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Optimal Solution of Reactive Power Dispatch in Transmission System to Minimize Power Losses Using Sine-Cosine Algorithm

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ABSTRACT Optimal reactive power dispatch (ORPD) has a crucial impact to enhance safety, reliability, and economical operation of the electric power system. ORPD is a non-linear, non-convex and mixed variable problem, which has been solved by many researchers via different meta-heuristic algorithms during the last decade. In this work, a novel algorithm named sine-cosine algorithm (SCA) is utilized to solve ORPD problem by considering both dependent and independent control variable constraints. SCA has been tested and validated on standard 14, 30 and 57-bus power systems. To validate the superiority of proposed algorithm, the outcomes obtained through SCA are compared with recent published results attained through particle swarm optimization (PSO), modified Gaussian barebones teaching–learning based optimization (BBTLBO), ant bee colony optimization (ABCO), whale optimization algorithm (WOA) and backtracking search algorithms (BSA). The results attained using SCA show the improvement in the power losses minimization. Thus, with standard 14-bus system, the power losses are minimized from 0.04% to 4.78%. While, using standard 30-bus, the power losses are minimized from 0.4% to 3.4% and with standard 57-bus, power losses are reduced from 0.9% to 1.99%. Furthermore, a comparative analysis with 30 independent runs on the above-mentioned bus systems is performed to examine the functioning of the proposed method in terms of probability density function (PDF) and cumulative density function (CDF). For such analysis, well-known meta-heuristic algorithms such as PSO, WOA, differential evolution (DE) are compared with proposed SCA in solving the ORPD problem. The results of this analysis clearly show that proposed algorithm is robust, effective, and computationally easy in solving the ORPD problem compared to the existing meta-heuristic algorithms.

INDEX TERMS Electric power system, optimal reactive power dispatch, electrical transmission system, sine-cosine algorithm.

I. INTRODUCTION

The remote power generation requires optimal transmission from generation heads to the load centers. Improper transmission of reactive power to the load centers has a negative and adverse effect on the power system stability. In a modern energy system, the reactive power control has become a crucial issue, because any mismanagement of reactive power would endanger the safety of the system. Further, after the addition of distributed energy sources, the reactive power of the power system have become an uncertainty issue [1], [2]. The objective in ORPD is to improve power system quality [3] and optimally tune the possible values of decision variables (bus voltages, transformer tapings and reactive power compensators) which further minimize the losses in the power system. ORPD is a nonlinear and

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non-convex problem composed of both continues and discrete variables. Generator bus voltage are continuous variable and transformer tapings, reactive power compensators (capacitor) are discrete variable. Previously, ORPD has been solved by classical algorithms. These classical algorithms include linear programming [4], nonlinear programming [5], quadratic programming [6], sequential quadratic programming [7] and interior point methods [8]. Unfortunately, these algorithms have several drawbacks such as sensitivity to initial search and non-convexity nature. In recent years, as an alternative to classical algorithms, various meta-heuristic techniques have been utilized for the solution of complex engineering problems. Although these metaheuristic techniques have provided the solution of ORPD to a limited extent, yet there is still enough scope of improvement in methodology.

In literature, many researchers have proposed meta-heuristic techniques to replace classical algorithms for solving the global optimization problem. Meta-heuristic algorithms can be classified as evolutionary algorithms, swarm intelligence algorithms, physical phenomena-based algorithms and human intelligence-based optimization algorithms as shown in Fig 1. Evolutionary algorithms include genetic algorithm [9], linear adaptive genetic algorithm [10] differential evolution [11] and evolutionary programming [12]. Multi objective evolutionary algorithm [13] have also been adopted to solve ORPD problem. Recently, further modified forms of these evolution-based algorithms have been used to solve optimal reactive power dispatch such as a modified differential evolution [14] which is being used to localize the solution around the best available solution. Another improved form of the evolutionary algorithm is a multi-objective fuzzy hybrid evolutionary algorithm [15], in which the probability of crossover and probability of mutation are dynamically changing the output of the fuzzy logic controller. Swarm intelligence algorithms include PSO [16], ant colony optimization algorithm [17], artificial bee colony algorithm [18], grey wolf optimization algorithm [19], enhanced firefly algorithm [20], Whale optimization algorithm [21] and Harris Hawk Optimizer algorithm [22]. Physics phenomena based algorithms include chaotic krill herd algorithm [23], Biogeography-based optimization algorithm [24], gauss bare-bone teaching learning-based optimization algorithm [25], harmony search algorithm [26], fuzzy guided tabu search [27] and backtracking search algorithm [28] are also used. ORPD has also been solved by hybrid meta-heuristic techniques. ORPD has been solved by hybrid formulation based analytical technique and two meta-heuristic optimization techniques [29]. The above-mentioned technique is the combination of loss sensitivity factor based analytical technique and two recently developed meta-heuristic techniques. Furthermore, a variant of two popular meta-heuristic techniques (ABC & TLBO) have also been utilized to optimize multi-objective power flow [30]. However, the above-mentioned algorithms are computationally complex and mathematical equations used in these algorithms are complex and including several random parameters which add uncertainty in the results. On the other hand, SCA is a swarm intelligence algorithm which starts the optimization process initially by selecting the solution randomly. This random solution is improved by the equations containing both sine and cosine function. In [31], SCA is tested on nineteen different work benches and successfully compared with different swarm intelligence algorithm.

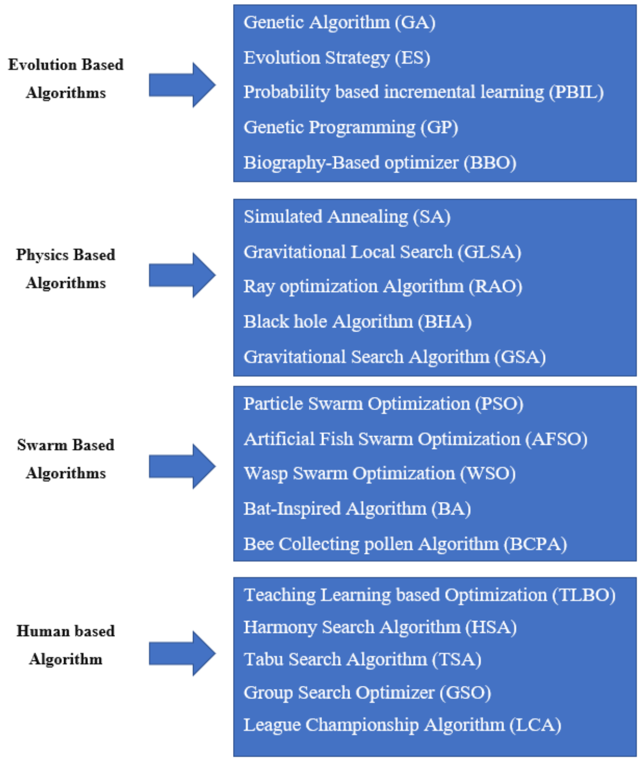

FIGURE 1. Depiction of meta-heuristic techniques.

In this manuscript, the problem of ORPD is solved using SCA as it has many benefits such as its adaptive characteristics and smooth transition from exploration to exploitation phase. SCA is tested and validated on different case studies including standard 14, 30 and 57 bus power systems. The results are then compared with different meta-heuristic techniques that have already been reported in the literature.

In this work, a novel optimization technique sine cosine algorithm (SCA) is used for the solution of ORPD problem. We have also performed a statistical analysis test to prove the superiority of our proposed algorithm. Moreover, a comparative analysis with 30 independent runs on the above-mentioned bus systems is performed to examine the functioning of the proposed method in terms of probability density function (PDF) and cumulative density function (CDF). To validate the superiority of proposed algorithm, the outcomes obtained through SCA are compared with recent published results attained through particle swarm optimization (PSO), modified Gaussian barebones teaching–learning based optimization (BBTLBO), ant bee colony optimization (ABCO), whale optimization algorithm (WOA) and backtracking search algorithms (BSA).

The manuscript includes mathematical formulation of optimal reactive power dispatch which is shown in Section 2. Section 3 explains the proposed SCA. Section 4 presents the process flow diagram of the anticipated solution. Simulations results are explained in Section 5. Section 6 derives some important conclusion based on the results obtained after performing statistical analysis between selective meta-heuristic techniques. Section 7 presents paper conclusion and summary.

II. FORMULATION OF THE ORPD PROBLEM

A. OBJECTIVE FUNCTION

The major objective of ORPD is to reduce the active power losses of the transmission system. Generally, power can be calculated as P = V^2/R. In practical case one supporting tower is considered as one bus; so, we have one incoming tower (i) and one outgoing tower (j). By above formula P = $(Vi\text{-}Vj)^2$/Z will be the equation to calculate losses. 1/Z is just replaced by conductance of each line. The $cos\theta_{ij}$ is the bus voltage angle between two buses. Below mentioned Equation 1 is the final form of loss formula.

$$\textbf{Min } F(t,v) = min\, P_{loss} = \sum\nolimits_{k=1}^{Ni} g_k[(V_i)^2 + V_j^2 - 2V_iV_jcos\theta_{ij}] \quad (1)$$

$$\text{Subject to } g(t,z) = 0 \quad (2)$$

$$k(t,z) \leq 0 \quad (3)$$

where,

F : objective function; z : control variables; t : dependent variables; g : equality constraint; k : inequality constraint; N_i *: No. of transmission lines;* g_k *: conductance; V : bus voltage magnitude;* θ_{ij} *: bus voltage angle*

The control variables are PV bus voltages, transformer tapping ratio and reactive power sources (capacitors) [32]. ORPD includes some equality constraints, inequality constraints and penalty function which are explained in the further sub sections.

The minimization of active power losses is cost saving. The fuel cost function is being used to calculate the cost that has been saved after the minimization of power losses [32], [33], which is shown in Equation 4:

$$F_s = a_s\Delta Pg_s^2 + b_s\Delta Pg_s + c_s \quad (4)$$

where,

F_s = operational cost; $Pg_s = P_{loss}$ [33].

