq T_i^{max}, i \in N_T \tag{8}$$

$$Q_c^{min} \leq Q_c \leq Q_C^{max}, i \in N_C \tag{9}$$

3. MOUNTAIN ZEBRA ALGORITHM

Natural behaviour of mountain zebra during the scavenging endeavors has been pretended in MZA. Mountain zebra search in group to find the food. Alike to plain zebras, mountain zebras do not be in cumulative into big herds. Only they compose as small family groups consisting of a solo stallion around one to five mares, jointly with their current offspring's. Single males reside in divided groups, and adult single try to confine young mares to set up a harem. In this they are divergent by the leading stallion of the group.

At a single time, mares give birth to one foal. For about a year, the foal feeds mainly on its mother's milk after which it is weaned onto hard search. Between the ages of 13 and 37 months mountain zebra foals commonly move away from their maternal herds for some time. Conversely Hartmann's mountain zebra mares force out their foals when they are aged around 14 to 16 months. For a while, young males may wander alone before joining a bachelor group, while females are either taken into another breeding herd or

are joined by a single male to structure a novel breeding herd. Independent nature of mountain zebra is identified and integrated into the algorithm. It has been represented by (10).

$$c_{k+1} = c_k + r_{g1}a_1(lo_{max} - d_k) + r_{g2}a_2(lf_{max} - d_k) \qquad (10)$$

Where c_k, d_k represents the exploration and exploitation; r_{g1}, r_{g2} are learning factors; a_1, a_2 are random numbers. To prominent (best) mountain zebra there will be an interface with numerous mountain zebra s (10), and comparison will be there with each mountain zebra. Movement to other locations is expressed by (11).

$$d_{k+1} = \lambda(c_k + d_k) \qquad (11)$$

Each mountain zebra's fitness will be updated and both the lf_{max} (individual Mountain Zebra's location) and lo_{max} (the Mountain Zebra's herd's best location) will be determined. When present fitness is superior then (lf_{max}) location vector of particular mountain zebra is protected. Movement of mountain zebra s to stay or exploit within the exploration space and can be controlled by (10) and (11). On consideration of the two competing forces (lo_{max}, lf_{max}) mountain zebra s move to search other areas through (11).

Dimensional element d_k is subtracted from the maximum vector and multiplied by an arbitrary number (a_1,a_2) (between 0.0 and 0.6) with learning parameter (r_{g1},r_{g2}). Movement is updated for global and local search by (12), (13).

$$V_{l_{i,d}}^{t+1} = V_{l_{i,d}}^{t+1}\omega^t + random(1,d)\odot\left(F_{Best,d}^t - Y_{i,d}^t\right) if\ random > P[for\ global\ search] \quad (12)$$

$$V_{l_{i,d}}^{t+1} = V_{l_{i,d}}^{t+1}\omega^t + random(1,d)\odot\left(G_{Best,d}^t - Y_{i,d}^t\right) if\ random \leq P[for\ local\ search] \quad (13)$$

Then the position is modified by (14).

$$Y_{i,d}^{t+1} = V_{l_{i,d}}^{t+1} + y_{i,d}^t \qquad (14)$$

Worst fitness value separator will be implemented by (15).

$$Y_{worst,li} = Y_{min} + (Y_{max} - Y_{min} + 1) \times random \qquad (15)$$

MZA algorithm for solving reactive power problem
Step a: Reactive power problem objective function has been initiated in the process.
Step b: At random mountain zebra s are initiated in the solution space
Step c: Fitness values has been updated by (10)
Step d: Location of mountain zebra is modified by (11)
Step e: Is lo_{max} updating? If yes, go to subsequent step or else go to b
Step f: If end criterion is not met, then go back to step c
Step g: Optimized output

4.   AUGMENTED BAT ALGORITHM

Bat algorithm is mimicked from the actions of the bat and it fly randomly to look for the prey. Wavelength can be adjusted regularly and can control the rate of pulse emission $r \in [0; 1]$, depend on the propinquity of the target [17]. Loudness is assumed to be varying from a large (positive) A_0 to minimum constant value A_{min}.

Fresh solutions are produced by (16)-(18).

$$f_i^{(t)} = f_{min} + (f_{max} - f_{min}) \cup (0,1) \qquad (16)$$

$$v_i^{(t+1)} = v_i^t + (x_i^t - best)Q_i^{(t)}, \qquad (17)$$

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t)} \qquad (18)$$

For local search a capricious walk with direct exploitation is used to modernize the present most excellent solution by (19).

$$x^{(t)} = best + \epsilon A_i^{(t)}(2U(0,1) - 1) \tag{19}$$

ϵ - scaling factor, $A_i^{(t)}$- loudness. Depending on the pulse rate r_i and new-fangled solutions are accepted with some proximity local search will be commenced. When bat finds a prey rate of pulse emission r_i augments and loudness Ai diminished, which mathematically written by (20).

$$A_i^{(t+1)} = \alpha A_i^{(t)}, r_i^{(t)} = r_i^{(0)}[1 - \exp(-\gamma\epsilon)] \tag{20}$$

Standard Bat algorithm often falls into the local optima when applied to many optimization problems [17]. In the proposed AB algorithm, an intermediate state is established at first, and then explore the intermediate state in order to obtain the global optima. Iterative local search implemented in this proposed algorithm as follows:

Step a. X_* defines the best solution and is perturbed to attain an intermediate state X_{**} given by (21).

$$X_{**} = X_* \times random( ) \tag{21}$$

Step b. Intermediate state X_{**} has been re-searched in order to get the local optimal solution X_*', the local optima $f(X_*')$.

