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Reduction of Active Power Loss and Improvement of Voltage Profile Index by Using Simulating Annealing Based Krill Herd Algorithm

[1]Mr.K.Lenin, [2]Dr.B.Ravindhranath Reddy, [3]Dr.M.Surya Kalavathi

[1,2,3] Jawaharlal Nehru Technological University Kukatpally, Hyderabad 500 085, India

Abstract: **In this paper, a new Bio-inspired algorithm, simulating annealing based krill herd algorithm (SAKHA) is proposed for solving reactive power dispatch problem. The krill herd (KH) algorithm is based on the imitation of the herd behavior of krill individuals. The least distance of each individual krill from food and from highest density of the herd are considered as the main task for the krill movement. A new krill Pick (KP) operator is used to purify krill performance when revising krill's position so as to augment its reliability and robustness dealing with optimization problems. In addition, a class of elitism system is used to save the best individuals in the population in the procedure of the krill updating. The proposed (SAKHA) algorithm has been tested on standard IEEE 57 bus test system and simulation results shows clearly about the high-quality performance of the proposed algorithm in tumbling the real power loss.**

Keywords: **Optimal Reactive Power, Transmission loss, Krill herd, simulated annealing, Bio-inspired algorithm.**

I. INTRODUCTION

Optimal reactive power dispatch (ORPD) problem is a multi-objective optimization problem that minimizes the real power loss and bus voltage deviation by satisfying a set of physical and operational constraints imposed by apparatus limitations and security requirements. Various mathematical techniques like the gradient method [1-2], Newton method [3] and linear programming [4-7] have been adopted to solve the optimal reactive power dispatch problem. Both the gradient and Newton methods has the complexity in managing inequality constraints. If linear programming is applied then the input- output function has to be uttered as a set of linear functions which mostly lead to loss of accurateness. The problem of voltage stability and collapse play a major role in power system planning and operation [8]. Global optimization has received extensive research awareness, and a great number of methods have been applied to solve this problem. Evolutionary algorithms such as genetic algorithm have been already proposed to solve the reactive power flow problem [9,10].Evolutionary algorithm is a heuristic approach used for minimization problems by utilizing nonlinear and non-differentiable continuous space functions. In [11], Genetic algorithm has been used to solve optimal reactive power flow problem. In [12], Hybrid differential evolution algorithm is proposed to improve the voltage stability index. In [13] Biogeography Based algorithm is projected to solve the reactive power dispatch problem. In [14], a fuzzy based method is used to solve the optimal reactive power scheduling method .In [15], an improved evolutionary programming is used to solve the optimal reactive power dispatch problem. In [16], the optimal reactive power flow problem is solved by integrating a genetic algorithm with a nonlinear interior point method. In [17], a pattern algorithm is used to solve ac-dc optimal reactive power flow model with the generator capability limits. In [18], proposes a two-step approach to evaluate Reactive power reserves with respect to operating constraints and voltage stability. In [19], a programming based proposed approach used to solve the optimal reactive power dispatch problem. In [20], presents a probabilistic algorithm for optimal reactive power provision in hybrid electricity markets with uncertain loads. This paper proposes a new bio-

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inspired optimization algorithm simulating annealing based krill herd algorithm (SAKHA) is used to solve the optimal reactive power dispatch problem. This method is based on the simulation of the herd of the krill swarms [21] in response to specific biological and environmental processes. With the plan of increasing the convergence speed, thus making the approach more feasible for a wider range of practical applications without losing the smart merits of the canonical KH approach. In SAKHA, firstly, we use a standard KH method to pick a good candidate solution set. And then, a new krill picking (KP) operator is introduced into the basic KH method. The introduced KP operator involves greedy strategy and accepting best solution with all level of probability originally used in simulated annealing (SA) [22, 23]. This greedy approach is applied to decide whether a good candidate solution is accepted so as to progress its efficiency and trustworthiness for solving global numerical optimization problem. The proposed algorithm SAKHA been evaluated in standard IEEE 57 bus test system & the simulation results shows that our proposed approach outperforms all reported algorithms in minimization of real power loss .