B. EQUALITY & INEQUALITY CONSTRAINTS

The complexity of ORPD increases with the prevalence of problem constraints. The penalty coefficients in ORPD problem are designated by tedious trial and error method [34]. The equality and inequality constraints are as follows;

$$P_{gi} - P_{Li} - V_i\sum_{j\in N_i} V_j\left(g_{ij}cos\theta_{ij} + B_{ij}\sin\theta_{ij}\right) = 0 \quad (5)$$

$$Q_{gi} - Q_{Li} - V_i\sum_{j\in N_i} V_j\left(g_{ij}sin\theta_{ij} + B_{ij}\cos\theta_{ij}\right) = 0 \quad (6)$$

where,

B_{ij} and g_{ij} = susceptance and conductance between bus i and j respectively.

P_{gi} = MW generated by bus i.

P_{Li} = MW mandate at bus i.

Q_{gi} = KVAR generated by bus i.

Q_{Li} = KVAR mandate at bus i.

The inequality constraints of ORPD problem are as follows;

$$V_i^{min} \leq V_i \leq V_i^{max}, \quad i \in N_B \quad (7)$$

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

$$Q_{ci}^{min} \leq Q_{ci} \leq Q_{ci}^{max} \quad (9)$$

$$T_k^{min} \leq T_k \leq T_k^{max} \quad (10)$$

$$S_i \leq S_i^{max} \quad (11)$$

where,

N_B = Total number of buses.

N_g = Total number of generators.

V_i = KV of i^{th} bus.

Q_{gi} = KVAR of i^{th} generator.

T_k = Tap changer of k^{th} transformer.

S_i = KVA of i^{th} branch.

C. FITNESS FUNCTION EVALUATION

The dependent variables of ORPD problem are added in the objective function for evaluating the fitness function using quadratic penalty function. Penalty function addition prevents the infeasible solution (violate constraints) from transferring to the next generation population. The objective function after the addition of penalty terms is given as follow;

$$f = F + \gamma_V\sum_{Nlim_V}\Delta V_{load}^2 + \gamma_{PS}\Delta P_S^2 + \gamma_{Sf}\sum_{Nlim_{Sf}}\Delta S_f^2 + \gamma_Q\sum_{Nlim_Q}\Delta Q_G^2 \quad (12)$$

where, γ_V, γ_{PS}, γ_{Sf} *and* γ_Q are the penalty factor terms. $N\,lim_V$ shows the no. of PQ buses which violate their limits. $N\,lim_Q$ shows the no. of PV buses in which reactive power output violate their limits. $N\,lim_{sf}$ shows overflow lines. Similarly, ΔV_{load}, ΔQ_G, ΔP_S *and* ΔS_f are defined below;

$$\Delta V_{load} = \begin{cases} V_{load}^{min} - V_{load} & if\ V_{load} < V_{load}^{min} \\ V_{load}^{max} - V_{load} & if\ V_{load} > V_{load}^{max} \end{cases} \quad (13)$$

$$\Delta Q_G = \begin{cases} Q_G^{min} - Q_G & if\ Q_G < Q_G^{min} \\ Q_G^{max} - Q_G & if\ Q_G > Q_G^{max} \end{cases} \quad (14)$$

$$\Delta P_S = \begin{cases} P_S^{min} - P_S & if\ P_S < P_S^{min} \\ P_S^{max} - P_S & if\ P_S > P_S^{max} \end{cases} \quad (15)$$

$$\Delta S_f = S_f^{max} - S_f \quad if\ S_f > S_f^{max} \quad (16)$$

III. SINE-COSINE ALGORITHM

SCA is proposed by Mirjalili [31]. It is a swarm intelligence technique in which number of search agents, their upper and lower limit and step size is defined at the start. Hence instead of going into high exploration phase it hunts the best solution in between our defined search space. The individual base techniques consider the optimization problem as a black box i.e. the mathematical model of such optimization paradigms is not required and such optimization prototypes just vary the inputs and monitor the outputs to maximize or minimize it, depending upon the best output obtained so far (feedback). Hence it is readily applicable to real challenging problems. Moreover, SCA switches between exploration and exploitation smoothly using the adaptive range, so there is a tendency of obtaining a better optimum as compared to other techniques which sometimes entrap into local optimum. The search space of SCA can be increased as shown in Fig. 2. For each iteration the best solution is saved and remaining other solutions discarded. In the next iteration the best solution of previous iteration is used as reference or initial solution.

If it is needed to increase the exploration range of our algorithm, we can change the controlling variables used in the SCA. These random variables will be discussed later in the mathematical modelling of proposed SCA and the exploitation of search space is performed using the remaining parameters in the SCA. The details of SCA in the specified range i.e. [−2, 2] is shown in Fig 2.

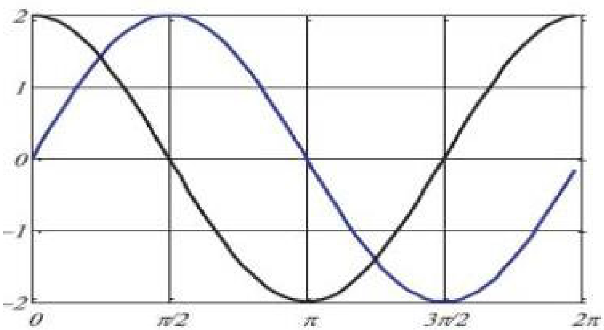

FIGURE 2. Range of SCA functions [−2, 2].

Fig 3 describes the effect of varying the range of sine and cosine functions that how this range change transfers the solution region in its next location inside or outside the search space.

The adaptive characteristics of sine and cosine functions are used in SCA to obtain the best results for the desired problem. The following are the equations used in the exploration and exploitation phases of SCA:

$$X_i^{t+1} = X_i^t + r_1 \times sin\,(r_2) \times \left|r_3 P_i^t - X_i^t\right| \tag{17}$$

$$X_i^{t+1} = X_i^t + r_1 \times cos\,(r_2) \times \left|r_3 P_i^t - X_{ii}^t\right| \tag{18}$$

where, X_i^t is the current search agent in ith dimension at t^{th} iteration, P_i^t is the destination points in ith dimension, ‖ represents the absolute value and the variables r_1, r_2, r_3 *and* r_4 are random numbers.

Equation 17 and 18 are combined for switching between sine and cosine function as shown below;

$$X_i^{t+1} = \begin{cases} X_i^t + r_1 \times sin\,(r_2) \times \left|r_3 P_i^t - X_i^t\right| & r_4 < 0.5 \\ X_i^t + r_1 \times cos\,(r_2) \times \left|r_3 P_i^t - X_{ii}^t\right| & r_4 \geq 0.5 \end{cases} \tag{19}$$

where,

$$r_1 = a - a\frac{t}{T} \quad a = 2, \tag{20}$$

where,

t = iteration number, T = No. of iterations, $r_2 = 2 * \text{pi} *$ random number, $r_3 = 2*$ random number and $r_4 =$ random number

r_1, r_2, r_3 *and* r_4 are liable for the behavior of the convergence curve. r_1 is responsible for the direction (movement) of search agents known as exploration phase. r_2 determines the best possible solution (exploitation) around the best available solution. r_3 is the arbitrarily weighted to emphasize and minimize the solution area. r_4 is responsible for equal alternation between sine and cosine functions, as shown in Equation 18. The flow chart of SCA is shown in Fig 4.

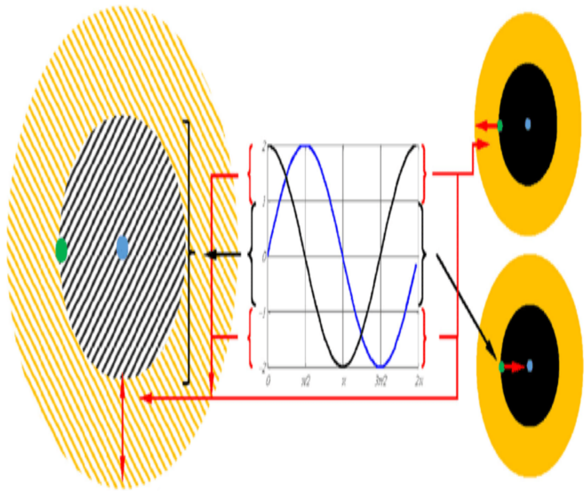

FIGURE 3. Exploration and exploitation.

IV. APPLICATION OF SCA ON ORPD PROBLEM

SCA is implemented to find the optimal solution of reactive power dispatch. The optimum values of control variables are considered for minimizing transmission losses. Flow diagram is described in Figure 4. The steps for solving the ORPD problem are shown below:

1. Define no. of Search agents and no. of iterations.
2. Initialize search agents (control variables) within the allowable range, such as PV-bus voltages, transformer tapings and KVAR compensators.
3. Control variables are mapped into load flow data.
4. MATPOWER is used to perform load flow analysis on IEEE systems and power losses are calculated.

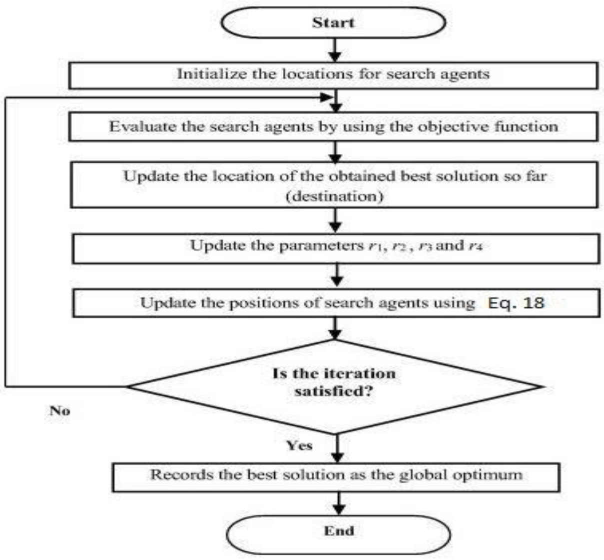

FIGURE 4. Basic flow chart of SCA.