Step c. When $f(X_*') < f(X_*)$, then $X_*' = X_* f(X_*) = f(X_*')$ otherwise $xp\left(-\left(f(X_*') - f(X_*)\right)\right) > random ( )$, then $X_*' = X_* f(X_*) = f(X_*')$.

Step d. Output the most excellent solution.

Stochastic inertia weight (SIW) is applied in the proposed algorithm.

$$\omega = \mu_{min} + (\mu_{max} - \mu_{min}) \times random + \sigma \times randomn( ) \tag{22}$$

The velocity of the population updated by (23).

$$V_i^t = \omega V_i^{t-1} + (X_i^t - X_*) \tag{23}$$

In the proposed algorithm balance between local and global search has been maintained. Movements of the bats by toggle between local search and global search is controlled by the pulse rate r and receipt or refusal of a new-fangled engendered solution is controlled by loudness A.

$$r^t = \left(\frac{r_0 - r_\infty}{1 - t_{max}}\right)(t - t_{max}) + r_\infty \tag{24}$$

$$A^t = \left(\frac{A_0 - A_\infty}{1 - t_{max}}\right)(t - t_{max}) + A_\infty \tag{25}$$

The pseudocode is:

```
Begin
Initialize the bat population
Position and velocity of the bat population initialized
```
Update $Q_i^{(t)} = Q_{min} + (Q_{max} - Q_{min}) \cup (0,1)$; position and velocity of bats are modernized by $x_i^{(t+1)} = x_i^{(t)} + v_i^{(t)}$; $V_i^t = \omega V_i^{t-1} + (X_i^t - X_*)$
```
Is random > rᵢ? ; if yes got to next step or else to step "g"
From most excellent solution chose a solution and local solution engendered by
```
$x^{(t)} = best + \epsilon A_i^{(t)}(2U(0,1) - 1)$

Is random < Aᵢ and f(xᵢ) = f(x∗) ; if yes go to next step or else got to step "i"

pulse rate and loudness are updated for new solutions by $r^t = \left(\frac{r_0 - r_\infty}{1 - t_{max}}\right)(t - t_{max}) + r_\infty$; $A^t = \left(\frac{A_0 - A_\infty}{1 - t_{max}}\right)(t - t_{max}) + A_\infty$
```
Update the most excellent solution and fitness value
Is i < n? ; if yes got to step "d" or else go to next step
Obtain the perturbed solution
```
X_i' by $X_{**} = X_* \times random( )$
```
Obtain the best perturbed solution
```
X_i'' and fitness $f(x_i'')$
```
Is f(xᵢ'') < f(Xᵢ) ; if yes go to next step or else
```
$e^{-\left(\left(f(x_i'') < f(x_i)\right)\right)} > random$
$X_i = X_i'', f(x_i'') = f(X_i)$
is i < M? ; if yes go to step "d" or else return with global best solution X_i and fitness value
End

5.   IMPROVED KIDNEY SEARCH ALGORITHM

Kidney search algorithm imitates assorted progression of a biological kidney. Four main activities: filtration, re-absorption, secretion, and excretion play major role in the operation of kidneys. In initial phase, a random population of probable solutions is created and re-absorption, secretion and excretion are imitated in the search process to check various conditions entrenched to the algorithm. The algorithm is built to improve the search even a potential solution moved to W and it will be brought back to the FB. GFR test is utilized to verify the fitness of kidneys [18]. The test approximately gives the capacity of blood that pass through the glomeruli every minute. Depend on the GFR test consequence which is less than 15 or falls between 15 and 60 or is more than 60 a particular deed will be executed. This procedure implemented to improve the rate of exploration and finding the optimal solution. The GFR testing procedure is added at the end of every iteration. When GFR level is less than 15, the procedure is repetitive with the population in Filtered Blood. When GFR level is between 15 and 60, a progress of practical solutions in Filtered blood is implemented as a treatment for shortened kidney function. This progression increases the exploration ability and is planned to help the algorithm in discovery of enhanced solution. If the GFR level is larger than 60, then kidney function is common, in which case no extra progression is added to algorithm. Movement equation is (26).

$$Z_{i+1} = Z_i + rand(Z_{best} - Z_i) \tag{26}$$

Filtering of the solutions is done with a filtration rate and Calculation of the filtration rate (l_r) is done using the following (27).