II. PROBLEM FORMULATION

The OPF problem is measured as a general minimization problem with constraints, and can be mathematically written in the following form:

Minimize f(x, u) (1)

Subject to g(x,u)=0 (2)

and

$h(x,u) \leq 0$ (3)

Where f(x,u) is the objective function. g(x.u) and h(x,u) are respectively the set of equality and inequality constraints. x is the vector of state variables, and u is the vector of control variables.

The state variables are the load buses (PQ buses) voltages, angles, the generator reactive powers and the slack active generator power:

$$x = \left(P_{g1}, \theta_2, .., \theta_N, V_{L1}, ., V_{LNL}, Q_{g1}, .., Q_{gng}\right)^T \quad (4)$$

The control variables are the generator bus voltages, the shunt capacitors/reactors and the transformers tap-settings:

$$u = \left(V_g, T, Q_c\right)^T \quad (5)$$

or

$$u = \left(V_{g1}, \dots, V_{gng}, T_1, .., T_{Nt}, Q_{c1}, .., Q_{cNc}\right)^T \quad (6)$$

Where Ng, Nt and Nc are the number of generators, number of tap transformers and the number of shunt compensators respectively.

III. OBJECTIVE FUNCTION

A. Active power loss

The objective of the reactive power dispatch is to minimize the active power loss in the transmission network, which can be described as follows:

$$F = PL = \sum_{k \in Nbr} g_k \left(V_i^2 + V_j^2 - 2V_iV_j cos\theta_{ij}\right) \quad (7)$$

or

$$F = PL = \sum_{i \in Ng} P_{gi} - P_d = P_{gslack} + \sum_{i \neq slack}^{Ng} P_{gi} - P_d \quad (8)$$

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Where g_k : is the conductance of branch between nodes i and j, Nbr: is the total number of transmission lines in power systems. P_d: is the total active power demand, P_{gi}: is the generator active power of unit i, and P_{gsalck}: is the generator active power of slack bus.

B. Voltage profile improvement

For minimizing the voltage deviation in PQ buses, the objective function becomes:

$$F = PL + \omega_v \times VD \qquad (9)$$

Where ω_v: is a weighting factor of voltage deviation.

VD is the voltage deviation given by:

$$VD = \sum_{i=1}^{Npq} |V_i - 1| \qquad (10)$$

C. Equality Constraint

The equality constraint g(x,u) of the ORPD problem is represented by the power balance equation, where the total power generation must cover the total power demand and the power losses:

$$P_G = P_D + P_L \qquad (11)$$

This equation is solved by running Newton Raphson load flow method, by calculating the active power of slack bus to determine active power loss.

D. Inequality Constraints

The inequality constraints h(x,u) reflect the limits on components in the power system as well as the limits created to ensure system security. Upper and lower bounds on the active power of slack bus, and reactive power of generators:

$$P_{gslack}^{min} \leq P_{gslack} \leq P_{gslack}^{max} \qquad (12)$$

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max}, i \in N_g \qquad (13)$$

Upper and lower bounds on the bus voltage magnitudes:

$$V_i^{min} \leq V_i \leq V_i^{max}, i \in N \qquad (14)$$

Upper and lower bounds on the transformers tap ratios:

$$T_i^{min} \leq T_i \leq T_i^{max}, i \in N_T \qquad (15)$$

Upper and lower bounds on the compensators reactive powers:

$$Q_c^{min} \leq Q_c \leq Q_C^{max}, i \in N_C \qquad (16)$$

Where N is the total number of buses, N_T is the total number of Transformers; N_c is the total number of shunt reactive compensators.