5. Save the Best solution and discard the remaining solutions.
6. Proposed algorithm is applied for updating best search agents.
7. Check whether the control variable violates the restriction, penalize them or else move to step 8.
8. Power Losses function is evaluated using Equation 1.
9. The process continues until the stopping criteria meets.

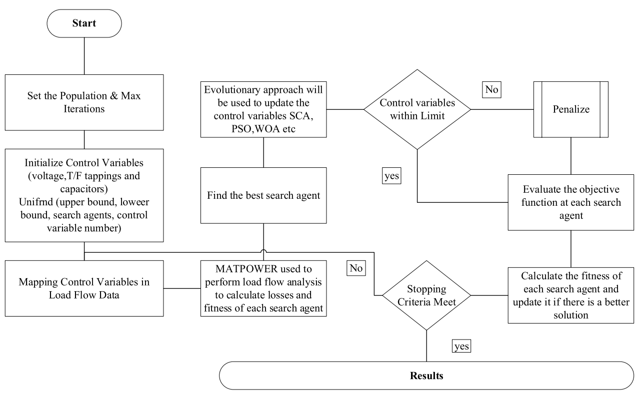

FIGURE 5. flowchart of ORPD solution.

V. SIMULATION RESULTS

SCA is tested and validated on standard 14-bus, 30-bus and 57-bus power systems. The results verify the efficiency, performance, and effectiveness of SCA. The description of the tested systems is given in Table 1. All the data are taken on 100 MVA base. The simulations are carried out in MATLAB R2014a.

Our goal is to reduce active power loss which in return improve system performance of our transmission system [35].

TABLE 1. Test systems description used for validation of SCA.

Description of System	Test System-1	Test System-2	Test System-3
No. of buses	14	30	57
No. of line flows	20	41	80
No. of power generating units	5	6	7
No. of the transformer tap changer	3	4	15
No. of reactive compensators	2	9	3
No. of PQ buses	9	24	50
P_{load} (MW)	259.00	283.40	1250.8
Q_{load} (MVAR)	73.50	126.20	336.4
P_{gen} (MW)	272.39	289.211	1279.26
Q_{gen} (MVAR)	82.44	108.922	345.45
$P_{loss}^{base\ case}$ (MW)	13.49	5.811	28.462
$Q_{loss}^{base\ case}$ (MVAR)	54.54	32.417	-124.27

A. TEST SYSTEM-1

In Test System-1, IEEE 14-bus system is used for the implementation of SCA on ORPD problem. The single line diagram is shown in Fig 5.

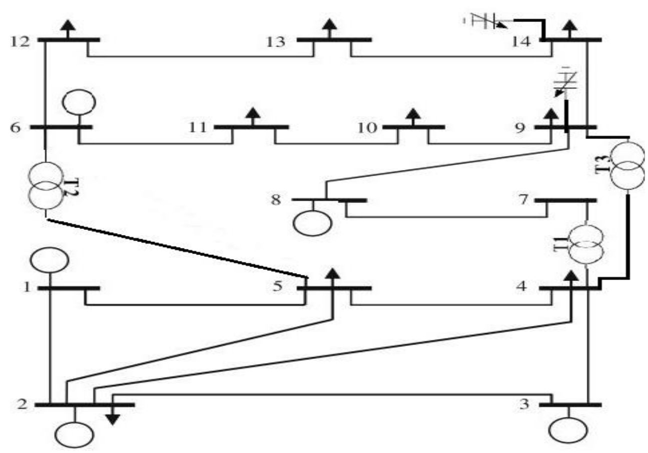

FIGURE 6. 14-bus power system single line diagram.

The above-mentioned power system consists of five generators which are connected at bus number 1, 2, 3, 6 and 8. It consist of 20 transmission lines. Three transformer tap changers located at branches 4-7, 4-9, 5-6 and two reactive

TABLE 2. Variable limits for the IEEE 14-bus test system.

Range	V_g	V_L	Tap	Q_C
Minimum (pu)	0.95	0.95	0.9	0.3
Maximum (pu)	1.1	1.05	1.1	0

TABLE 3. Results comparison of IEEE 14-bus system.

	Base case	MTLA -DDE [37]	MGB TLBO [25]	PSO-TVA C [21]	BSO [32]	SCA
V_{g1}	1.06	1.075	1.1	1.10	1.09	1.09
V_{g2}	1.04	1.057	1.07	1.08	1.07	1.08
V_{g3}	1.01	1.02	1.04	1.05	1.04	1.05
V_{g6}	1.07	1.05	1.05	1.0	1.05	1.09
V_{g8}	1.09	1.03	1.03	1.04 4	1.05	1.09
T_{4-7}	0.94	1.08	1.01	1.04	0.99	0.95
T_{4-9}	0.95	0.91	1.01	1.01	0.99	0.94
T_{5-6}	0.90	1.01	1.03	1.07	0.98	1.03
Q_{C9}	0.18	0.3	0.3	0.17 1	0.15	0.16
Q_{C14}	0.18	0.08	0.07	0.08	0.06	0.05
P_{loss} (MW)	13.4	12.89	12.3	12.2 7	12.4	12.2
% red	-	4.440	8.74	8.97 7	7.64	9.01
Cost ($/hr)	-	21.215	22.4	22.4 8	22.1 0	22.49

power sources are connected at buses 9 and 14. MATPOWER [36] is used for simulation of this test system. The limits of control variables [32] are shown in Table 2.

The results obtained from SCA are shown in Table 3. Power losses obtained by SCA is 12.274 MW which is less than the losses obtained by the other algorithms described in the literature.

Fig 7-10 shows the bar graph comparison of control variables i.e. voltage profiles, Transformer tapping, reactive power injection and percentage loss reduction & cost saved in $/hr respectively.

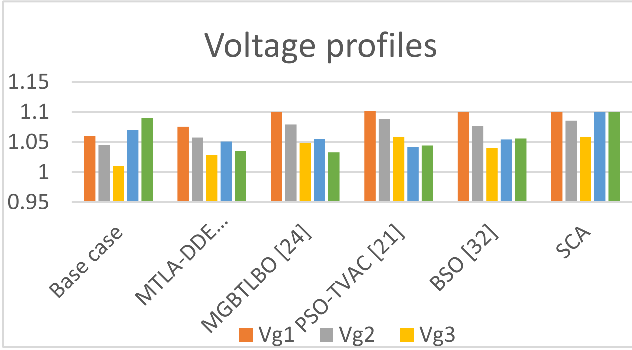

FIGURE 7. Voltage profile comparison.

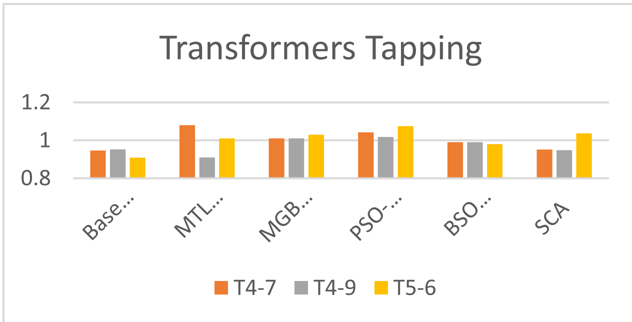

FIGURE 8. Transformer tapping comparison.

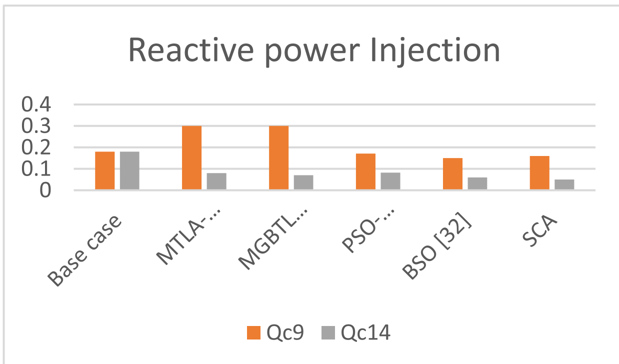

FIGURE 9. Reactive power injection comparison.

The convergence characteristics are shown in Fig. 11.

Fig. 10 illustrates that for 14-bus test system, power losses reduced to the value of 12.5 MW (approximately) before the 44th iteration (Exploration phase). After 44th iteration, exploitation phase reduced the power losses to minimum till the stopping criteria is reached.

The comparison of SCA for 14-bus system with other meta-heuristic techniques is shown in Table 4.

B. TEST SYSTEM-2

In Test system 2 IEEE 30-bus system is used for the implementation of SCA for ORPD problem. The single line diagram is shown in Fig 12.

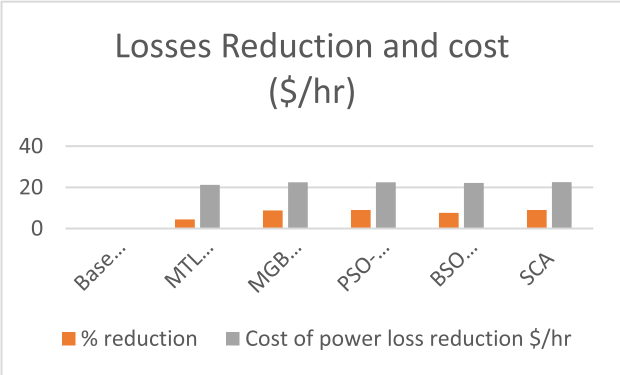

FIGURE 10. Losses Reduction and cost comparison.