$$l_r = \beta \times \frac{\sum_{i=1}^{s} f(y_i)}{s} \tag{27}$$

β is a constant value between 0 and 1 and is attuned in advance, s represents the size of the population, and $f(y_i)$ represents an objective function of solution y at ith iteration. In every iteration, previous to integration the FB and W will be population for the subsequent iteration. The algorithm computes the GFR level based on the fr in FB.

$$\text{Glomerular filtration rate}_{minimum} = 120 - \left(\frac{fr_{FB}*100}{fr}\right) \tag{28}$$

The pseudocode is:

```
Define the Population
Calculate approximate solution in the population
Most excellent solution Z_best , is found
By (27) find the Filtration rate- l_r,
Define waste (W)
Define filtered blood (FB)
Number of iteration will be found
Do while (iteration < number of iterations)
For Z_i ; compute new Z_i by using (26)
Check the value of Z_i using l_r
If Z_i allocated to W then place on re-absorption and produce Z_new by using (26)
If re-absorption is not fulfilled then Z_new will not be part of FB
Eradicate Z_i from W (excretion)
Place randomly Z into W to exchange Z_i
End if
Z_i is reabsorbed
Else
If it is superior than the Z_worst in FB
Z_worst is secreted
Calculate the GFR level solutions in FB by using (28)
if 15 < GFR level < 60 ; then implement movement of solutions in FB
End if
if GFR level < 15 ; then algorithm proceeded with the same population in FB
End if
End if
End for
Rank the Z_s from FB and modernize the  Z_best
Merge W and FB
By (27) amend filtration rate l_r
End while
Return  Z_best
```

6. SIMULATION RESULTS

At first in standard IEEE 14 bus system, the validity of the proposed MZA, AB and IKS algorithm has been tested. The comparison of results is presented in Table 1.

Table 1. Comparison results

Control variables	ABCO [19]	IABCO [19]	MZA	AB	IKS
V1	1.06	1.05	1.00	1.05	1.01
V2	1.03	1.05	1.01	1.04	1.00
V3	0.98	1.03	1.00	1.01	1.05
V6	1.05	1.05	1.04	1.02	1.06
V8	1.00	1.04	0.92	0.90	0.91
Q9	0.139	0.132	0.110	0.109	0.106
T56	0.979	0.960	0.922	0.920	0.918
T47	0.950	0.950	0.910	0.908	0.913
T49	1.014	1.007	1.002	1.000	1.001
Ploss (MW)	5.92892	5.50031	4.99204	4.50009	4.49971

Validity of proposed MZA, AB and IKS algorithm has been verified in standard IEEE 118-bus test system. Limitations on reactive power source are listed in Table 2, and Table 3 shows good performance of the proposed algorithms.

Table 2. Reactive power sources limits

BUS NO	5	34	37	44	45	46	48
QC MAX	0.00	14.00	0.00	10.00	10.00	10.00	15.00
QC MIN	-40.00	0.00	-25.00	0.00	0.00	0.00	0.00
BUS NO	74	79	82	83	105	107	110
QC MAX	12.00	20.00	20.00	10.00	20.00	6.00	6.00
QC MIN	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Then IEEE 300-bus system [21] is used as test system to validate the performance of the proposed MZA, AB and IKS algorithm. Table 4 shows the comparison of real power loss obtained after optimization. Real power loss has been considerably reduced when compared to the other standard reported algorithms. Compared to EEA method, proposed IKS algorithm reduces 4.77% real power loss.

Table 3. Real power loss comparison results

Active power loss (p.u)	Method- BBO [20]	Method- ILSBBO/ Strategy I [20]	Method -ILSBBO/ Strategy II [20]	MZA	AB	IKS
Minimum value	128.7700	126.9800	124.7800	118.7920	116.9900	116.0405
Maximumvalue	132.640	137.3400	132.3900	123.8430	123.4127	122.7196
Average value	130.2100	130.3700	129.2200	120.1249	119.7901	119.0012

Table 4. Comparison of real power loss

Parameter	EEA Method [22]	EGA Method [22]	CSA Method [23]	MZA	AB	IKS
PLOSS (MW)	650.6027	646.2998	635.8942	620.1982	620.1041	619.5427

7. CONCLUSION

In this paper, optimal reactive power problem has been successfully solved by MZA, augmented AB and IKS algorithm. Proposed MZA utilizes its special logical, cooperative and self-determining approach in the search of a best path to arrive at grassland. This confers it to reach optimum results faster than some other searching agents. In the proposed AB algorithm, balance between local and global search has been maintained. Movements of the bats by toggle between local search and global search is controlled by the pulse rate r and receipt or refusal of a new-fangled engendered solution is controlled by loudness A. IKS algorithm has been built to advance the search, even a potential solution moved to W and it will be brought back to the FB. GFR test is utilized to verify the fitness of kidneys. The test approximately gives the capacity of blood that pass through the glomeruli every minute. Proposed MZA, AB and IKS algorithms have

performed well when evaluated in standard IEEE 14-bus, 118-bus, and 300-bus test systems. True power loss reduced considerably when compared to other standard algorithms.

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