IV. KRILL HERD ALGORITHM

Krill is one of the finest-studied classes of marine animal. The krill herds are aggregations with no parallel direction of existing on time scales of hours to days and space scales of 10 s to 100 s of meters. One of the main characteristics of this specie is its ability to form large swarms. The KH algorithm imitates the systematic activities of krill. When predators, such as seals, penguins or seabirds, attack krill, they eliminate individual krill. This results in dropping the krill density. The configuration of the krill herd after predation depends on many parameters. The herding of the krill individuals is a multi-objective process including two key goals: (1) escalating krill density, and (2) attainment food. In the present study, this process is taken into account to propose a new metaheuristic algorithm for solving global optimization problems. Thickness-dependent hold of krill (increasing density) and finding food (areas of high food concentration) are used as objectives which finally lead the krill to herd around the global minima. In this process, an individual krill moves toward the best solution when it searches for the highest density and food. They are (i) progress induced by other krill individuals; (ii) Foraging activity; and (iii) Random diffusion.

The krill individuals try to maintain a high density and move due to their mutual effects [21]. The direction of motion induced, α_i , is estimated from the local swarm density (local effect), a target swarm density (target effect), and a repulsive swarm density (repulsive effect) . For a krill individual, this movement can be defined as:

$$N_i^{new} = N^{max}\alpha_i + \omega_n N_i^{old} \qquad (17)$$

Where

$$\alpha_i = \alpha_i^{local} + \alpha_i^{target} \qquad (18)$$

And N^{max} is the maximum induced speed, ω_n is the inertia weight of the motion induced in the range [0, 1], N_i^{old} is the last motion induced, α_i^{local} is the local effect provided by the neighbours and α_i^{target} is the target direction effect provided by the best krill individual. According to the measured values of the maximum induced speed.

The effect of the neighbours in a krill movement individual is determined as follows:

$$\alpha_i^{local} = \sum_{j=1}^{NN} \hat{K}_{ij}\,\hat{X}_{ij} \qquad (19)$$

$$\hat{X}_{i,j} = \frac{X_j - X_i}{\|X_j - X_i\| + \varepsilon} \qquad (20)$$

$$\hat{K}_{i,j} = \frac{K_i - K_j}{K^{worst} - K^{best}} \qquad (21)$$

where K^{best} and K^{worst} are the best and the worst fitness values of the krill individuals so far; K_i represents the fitness or the objective function value of the ith krill individual; K_j is the fitness of jth (j = 1,2,. . .,NN) neighbour; X represents the related positions; and NN is the number of the neighbours. For avoiding the singularities, a small positive number, ε, is added to the denominator.

The sensing distance for each krill individual can be determined by using the following formula for each iteration:

$$d_{s,i} = \frac{1}{5N}\sum_{j=1}^{N}\|X_i - X_j\| \qquad (22)$$

Where $d_{s,i}$ the sensing distance for the ith krill is individual and N is the number of the krill individuals. The factor 5 in the denominator is empirically obtained. Using Eq. (22), if the distance of two krill individuals is less than the defined sensing distance, they are neighbours.

The effect of the individual krill with the best fitness on the ith individual krill is taken into account by using the formula

$$\alpha_i^{target} = C^{best}\hat{K}_{i,best}\hat{X}_{i,best} \qquad (23)$$

Where, C^{best} is the effective coefficient of the krill individual with the best fitness to the ith krill individual. This coefficient is defined since α_i^{target} leads the solution to the global optima and it should be more effective than other krill individuals such as neighbours. Herein, the value of C^{best} is defined as:

$$C^{best} = 2\left(rand + \frac{I}{I_{max}}\right) \qquad (24)$$

Where rand is a random value between 0 and 1 and it is for enhancing exploration, I is the actual iteration number and I_{max} is the maximum number of iterations.

The Foraging motion can be expressed for the ith krill individual as follows:

$$F_i = V_f\beta_i + \omega_f F_i^{old} \qquad (25)$$

Where

$$\beta_i = \beta_i^{food} + \beta_i^{best} \qquad (26)$$

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And V_f is the foraging speed, ω_f is the inertia weight of the foraging motion in the range [0, 1], is the last foraging motion, β_i^{food} is the food attractive and β_i^{best} is the effect of the best fitness of the ith krill so far. According to the measured values of the foraging speed.