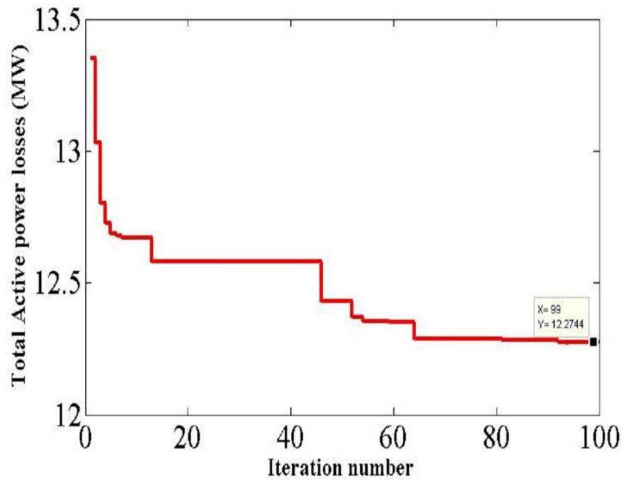

FIGURE 11. Convergence characteristics of SCA for Test System-1.

TABLE 4. 14-bus system comparison table.

Meta-heuristic Technique	Minimized Power losses (MW) 14-bus system
SCA	12.27
SPSO [38]	13.21
OGWO [39]	13.20
GWO-PSO [40]	13.2716
ISSA [41]	12.2834
MTLA-DDE [37]	12.89
MGBTLBO [25]	12.3
PSO-TVAC [21]	12.27
BSO [32]	12.4

The above mentioned power system consists of six generators connected at bus number 1, 2, 5, 8, 11 and 13. It contains 41 transmission lines having 4 transformers tap changers connected at branches 6-9,6-10,6-12,28-27 and 9 reactive power compensators connected at bus number 10,12,15,17,20,21,23,24 and 29. Maximum and minimum

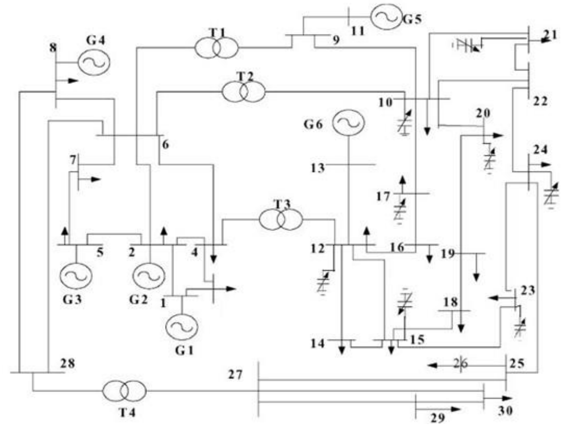

FIGURE 12. 30-bus power system single line diagram.

TABLE 5. Variable limits for the IEEE 30-bus test system.

Range	V_g	V_L	Tap	Q_C
Minimum	0.90	0.90	0.90	0.05
Maximum	1.1	1.1	1.05	0

limits of PQ-bus voltage, PV-bus voltages, tap changing transformers and reactive power compensators taken from [21] are shown in Table 5.

SCA has been implemented for the minimization of transmission power losses and results obtained after optimization are shown in Table 6.

From Table 5 it is obvious that the SCA has reduced the power losses to 4.6154 MW which is lowest among all the techniques with which it is compared in Table 5. Percentage reduction and cost value of power losses in $/hr are shown in the last row of Table 5. Fig. 13-16 shows the bar graph comparison of control variables i.e., voltage profiles, Transformer tapping, reactive power injection and percentage loss reduction & cost saved in $/hr respectively.

The convergence characteristics are shown in Fig. 17.

Fig. 17 illustrates that for 30-bus test system, power losses have been reduced to the value of 4.9 MW (approximately) before the 9th iteration (Exploration phase). After 9th iteration, exploitation phase reduced the power losses to minimum till the stopping criteria is reached.

The comparison of SCA for 30-bus system with other meta-heuristic techniques is shown in Table 7.

C. TEST SYSTEM-3

In Test system-3, 57-bus power system is used for the implementation of SCA for ORPD problem. Fig 18 shows the single line diagram of 57-bus power system.

This power system consists of seven generators connected at bus number 1, 2, 3 6, 8, 9 and 12. It contains 80 transmission lines having 15 transformer tap changers connected

TABLE 6. Results comparison of IEEE 30-bus system.

	Base case	ABC [18]	PSO [21]	PSO-TVAC [21]	BSO [32]	SCA
V_{g1}	1.05	1.1	1.1	1.0971	1.0998	1.1
V_{g2}	1.04	1.0615	1.093	1.0876	1.0920	1.1
V_{g5}	1.01	1.0711	1.0731	1.0658	1.0711	1.0750
V_{g8}	1.01	1.0849	1.0743	1.07	1.0721	1.0870
V_{g11}	1.05	1.1	1.0275	1.0669	1.0879	1.0946
V_{g13}	1.05	1.0665	1.0335	1.0995	1.0998	1.1
T_{6-9}	1.078	0.97	1.0161	0.9757	0.990	0.9899
T_{6-10}	1.069	1.05	1.0008	0.9269	1.00	0.9215
T_{4-12}	1.032	0.99	1.0089	0.9996	0.97	0.9948
T_{28-27}	1.068	0.99	1.0245	0.9648	0.95	0.9585
Q_{C3}	0	0	0	0	0.1	0
Q_{C10}	0	0.05	0.0364	0.0103	0.26	0.00729
Q_{C12}	0	0.05	0.0354	0.0326	0	0.04671
Q_{C15}	0	0.05	0.0166	0.0449	0	0.04671
Q_{C17}	0	0.05	0.0400	0.0462	0	0.04573
Q_{C20}	0	0.041	0.0406	0.0148	0	0.04671
Q_{C21}	0	0.033	0.0408	0.0458	0	0.04671
Q_{C23}	0	0.009	0.0414	0.0357	0	0.04394
Q_{C24}	0	0.05	0.0394	0.0465	0.10	0.04798
Q_{C29}	0	0.024	0.0224	0.0324	0	0.01326
P_{loss} (MW)	5.812	4.6022	4.7779	4.6469	4.6338	4.6154
% reduction	-	20.81	17.79	20.04	20.271	20.5884
Cost of power loss reduction $/hr	-	2.4250	2.0722	2.3352	2.3295	2.3973

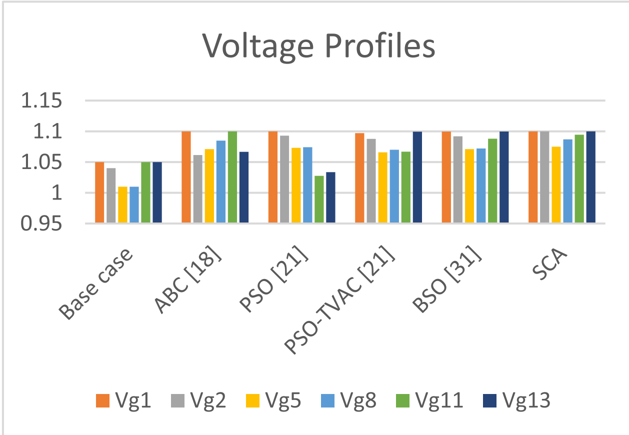

FIGURE 13. Voltage profile comparison.

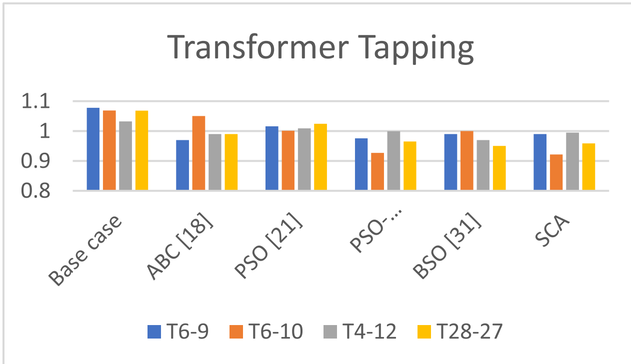

FIGURE 14. Transformer tapping comparison.

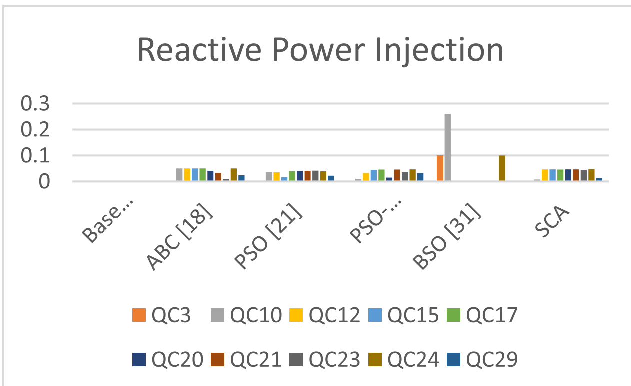

FIGURE 15. Reactive power injection comparison.

at branches 4-18, 4-18, 21-20, 24-26, 7-29, 34-32, 11-41, 15-45, 14-46, 10-51, 13-49, 11-43, 40-56, 39-57, 9-55, 4-18, 4-18, 21-20, 24-26, 7-29, 34-32, 11-41, 15-45, 14-46, 10-51, 13-49, 11-43, 40-56, 39-57 and 9-55and three reactive power compensators connected at buses 18, 25 and 53. Limits for PQ-bus voltage, PV-bus voltages, transformer tap changers and reactive power compensators are taken from [32] as shown in Table 8.

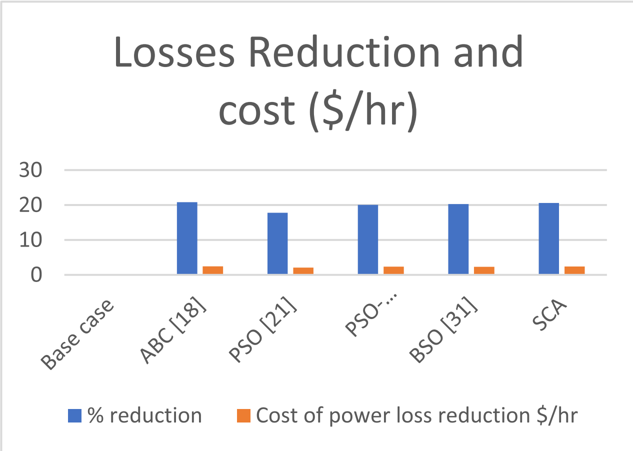

FIGURE 16. Losses Reduction and cost comparison.

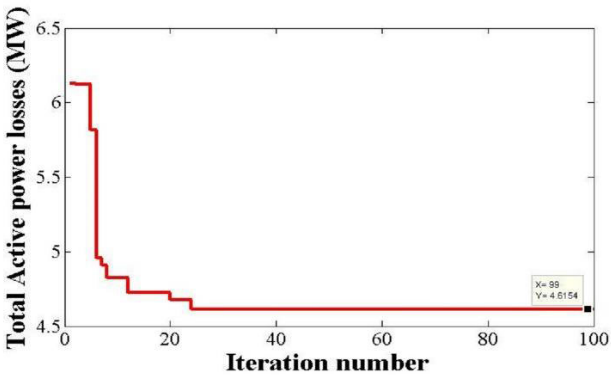

FIGURE 17. Convergence characteristics of SCA for Test System-2.

TABLE 7. 30-bus system comparison table.

Meta-heuristic Technique	Minimized Power losses (MW) 30-bus system
SCA	4.6154
PSO [21]	4.7779
PSO-TVAC [21]	4.6469
BSO [32]	4.6338
JA [42]	4.621
PGSWT-PSO [43]	4.79140
SWT-PSO [43]	4.65780
GA [44]	6.81
SPSO [38]	6.84
OGWO [39]	6.99

The proposed SCA is implemented for the minimization of transmission power losses. Optimum values of control variables are shown in Table 7. SCA is compared with different techniques that have already been used to solve ORPD. The results in Table 9 show that SCA gives the best results among all techniques.

Fig.19-22 shows the bar graph comparison of control variables i.e., voltage profiles, Transformer tapping, reactive power injection and percentage loss reduction & cost saved in $/hr respectively.

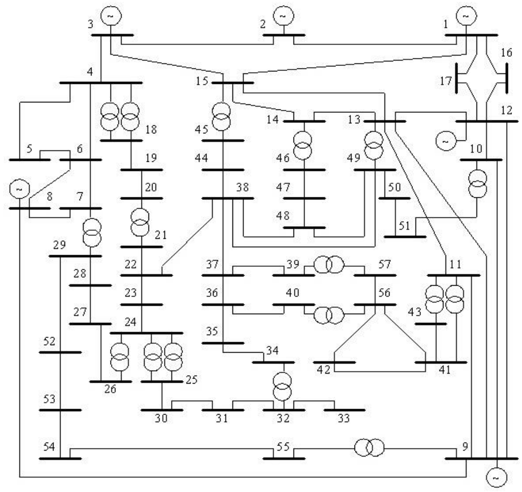

FIGURE 18. 57-bus power system single line diagram.

TABLE 8. Variable limits for the IEEE 57-bus test system.

Range	V_g	V_L	Tap	Q_{C18}	Q_{C25}	Q_{C53}
Minimum	0.90	0.94	0.90	0	0	0
Maximum	1.1	1.06	1.05	0.01	0.0059	0.0063

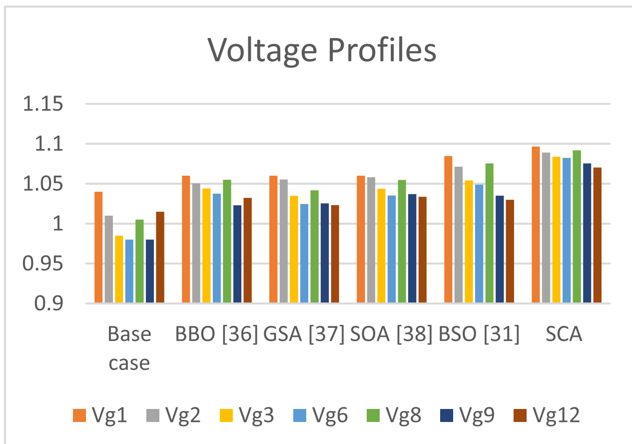

FIGURE 19. Voltage profile comparison.

The convergence characteristics are shown in Fig. 23.

Fig. 23 illustrates that for 57-bus test system, power losses have been reduced to the value of 26 MW (approximately) before the 25th iteration (Exploration phase). After 25th iteration, exploitation phase reduced the power losses to minimum till the stopping criteria is reached.

TABLE 9. Results comparison of IEEE 57-bus system.

	Base case	BBO [45]	GSA [46]	SOA [47]	BSO [32]	SCA
V_{g1}	1.04	1.06	1.06	1.06	1.084	1.096
V_{g2}	1.01	1.05	1.05	1.058	1.071	1.089
V_{g3}	0.985	1.044	1.03	1.0437	1.054	1.083
V_{g6}	0.98	1.03	1.02	1.0352	1.048	1.082
V_{g8}	1.005	1.05	1.04	1.0548	1.075	1.091
V_{g9}	0.98	1.02	1.02	1.0369	1.035	1.075
V_{g12}	1.015	1.03	1.02	1.0336	1.029	1.070
T_{4-18}	0.97	0.96	0.93	1	0.98	1.004
T_{4-18}	0.978	0.990	0.99	0.96	1.01	1.029
T_{21-20}	1.043	1.01	1.00	1.01	1.03	1.039
T_{24-26}	1.043	1.00	1.00	1.01	1.02	1.022
T_{7-29}	0.967	0.97	0.96	0.97	1	0.990
T_{34-32}	0.975	0.96	0.97	0.97	0.95	1.029
T_{11-41}	0.955	0.90	0.90	0.9	0.97	0.998
T_{15-45}	0.955	0.96	0.96	0.97	0.97	1.023
T_{14-46}	0.9	0.95	0.94	0.95	1	1.016
T_{10-51}	0.93	0.96	0.95	0.96	0.99	0.999
T_{13-49}	0.895	0.92	0.91	0.92	0.95	1.022
T_{11-43}	0.958	0.95	0.94	0.96	0.96	0.998
T_{40-56}	0.958	0.99	1.00	1	1.01	1.022
T_{39-57}	0.98	0.96	0.96	0.96	1	0.992
T_{9-55}	0.94	0.96	0.96	0.97	0.99	0.984
Q_{C18}	0.1	0.09	0.08	0.0998	0.04	0.066
Q_{C25}	0.059	0.05	0.05	0.0590	0.058	0.046
Q_{C53}	0.063	0.06	0.0	0.0628	0.041	0.030
P_{loss} (MW)	27.86	24.54	24.43	24.2654	24.37	24.05
% red	-	11.91	12.29	12.916	12.52	13.67
Cost ($/hr)	-	27.49	21.17	28.2017	27.92	28.75

The comparison of SCA for 57-bus system with other meta-heuristic techniques is shown in Table 10.

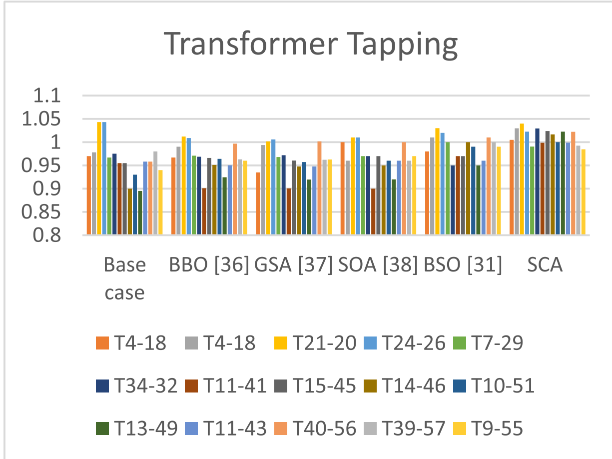

FIGURE 20. Transformer tapping comparison.

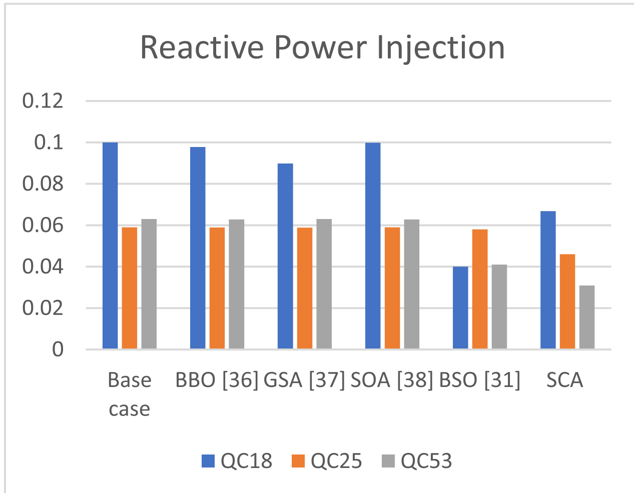

FIGURE 21. Reactive power injection comparison.

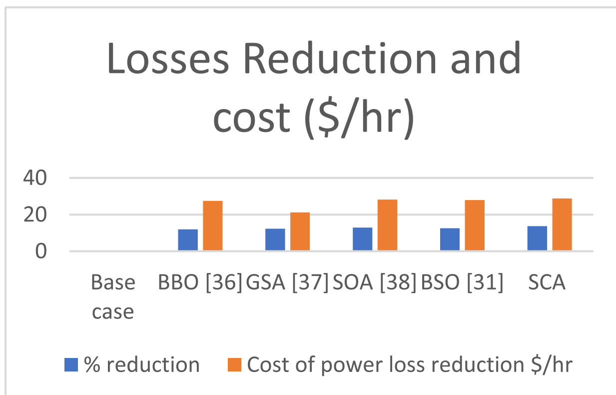

FIGURE 22. Losses Reduction and cost comparison.