The centre of food for each iteration is formulated as:

$$X^{food} = \frac{\sum_{i=1}^{N}\frac{1}{K_i}X_i}{\sum_{i=1}^{N}\frac{1}{K_i}} \qquad (27)$$

Therefore, the food attraction for the ith krill individual can be determined as follows:

$$\beta_i^{food} = C^{food}\hat{K}_{i,food}\hat{X}_{i,food} \qquad (28)$$

Where C^{food} is the food coefficient. Because the effect of food in the krill herding decreases during the time, the food coefficient is determined as:

$$C^{food} = 2\left(1 - \frac{I}{I_{max}}\right) \qquad (29)$$

The food attraction is defined to possibly attract the krill swarm to the global optima. Based on this definition, the krill individuals normally herd around the global optima after some iteration. This can be considered as an efficient global optimization strategy which helps improving the globalist of the KH algorithm. The effect of the best fitness of the ith krill individual is also handled using the following equation:

$$\beta_i^{best} = \hat{K}_{i,ibest}\hat{X}_{i.ibest} \qquad (30)$$

Where $K_{i.ibest}$ is the best previously visited position of the ith krill individual.

The physical diffusion of the krill individuals is considered to be a random process. This motion can be express in terms of a maximum diffusion speed and a random directional vector. It can be formulated as follows:

$$D_i = D^{max}\delta \qquad (31)$$

Where D^{max} is the maximum diffusion speed, and δ is the random directional vector and its arrays are random values between -1 and 1. This term linearly decreases the random speed with the time and works on the basis of a geometrical annealing schedule:

$$D_i = D^{max}\left(1 - \frac{I}{I_{max}}\right)\delta \qquad (32)$$

The physical diffusion performs a random search in the proposed method. Using different effective parameters of the motion during the time, the position vector of a krill individual during the interval t to t + Δt is given by the following equation

$$X_i(t + \Delta t) = X_i(t) + \Delta t\frac{dX_i}{dt} \qquad (33)$$

It should be noted that Δt is one of the most important constants and should be carefully set according to the optimization problem. This is because this parameter works as a scale factor of the speed vector. Δt Completely depends on the search space and it seems it can be simply obtained from the following formula:

$$\Delta t = C_t\sum_{j=1}^{NV}(UB_j - LB_j) \qquad (34)$$

Where NV is the total number of variables, LB_j and UB_j are lower and upper bounds of the jth variables (j = 1,2,. . .,NV),respectively. Therefore, the absolute of their subtraction shows the search space. It is empirically found that C_t is a constant number between [0, 2]. It is also obvious that low values of C_t let the krill individuals to search the space carefully.

To improve the performance of the algorithm, genetic reproduction mechanisms are integrated into the algorithm.

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a. Crossover

The binomial scheme performs crossover on each of the d components or variables/parameters. By generating a uniformly distributed random number between 0 and 1, the mth component of X_i , $X_{i,m}$, is manipulated as:

$$X_{i,m} = \begin{cases} X_{r,m} & rand_{i,m}<Cr \\ X_{i,m} & else \end{cases} \qquad (35)$$

$$C_r = 0.2\widehat{K}_{i,best} \qquad (36)$$

Where r ∈ {1, 2,. .., N}. Using this new crossover probability, the crossover probability for the global best is equal to zero and it increases with decreasing the fitness.

b. Mutation

The mutation process used here is formulated as:

$$X_{i,m} = \begin{cases} X_{gbes,m} + \mu(X_{p,m} - X_{q,m}) & rand_{i,m} < Mu \\ X_{i,m} & else \end{cases} \qquad (37)$$

$$Mu = 0.05/\widehat{K}_{i,best} \qquad (38)$$

Where p, q ∈{1, 2,.,K} and l is a number between 0 and 1. It should be noted in $\widehat{K}_{i,best}$the nominator is K_i-K^{best}

Krill herd Algorithm

- Defining the simple limits and determination of algorithm constraint
- Initialization: Randomly create the initial population in the search space.
- Fitness evaluation: Evaluation of each krill individual according to its position.
- Motion calculation:
  - Motion induced by the presence of other individuals,
  - Foraging motion
  - Physical diffusion
- Implementing the genetic operators
- Updating: updating the krill individual position in the search space.
- Repeating: go to step fitness evaluation until the stop criteria is reached.
- End