VI. STATISTICAL ANALYSIS

The superiority of the results of proposed technique can be determined by performing statistical analysis. In Statistical analysis some parameters such as minimum power losses, maximum power losses, mean value of power losses, deviation and rank of each algorithm are determined as calculated in [54]. It is worth mentioning that ORPD has colossal contribution to the secure, reliable and economic operation

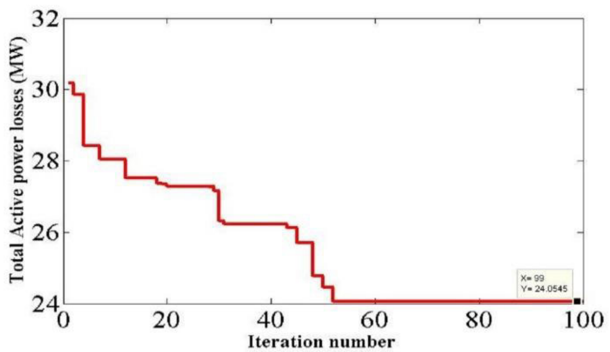

FIGURE 23. Convergence characteristics of SCA for Test System-3.

TABLE 10. 57-bus system comparison table.

Meta-heuristic Technique	Minimized Power losses (PL) 57-bus system
SCA	24.05
ABC [48]	24.1025
ISMA [49]	24.5856
MJAYA [50]	23.4705
MFOM [51]	24.2529
BBO [45]	24.54
GSA [46]	24.43
SOA [47]	24.2654
BSO [32]	24.37
OGWO [39]	24.72
OGWO-VCPI [52]	24.75
HHO-PSO [53]	24.46

TABLE 11. Experimental setup for 14-bus power system.

PV buses	5
transformer tap changers	3
reactive power sources	2
search agents	30
Iterations	100
Trail runs	30

of electric power system [44], [45]. The reliability of proposed solution for ORPD is proved by the statistical analysis. It is performed on 30 independent runs of DE, PSO, WOA and SCA. Statistical analysis of all test systems is shown below.

A. 14-BUS POWER SYSTEM STATISTICAL RESULTS

Table 11 shows the simulation setup for statistical analysis of 14-bus system.

TABLE 12. Statistical analysis results of 14-bus test system.

Evolutionary Algorithm	DE	PSO	WOA	SCA
Minimum power losses (MW)	12.853	12.4674	12.6991	12.274
Maximum power losses (MW)	14.407	14.3697	13.9989	12.541
Mean value of power losses (MW)	13.511	13.0705	13.1384	12.410
Variance from mean value	0.1522	0.1514	0.09278	0.0033
Time of Execution (s)	138.74	124.3201	104.1256	92.32
Standard deviation	0.3901	0.3892	0.3046	0.0581
Rank	4	3	2	1

Table 9 shows some important results derived from the statistical analysis of 30-bus system. Rank have been assigned based on standard deviation. It can be seen in Table 9 that SCA showed the lowest standard deviation, so it is ranked 1 while the results obtained by applying DE showed highest standard deviation, so it is ranked 4 as shown in Table 12.

Several tests can be performed on different data sets to find which data set is best among all data sets. These types of tests are called non-parametric tests. One of the non-parametric tests is the Wilcoxon rank sum test performed to prove the superiority of one technique over another. The results obtained by Wilcoxon rank sum test proves that SCA outshines all other proposed techniques. Table 10 shows that there is a very low probability that the other algorithms have power losses values less than SCA in 14-bus system. In Table 13 the hypothesis is true.

One more statistical parameter is to compare the strength of techniques is Probability density function (PDF) and

TABLE 13. Wilcoxon rank sum test conclusive table for 14-bus power system.

Algorithm	Results	
	Probability-value	Hypothesis
SCA VS PSO	5.2891e-14	1
SCA VS WOA	5.2891e-14	1
SCA VS DE	5.2891e-14	1

Cumulative density function (CDF). Thirty independent trail runs of all four algorithms for 14-bus system have been plotted using MATLAB as shown in Figure 24 and Figure 25.

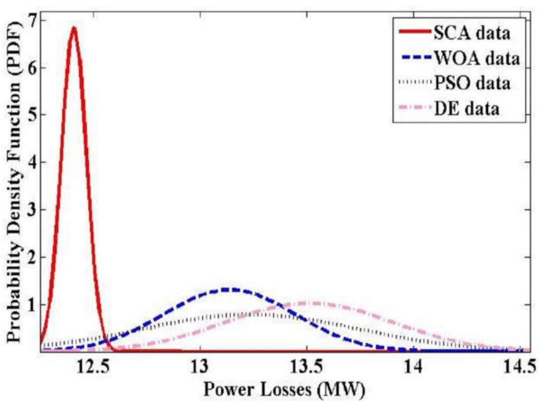

FIGURE 24. PDF plot for 14-bus system.

Fig 24 shows that the highest peak obtained for SCA and data distribution is widest in DE. It can also be derived from Figure 8 that most of results obtained in SCA are close to best result obtained during 30 independent runs. So, statistically SCA is best and DE is worst.

Fig 25 shows that slope of CDF is highest in case of SCA and lowest in case of DE, so it also statistically proves the superiority of SCA over other own run algorithms.

B. 30-BUS POWER SYSTEM STATISTICAL RESULTS

Table 14 shows the simulation setup for statistical analysis of 30-bus system.

Table 15 shows some important results derived from the statistical analysis of 30-bus system. It can be seen lowest standard deviation in case of SCA and highest deviation in case of DE algorithm. Rank shows that SCA outperforms all other techniques.

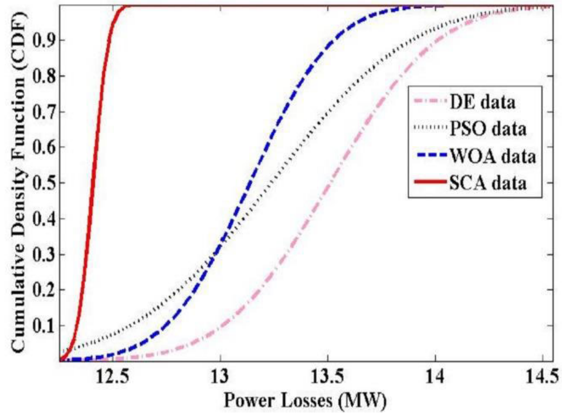

FIGURE 25. CDF plot for14-bus system.

TABLE 14. Experimental setup for 30-bus power system.

PV buses	6
Transformer tap changers	4
Reactive power sources	9
Search agents	30
Iterations	100
Trail runs	30

Table 16 shows the results of Wilcoxon rank sum test for 30-bus system.

The results showed that there is minimum probability that the results of other algorithms (DE, PSO, WOA) are better than SCA.

PDF and CDF of 30 independent trail runs of all four algorithms for 30-bus system have been plotted using MATLAB as shown in Figure 26 and Figure 27.

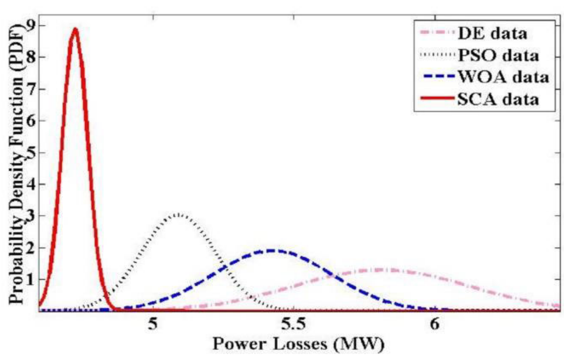

FIGURE 26. PDF plot for 30-bus system.

TABLE 15. Statistical analysis results of 30-bus test system.

Evolutionary Algorithm	DE	PSO	WOA	SCA
Best result (MW)	5.2355	4.8020	5.0514	4.6154
Worst result (MW)	6.4265	5.3268	5.8742	4.7887
Mean result (MW)	5.8091	5.0898	5.4230	4.7239
Variance from mean	0.0949	0.01728	0.04393	0.0019
Time of Execution (s)	147.76	150.9430	138.5645	116.435
Standard deviation	0.3081	0.1314	0.2096	0.0446
Rank	4	2	3	1

TABLE 16. Results of Wilcoxon rank sum test for 30-bus power system.

Algorithm	Results	
	Probability-value	Hypothesis
SCA VS PSO	2.57E-08	1
SCA VS WOA	3.93E-07	1
SCA VS DE	5.28E-15	1

Fig 26 shows that the highest peak obtained for SCA and widest data distribution is in DE. So, statistically the SCA is best and DE is worst.

Fig 27 shows that highest slope of CDF occurs for SCA and lowest slope of CDF occur for DE algorithm which statistically proves the superiority of SCA over all other own run algorithms.

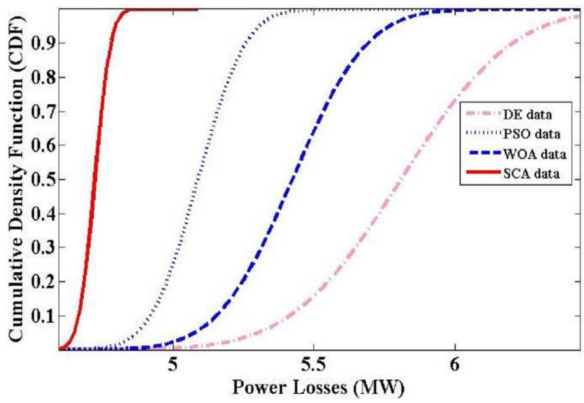

FIGURE 27. CDF plot for 30-bus system.

TABLE 17. Experimental setup for 57-bus power system.