V. SIMULATING ANNEALING BASED KRILL HERD ALGORITHM (SAKHA)

Simulated annealing (SA) algorithm is a stochastic probe technique that originated from arithmetical mechanics. The SA method is enthused by the annealing process of metals. In the annealing procedure, a metal is heated to a high temperature and slowly cooled to a low temperature that can crystallize. As the heating procedure lets the atoms travel arbitrarily, if the cooling is done slowly enough, so the atoms have enough time to regulate themselves so as to reach a minimum energy state. This similarity can be applied in function optimization with the state of metal corresponding to the possible and the minimum energy state being the final best solution [23]. The SA method repeats a neighbour generation process and follows explore paths that diminish the objective function value. When exploring search space, the SA provides the opportunity of accepting worse generating solutions in an extraordinary manner in order to stay away from trapping into local minima. More accurately, in each generation, for a current solution X whose value is (X), a neighbour X' is chosen

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from the neighbourhood of X denoted by (X). For each step, the objective difference $\Delta = \left(fX' - f(X)\right)$. X' could be accepted with a probability calculated by [23].

$$P_s = exp\left(-\frac{\Delta}{T}\right) \qquad (39)$$

And then, this acceptance probability is compared to a arbitrary number $r \in (0, 1)$ and X' is accepted whenever $p > r$.T is temperature controlled by a cooling scheme [23]. The SA method contains precise features like: a neighbour generation move, objective function calculation, a method for assigning the initial temperature, a procedure to update the temperature, and a cooling scheme including stopping criteria [23].

In our present cram, to progress the performance of KH, a modified greedy strategy and mutation scheme, called krill Pick (KP) operator, is introduced into the KH method to design a novel simulated annealing-based krill herd algorithm (SAKHA). The introduced KP operator is inspired from the conventional simulated annealing algorithm. In our work, the physical property of metal is added to the krill to create a type of super krill that is able to perform the KP operator. The difference between SAKHA and KH is that the KP operator is applied to only accept the basic KH creating novel better solution for each krill instead of accepting all the krill updating adopted in KH. This is quite greedy. The standard KH is very efficient and powerful, but the solutions have slender changes as the optima are approaching in the later run phase of explore. Therefore, to avoid early convergence and further progress the exploration ability of the KH, KP operator also accepts few not-so-good krill with a low acceptance probability p as novel solution. This probability p is also called changeover probability. This acceptance probability technique can augment diversity of the population in an effort to stay away from early convergence and discover a large promising region in the prior run phase to explore the whole space extensively.

To begin with, the temperature is updated according to,

$$T = \alpha * T \qquad (40)$$

Here, T is the temperature for controlling the acceptance probability p.And then, the change of the objective function value Δf is calculated by (41).

$$\Delta f = f(X_i') - f(X_i) \qquad (41)$$

Here, X_i' is new generating krill for krill i by three motions in basic KH.Whether or not we accept a change, we usually use a constant number f_n as a threshold. If $-\Delta f > f_n$, the newly generating krill X_i' is accepted as its latest position for krill i. Otherwise, when (42) is true, the newly generating krill X_i' is also accepted as its latest position for krill i.

$$P = exp\left(\frac{-\Delta f}{k*T}\right) > r \qquad (42)$$

Here, r is random number drawn from uniform distribution in (0, 1). k is Boltzmann's constant. For simplicity without losing generality, we use $k = 1$ in our present study.

In SAKHA, the significant operator is the KP operator that comes from SA algorithm, which is similar to the LLF operator used in LKH [24]. The centre idea of the projected KP operator is based on two considerations. Firstly, good solutions can make the process converge quicker. Secondly, the KP operator can considerably perk up the exploration of the new search space. In SAKHA, at first, standard KH method with elevated convergence speed is used to shrivel the search region to a more capable area. And then, KP operator with great gluttonous ability is applied to only recognize better solutions to perk up the quality of the whole population. In this way, SAKHA method can discover the new search space with KH and pull out optimal population information by KP operator. In addition, transition probability p in KP operator is applied to recognize few non-improved krill with a little acceptance probability p in an effort to augment diversity of the population and dodge premature convergence.