PV buses	7
transformer tap changers	15
reactive power sources	3
search agents	30
Iterations	100
Trail runs	30

C. 57-BUS POWER SYSTEM STATISTICAL RESULTS

Table 17 shows the simulation setup for the statistical analysis performed on 57-bus system.

Table 18 shows some important results derived from statistical analysis of 57-bus system. It can be seen lowest standard deviation is in case of SCA and highest deviation in case of DE algorithm. Rank shows that SCA outperforms all other techniques.

Table 19 shows results obtained from Wilcoxon rank sum test.

The results showed that there is minimum probability that other algorithms (DE, PSO, WOA) give better result than SCA.

Figure 28 and Figure 29 shows the PDF and CDF plot of all four algorithms for 57-bus power system.

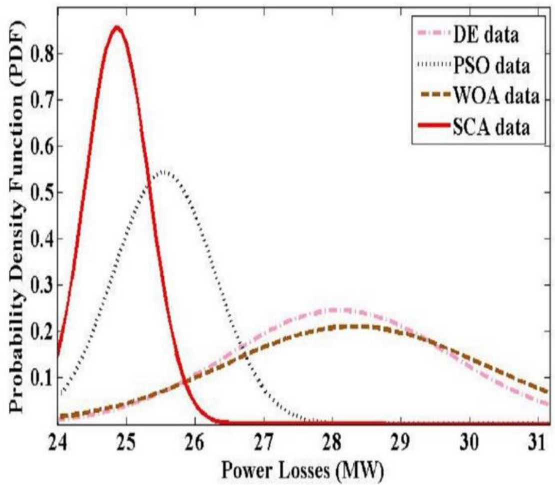

FIGURE 28. PDF plot for 57-bus system.

TABLE 18. Statistical analysis results of 57-bus test system.

Evolutionary Algorithm	DE	PSO	WOA	SCA
Best result (MW)	25.6093	24.4293	24.5631	24.0545
Worst result (MW)	31.0995	26.9517	31.0917	25.8977
Mean result (MW)	28.1054	25.5460	28.3183	24.8607
Variance from mean	2.6305	0.5373	3.5613	0.2169
Time of Execution (s)	411.385	255.977	232.320	155.534
Standard deviation	1.6219	0.7330	1.8871	0.4657
Rank	3	2	4	1

Fig 28 shows that lowest data distribution exists in case of SCA while widest data distribution occurs in case of WOA. So, statistically for 57-bus system SCA gives the best result.

TABLE 19. Results of Wilcoxon rank sum test for 57-bus power system.

Algorithm	Results	
	Probability-value	Hypothesis
SCA VS PSO	8.49E-06	1
SCA VS WOA	5.28E-15	1
SCA VS DE	5.28E-15	1

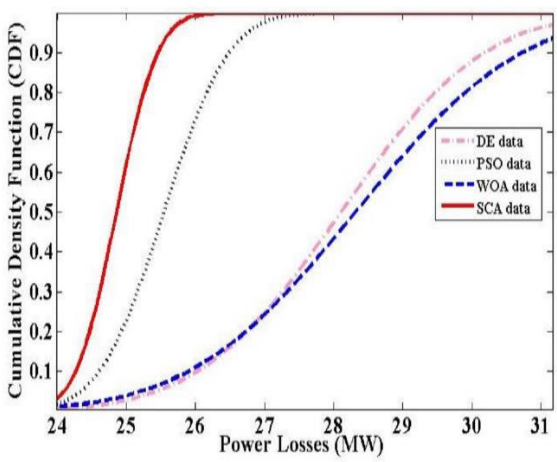

FIGURE 29. CDF plot 57-bus system.

Fig 29 shows that highest slope exist in case of SCA, and lowest slope exist in case of WOA. So, in CDF plot function the SCA has been proved to be the best. These graphs show that PDF and CDF values of SCA are best among all the implemented algorithms and in all test systems.

VII. CONCLUSION

This paper proposes a swarm based intelligent SCA to resolve the ORPD problem. In this work, the ORPD has been modelled to minimize losses in power system considering both dependent and independent constraints. The SCA utilizes the flexible behavior of sine and cosine functions which smoothly transits from exploration to exploitation phase. Three standard power systems (i.e. 14, 30 and 57-bus system) are utilized to check the performance and efficiency of proposed algorithm. To validate the superiority of proposed algorithm over the existing techniques, the obtained results are compared with the results already published in the related research work. Additionally, the statistical analysis is performed on the results attained by means of proposed SCA algorithm as well as DE, PSO and WOA. The results showed that SCA has achieved global minimum position with less iterations and less time compared to other implemented algorithms. Thus, the analysis proves the superiority and success of proposed algorithm to solve the ORPD problem. In addition, when SCA is compared with other meta-heuristic techniques already published in literature, it achieves better results.

VIII. FUTURE SCOPE OF WORK

In this manuscript we have utilized initially developed SCA [31]. Recently, modified forms of SCA [55]–[57] have been presented by researchers that may be used to get better results for ORPD. Furthermore, SCA can be hybrid with other optimization to get optimal values of control variables [58]–[60]. In future, we intend to use SCA for minimizing power losses in distribution system. The proposed SCA can be used to solve other optimization problems.

REFERENCES

[1] S. Fang, H. Cheng, G. Xu, Q. Zhou, H. He, and P. Zeng, "Stochastic optimal reactive power reserve dispatch considering voltage control areas," *Int. Trans. Electr. Energy Syst.*, vol. 27, no. 3, p. e2269, 2017.

[2] R. Kumar, R. Singh, and H. Ashfaq, "Stability enhancement of multimachine power systems using ant colony optimization-based static synchronous compensator," *Comput. Electr. Eng.*, vol. 83, May 2020, Art. no. 106589.

[3] S. Subramaniyan and J. Ramiah, "Improved football game optimization for state estimation and power quality enhancement," *Comput. Electr. Eng.*, vol. 81, Jan. 2020, Art. no. 106547.

[4] K. Aoki, M. Fan, and A. Nishikori, "Optimal VAr planning by approximation method for recursive mixed-integer linear programming," *IEEE Trans. Power Syst.*, vol. PS-3, no. 4, pp. 1741–1747, Nov. 1988.

[5] S. S. Sachdeva and R. Billinton, "Optimum network VAr planning by nonlinear programming," *IEEE Trans. Power App. Syst.*, vols. PAS–92, no. 4, pp. 1217–1225, Jul. 1973.

[6] V. H. Quintana and M. Santos-Nieto, "Reactive-power dispatch by successive quadratic programming," *IEEE Trans. Energy Convers.*, vol. 4, no. 3, pp. 425–435, Sep. 1989.

[7] J. Aghaei, M. Gitizadeh, and M. Kaji, "Placement and operation strategy of FACTS devices using optimal continuous power flow," *Scientia Iranica*, vol. 19, no. 6, pp. 1683–1690, Dec. 2012.

[8] S. Granville, "Optimal reactive dispatch through interior point methods," *IEEE Trans. Power Syst.*, vol. 9, no. 1, pp. 136–146, Feb. 1994.

[9] P. Subbaraj and P. N. Rajnarayanan, "Optimal reactive power dispatch using self-adaptive real coded genetic algorithm," *Electr. Power Syst. Res.*, vol. 79, no. 2, pp. 374–381, Feb. 2009.

[10] A. M. Abusorrah, "The application of the linear adaptive genetic algorithm to optimal power flow problem," *Arabian J. Sci. Eng.*, vol. 39, no. 6, pp. 4901–4909, Jun. 2014.

[11] M. A. Abido and N. A. Al-Ali, "Multi-objective optimal power flow using differential evolution," *Arabian J. Sci. Eng.*, vol. 37, no. 4, pp. 991–1005, Jun. 2012.

[12] C. M. Huang, S. J. Chen, Y. C. Huang, and H. T. Yang, "Comparative study of evolutionary computation methods for active-reactive power dispatch," *IET Gener., Transmiss. Distrib.*, vol. 6, no. 7, pp. 636–645, Jul. 2012.

[13] L. Hongxin, L. Yinhong, and C. Jinfu, "Adaptive multiple evolutionary algorithms search for multi-objective optimal reactive power dispatch," *Int. Trans. Electr. Energy Syst.*, vol. 24, no. 6, pp. 780–795, Jun. 2014.

[14] S. B. Raha and N. Chakraborty, "Tuned reactive power dispatch through modified differential evolution technique," *Frontiers Energy*, vol. 6, no. 2, pp. 138–147, Jun. 2012.

[15] A. Saraswat and A. Saini, "Multi-objective optimal reactive power dispatch considering voltage stability in power systems using HFMOEA," *Eng. Appl. Artif. Intell.*, vol. 26, no. 1, pp. 390–404, Jan. 2013.

[16] B. Zhao, C. X. Guo, and Y. J. Cao, "A multiagent-based particle swarm optimization approach for optimal reactive power dispatch," *IEEE Trans. Power Syst.*, vol. 20, no. 2, pp. 1070–1078, May 2005.

[17] A. A. Abou El-Ela, A. M. Kinawy, R. A. El-Sehiemy, and M. T. Mouwafi, "Optimal reactive power dispatch using ant colony optimization algorithm," *Electr. Eng.*, vol. 93, no. 2, pp. 103–116, Jun. 2011.

[18] K. Ayan and U. Kılc, "Artificial bee colony algorithm solution for optimal reactive power flow," *Appl. Soft Comput.*, vol. 12, pp. 1477–1482, May 2012.

[19] Z. B. Parekh and B. N. Suthar, "Optimal reactive power dispatch using grey wolf optimization technique," *IUP J. Electr. Electron. Eng.*, vol. 10, no. 3, pp. 64–74, 2017.

[20] R.-H. Liang, J.-C. Wang, Y.-T. Chen, and W.-T. Tseng, "An enhanced firefly algorithm to multi-objective optimal active/reactive power dispatch with uncertainties consideration," *Int. J. Elect. Power Energy Syst.*, vol. 64, pp. 1088–1097, Jan. 2015.

[21] K. B. O. Medani, S. Sayah, and A. Bekrar, "Whale optimization algorithm based optimal reactive power dispatch: A case study of the Algerian power system," *Electr. Power Syst. Res.*, vol. 163, pp. 696–705, Oct. 2017.

[22] S. S. Gudadappanavar and S. Mahapatra, "Metaheuristic nature-based algorithm for optimal reactive power planning," *Int. J. Syst. Assurance Eng. Manage.*, vol. 64, pp. 1–14, Nov. 2021.

[23] A. Mukherjee and V. Mukherjee, "Chaotic krill herd algorithm for optimal reactive power dispatch considering FACTS devices," *Appl. Soft Comput.*, vol. 44, no. 1, pp. 163–190, 2016.

[24] P. K. Roy, S. P. Ghoshal, and S. S. Thakur, "Optimal reactive power dispatch considering flexible AC transmission system devices using biogeography-based optimization," *Electr. Power Compon. Syst.*, vol. 39, no. 8, pp. 733–750, Apr. 2011.

[25] M. Ghasemi, M. Taghizadeh, S. Ghavidel, J. Aghaei, and A. Abbasian, "Solving optimal reactive power dispatch problem using a novel teaching–learning-based optimization algorithm," *Eng. Appl. Artif. Intell.*, vol. 39, pp. 100–108, Mar. 2015.

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

[27] D. S. Stephen and P. Somasundaram, "Solution for multi-objective reactive power optimization using fuzzy guided Tabu search," *Arabian J. Sci. Eng.*, vol. 37, no. 8, pp. 2231–2241, Dec. 2012.

[28] A. M. Shaheen, R. A. El-Sehiemy, and S. M. Farrag, "Optimal reactive power dispatch using backtracking search algorithm," *Austral. J. Elect. Electron. Eng.*, vol. 13, no. 3, pp. 200–210, 2016.

[29] A. Selim, S. Kamel, and F. Jurado, "Capacitors allocation in distribution systems using a hybrid formulation based on analytical and two Metaheuristic optimization techniques," *Comput. Electr. Eng.*, vol. 85, Jul. 2020, Art. no. 106675.

[30] M. A. Medina, S. Das, C. A. Coello Coello, and J. M. Ramírez, "Decomposition-based modern metaheuristic algorithms for multi-objective optimal power flow—A comparative study," *Eng. Appl. Artif. Intell.*, vol. 32, pp. 10–20, Jun. 2014.

[31] S. Mirjalili, "SCA: A sine cosine algorithm for solving optimization problems," *Knowl.-Based Syst.*, vol. 96, pp. 120–133, Mar. 2016.

[32] A. M. Shaheen, R. A. El-Sehiemy, and S. M. Farrag, "Integrated strategies of backtracking search optimizer for solving reactive power dispatch problem," *IEEE Syst. J.*, vol. 12, no. 1, pp. 424–433, Mar. 2018.

[33] A. M. Shaheen, R. A. El-Sehiemy, and S. M. Farrag, "Adequate planning of shunt power capacitors involving transformer capacity release benefit," *IEEE Syst. J.*, vol. 12, no. 1, pp. 373–382, Mar. 2018.

[34] P. P. Biswas, P. N. Suganthan, R. Mallipeddi, and G. A. J. Amaratunga, "Optimal power flow solutions using differential evolution algorithm integrated with effective constraint handling techniques," *Eng. Appl. Artif. Intell.*, vol. 68, pp. 81–100, Feb. 2018.

[35] S. Jeyadevi, S. Baskar, C. K. Babulal, and M. W. Iruthayarajan, "Solving multiobjective optimal reactive power dispatch using modified NSGA-II," *Int. J. Elect. Power Energy Syst.*, vol. 33, no. 2, pp. 219–228, 2011.

[36] R. D. Zimmerman, C. E. Murillo-Sánchez, and D. Gan. (1997). *Matpower*. PSERC. [Online]. Available: http://www. pserc. cornell. edu/matpower

[37] M. Ghasemi, M. M. Ghanbarian, S. Ghavidel, S. Rahmani, and E. M. Moghaddam, "Modified teaching learning algorithm and double differential evolution algorithm for optimal reactive power dispatch problem: A comparative study," *Inf. Sci.*, vol. 278, pp. 231–249, Sep. 2014.

[38] B. Bhattacharyya and S. Raj, "PSO based bio inspired algorithms for reactive power planning," *Int. J. Electr. Power Energy Syst.*, vol. 74, pp. 396–402, Jan. 2016.
[39] S. Raj and B. Bhattacharyya, "Reactive power planning by opposition-based grey wolf optimization method," *Int. Trans. Electr. Energy Syst.*, vol. 28, no. 6, p. e2551, Jun. 2018.
[40] M. A. M. Shaheen, H. M. Hasanien, and A. Alkuhayli, "A novel hybrid GWO-PSO optimization technique for optimal reactive power dispatch problem solution," *Ain Shams Eng. J.*, vol. 12, no. 1, pp. 621–630, Mar. 2021.
[41] A. M. Tudose, I. I. Picioroaga, D. O. Sidea, and C. Bulac, "Solving single- and multi-objective optimal reactive power dispatch problems using an improved salp swarm algorithm," *Energies*, vol. 14, no. 5, p. 1222, Feb. 2021.
[42] S. Mandal, K. K. Mandal, and S. Kumar, "A new optimization technique for optimal reactive power scheduling using Jaya algorithm," in *Proc. Innov. Power Adv. Comput. Technol. (i-PACT)*, Apr. 2017, pp. 1–5.
[43] J. Polprasert, W. Ongsakul, and V. N. Dieu, "Optimal reactive power dispatch using improved pseudo-gradient search particle swarm optimization," *Electric Power Compon. Syst.*, vol. 44, no. 5, pp. 518–532, Mar. 2016.
[44] B. Bhattacharyya and S. Raj, "A novel approach for the voltage stability assessment and reactive power planning," in *Proc. IEEE 10th Conf. Ind. Electron. Appl. (ICIEA)*, Jun. 2015, pp. 1534–1538.
[45] A. Bhattacharya and P. K. Chattopadhyay, "Solution of optimal reactive power flow using biogeography-based optimization," *Int. J. Electr. Electron. Eng.*, vol. 4, no. 8, pp. 568–576, 2010.
[46] P. K. Roy, B. Mandal, and K. Bhattacharya, "Gravitational search algorithm based optimal reactive power dispatch for voltage stability enhancement," *Electric Power Compon. Syst.*, vol. 40, no. 9, pp. 956–976, Jun. 2012.
[47] C. Dai, W. Chen, Y. Zhu, and X. Zhang, "Seeker optimization algorithm for optimal reactive power dispatch," *IEEE Trans. Power Syst.*, vol. 24, no. 3, pp. 1218–1231, May 2009.
[48] M. Ettappan, V. Vimala, S. Ramesh, and V. T. Kesavan, "Optimal reactive power dispatch for real power loss minimization and voltage stability enhancement using artificial bee colony algorithm," *Microprocessors Microsyst.*, vol. 76, Jul. 2020, Art. no. 103085.
[49] Y. Wei, Y. Zhou, Q. Luo, and W. Deng, "Optimal reactive power dispatch using an improved slime mould algorithm," *Energy Rep.*, vol. 7, pp. 8742–8759, Nov. 2021.
[50] T. Das, R. Roy, and K. K. Mandal, "Optimal reactive power dispatch based on modified Jaya algorithm," in *Proc. Int. Conf. Comput., Electr. Commun. Eng. (ICCECE)*, Jan. 2020, pp. 1–7.
[51] R. N. S. Mei, M. H. Sulaiman, Z. Mustaffa, and H. Daniyal, "Optimal reactive power dispatch solution by loss minimization using moth-flame optimization technique," *Appl. Soft Comput.*, vol. 59, pp. 210–222, Oct. 2017.
[52] R. Babu, S. Raj, B. Dey, and B. Bhattacharyya, "Optimal reactive power planning using oppositional grey wolf optimization by considering bus vulnerability analysis," *Energy Convers. Econ.*, pp. 38–49, Dec. 2021.
[53] S. Shekarappa G, S. Mahapatra, and S. Raj, "Voltage constrained reactive power planning problem for reactive loading variation using hybrid Harris hawk particle swarm optimizer," *Electric Power Compon. Syst.*, vol. 49, nos. 4–5, pp. 421–435, Mar. 2021.
[54] Y. Zhou, J. Zhang, X. Yang, and Y. Ling, "Optimal reactive power dispatch using water wave optimization algorithm," *Oper. Res.*, vol. 20, pp. 1–17, Dec. 2018.
[55] L. Abualigah and A. Diabat, "Advances in sine cosine algorithm: A comprehensive survey," *Artificial Intelligence Review*, vol. 54, no. 4, pp. 1–42, 2021.
[56] M. A. Elaziz, D. Oliva, and S. Xiong, "An improved opposition-based sine cosine algorithm for global optimization," *Expert Sys. Appl.*, vol. 90, pp. 484–500, Dec. 2017.
[57] S. Gupta and K. Deep, "Improved sine cosine algorithm with crossover scheme for global optimization," *Knowl.-Based Syst.*, vol. 165, pp. 374–406, Feb. 2019.
[58] R. M. Rizk-Allah, "A quantum-based sine cosine algorithm for solving general systems of nonlinear equations," *Artif. Intell. Rev.*, vol. 54, no. 5, pp. 3939–3990, Jun. 2021.
[59] R. M. Rizk-Allah, "An improved sine–cosine algorithm based on orthogonal parallel information for global optimization," *Soft Comput.*, vol. 23, no. 16, pp. 7135–7161, Aug. 2019.
[60] R. M. Rizk-Allah, "Hybridizing sine cosine algorithm with multi-orthogonal search strategy for engineering design problems," *J. Comput. Des. Eng.*, vol. 5, no. 2, pp. 249–273, 2018.

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