In addition, except krill selecting operator, another vital improvement is the addition of elitism approach into the SAKHA approach. Undoubtedly, both KH and SA have some basic elitism. However, it can be further improved. As with other optimization approaches, we introduce some sort of elitism with the aim of holding some optimal krill in the population. Here, a more rigorous elitism on the optimal krill is applied, which can stop the optimal krill from being contaminated by

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three motions and krill selecting operator. In SAKHA, at first, the *KEEP* optimal krill are memorized in a vector *KEEPKRILL*. In the end, the *KEEP* worst krill are reinstating by the *KEEP* stored optimal krill. This elitism approach always has an assurance that the whole population cannot demur to the population with worse fitness. Note that, in SAKHA, an elitism strategy is applied to keep some outstanding krill that have the optimal fitness, so even if three motions and krill selecting operator corrupts its corresponding krill, we have memorized it and can be recuperated to its preceding good status if needed. By amalgamate previously mentioned krill selecting operator and intensive elitism strategy into basic KH approach, the SAKHA has been premeditated.

Algorithm for solving ORPD problem

Step 1: Initialization. Set the generation counter t, the population P of NP krill, the foraging speed V_f, the diffusion speed D^{max}, and the maximum speed N^{max}, temperature T_0, Boltzmann constant k, cooling factor α, and an acceptance threshold number f_n , and elitism parameter *KEEP*.

Step 2: Fitness calculation. Compute the fitness for each krill based on their initial location.

Step 3: While t < MaxGeneration **do**

Sort all the krill according to their fitness.

Store the *KEEP* best krill.

for $i = 1 : NP$ (all krill) **do**

Implement three motions

- Motion induced by the presence of other individuals,
- Foraging motion
- Physical diffusion

Update position for krill i by krill selecting operator.

Calculate the fitness for each krill based on its new position X_{i+1}.

End for i

Surrogate the *KEEP* best krill for the *KEEP* worst krill. Sort all the krill according to their fitness and find the current best.

$t = t + 1$;

Step 4: end while

Step 5: Output the best solution.

End.

VI. SIMULATION RESULTS

The proposed SAKHA algorithm for solving ORPD problem is tested for standard IEEE-57 bus power system. The IEEE 57-bus system consists of 80 branches, seven generator-buses and 17 branches under load tap setting transformer branches. The possible reactive power compensation buses are 18, 25 and 53. Bus 2, 3, 6, 8, 9 and 12 are PV buses and bus 1 is selected as slack-bus. In this case, the search space has 27 dimensions, i.e., the seven generator voltages, 17 transformer taps, and three capacitor banks. The system variable limits are given in Table 1. The initial conditions for the IEEE-57 bus power system are given as follows:

$P_{load} = 12.332$ p.u. $Q_{load} = 3.353$ p.u.

The total initial generations and power losses are obtained as follows:

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$\sum P_G$ = 12.6755 p.u. $\sum Q_G$ = 3.3576 p.u.

P_{loss} = 0.26572 p.u. Q_{loss} = -1.2248 p.u.

Table 2 shows the various system control variables i.e. generator bus voltages, shunt capacitances and transformer tap settings obtained after SAKHA based optimization which are within their acceptable limits. In Table 3, a comparison of optimum results obtained from proposed SAKHA with other optimization techniques for ORPD mentioned in literature for IEEE-57 bus power system is given. These results indicate the robustness of proposed SAKHA approach for providing better optimal solution in case of IEEE-57 bus system.

Table 1: Variables limits for ieee-57 bus power system (p.u.)

REACTIVE POWER GENERATION LIMITS							
BUS NO	1	2	3	6	8	9	12
Q_{GMIN}	-1.3	-.011	-.01	-0.03	-1.3	-0.02	-0.2
Q_{GMAX}	2	0.4	0.3	0.23	2	0.04	1.45

VOLTAGE AND TAP SETTING LIMITS					
V_{GMIN}	V_{GMAX}	V_{PQMIN}	V_{PQMAX}	T_{KMIN}	T_{KMAX}
0.7	1.0	0.93	1.06	0.5	1.2

SHUNT CAPACITOR LIMITS			
BUS NO	18	25	53
Q_{CMIN}	0	0	0
Q_{CMAX}	10	5.6	6.2

Table 2: control variables obtained after optimization by SAKHA method for ieee-57 bus system (p.u.).

Control Variables	SAKHA
V1	1.4
V2	1.076
V3	1.062
V6	1.055
V8	1.076
V9	1.047
V12	1.055
Qc18	0.0836
Qc25	0.325
Qc53	0.0616
T4-18	1.014
T21-20	1.066
T24-25	0.966
T24-26	0.936
T7-29	1.092
T34-32	0.947
T11-41	1.011
T15-45	1.065
T14-46	0.935
T10-51	1.048
T13-49	1.066
T11-43	0.913
T40-56	0.904
T39-57	0.965
T9-55	0.985

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Table 3: comparative optimization results for ieee-57 bus power system (p.u.)

S.No.	Optimization Algorithm	Best Solution	Worst Solution	Average Solution
1	NLP [25]	0.25902	0.30854	0.27858
2	CGA [25]	0.25244	0.27507	0.26293
3	AGA [25]	0.24564	0.26671	0.25127
4	PSO-w [25]	0.24270	0.26152	0.24725
5	PSO-cf [25]	0.24280	0.26032	0.24698
6	CLPSO [25]	0.24515	0.24780	0.24673
7	SPSO-07 [25]	0.24430	0.25457	0.24752
8	L-DE [25]	0.27812	0.41909	0.33177
9	L-SACP-DE [25]	0.27915	0.36978	0.31032
10	L-SaDE [25]	0.24267	0.24391	0.24311
11	SOA [25]	0.24265	0.24280	0.24270
12	LM [26]	0.2484	0.2922	0.2641
13	MBEP1 [26]	0.2474	0.2848	0.2643
14	MBEP2 [26]	0.2482	0.283	0.2592
15	BES100 [26]	0.2438	0.263	0.2541
16	BES200 [26]	0.3417	0.2486	0.2443
17	Proposed SAKHA	0.22252	0.23763	0.23120

VII. CONCLUSION

In this paper, the SAKHA has been successfully implemented to solve ORPD problem. The main advantages of the SAKHA to the ORPD problem are optimization of different type of objective function, real coded of both continuous and discrete control variables, and easily handling nonlinear constraints. The proposed algorithm has been tested on the IEEE 57-bus system. The active power loss has been minimized and the voltage stability index has been enhanced.

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Authors Biography:

K. Lenin has received his B.E., Degree, electrical and electronics engineering in 1999 from university of madras, Chennai, India and M.E., Degree in power systems in 2000 from Annamalai University, TamilNadu, India. At present pursuing Ph.D., degree at JNTU, Hyderabad,India.

Bhumanapally. RavindhranathReddy, Born on 3rd September,1969. Got his B.Tech in Electrical & Electronics Engineering from the J.N.T.U. College of Engg., Anantapur in the year 1991. Completed his M.Tech in Energy Systems in IPGSR of J.N.T.University Hyderabad in the year 1997. Obtained his doctoral degree from JNTUA,Anantapur University in the field of Electrical Power Systems. Published 12 Research Papers and presently guiding 6 Ph.D. Scholars. He was specialized in Power Systems, High Voltage Engineering and Control Systems. His research interests include Simulation studies on Transients of different power system equipment.

M. Surya Kalavathi has received her B.Tech. Electrical and Electronics Engineering from SVU, Andhra Pradesh, India and M.Tech, power system operation and control from SVU, Andhra Pradesh, India. she received her Phd. Degree from JNTU, hyderabad and Post doc. From CMU – USA. Currently she is Professor and Head of the electrical and electronics engineering department in JNTU, Hyderabad, India and she has Published 16 Research Papers and presently guiding 5 Ph.D. Scholars. She has specialised in Power Systems, High Voltage Engineering and Control Systems. Her research interests include Simulation studies on Transients of different power system equipment. She has 18 years of experience. She has invited for various lectures in institutes.