ORIGINAL PAPER

Application of Sine–Cosine Optimization Algorithm for Minimization of Transmission Loss

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Abstract
On recent trends, the reactive power planning problem has received a considerable amount of attention for the allocation of reactive power resources, both static and dynamic such as switchable capacitors and/or reactors, as well as Var compensators, respectively. The reactive power has a significant impact on voltage profile, stability and transmission loss in power systems. In recent years, voltage instability is recognized as a major threat to system operation due to a shortage of reactive power in an interconnected transmission line. These voltage conditions could be analyzed and improved by proper coordination of reactive sources/sink. In this article, the minimization of transmission loss and operating cost is performed by using the sine cosine algorithm (SCA) and quasi-oppositional based sine cosine algorithm (QOSCA) technique for standard IEEE 14 and IEEE 30 and IEEE 57 bus test system of the connected power network. The proposed QOSCA reduces the transmission losses by 6.38% in IEEE 14, 4.56% in IEEE 30 and 12.77% in IEEE 57 bus system. The results obtained by QOSCA and SCA are compared with other popular techniques recently reported in recent state-of-literature. It is observed that QOSCA yields better results in terms of reducing transmission loss, operating costs, and improving the voltage profile of each bus.

Keywords Reactive Power Planning · Active Power Loss · Sine Cosine Algorithm · Quasi-oppositional method

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Introduction

Generally, reactive power planning (RPP) is defined as an allocation of additional reactive power sources that should be installed in the network for a predefined horizon of planning at minimum cost while satisfying equality and inequality constraints. The optimal implementation of new reactive sources can be deployed according to specific indices, satisfying the objectives of the problem. However, reactive power sources are needed for increasing the capacity of transmission lines, correction of power factor, reduction of losses, and voltage profile improvement. RPP is an essential issue, especially in modern power systems. It can also be applied without supporting reactive power in some transmission networks.

Further, load bus voltages magnitudes may differ from their permissible limits, which may cause not only unacceptable power quality but the increment in loss of real power. In such cases, additions of the transmission line in an existing network is required which may not be economical. However, the RPP problem is combinatorial and is required to be solved via mixed-integer nonlinear programming. The objective of the RPP problem is to determine 'where,' 'what,'

'when' and 'how much' new devices are needed to an existing network to make its process reasonable for a pre-defined horizon of planning at minimum total costs.

Authors have implemented simulated annealing techniques in [1, 2] to determine locations to install capacitors and optimal control settings of these reactive sources. A convex chance-constrained model for long term investment planning and operation is discussed in [3]. The solution for reactive power planning is determined for the Iranian power grid using a Genetic algorithm in [4]. The mathematical model for solving transmission expansion and reactive power planning problems is discussed in [5]. An adaptive differential evolution procedure is presented in [6] to solve optimal reactive power dispatch problem, and authors have adopted an adaptive penalty factor to alleviate the effects of the dependent variable violation. A parallel hurricane optimization algorithm is proposed in [7] for solving the economic load dispatch problem. A novel application of Tree-shed algorithm to solve optimal power flow problem in a large-scale electric power system are described in [8]. Energy storage in grid-connected microgrid under uncertain real-time prices are discussed in [9]. The chance-constrained optimization algorithm is studied in [10] for the risk-assessment approach for the solution of the RPP problem.

Transmission expansion and reactive power problems are formulated as mixed-integer linear programming in [11]. The expected violation index for security-constrained RPP problems is discussed in [12]. An RPP optimization model is discussed in [13] by an enhanced simulated annealing (SA) algorithm taking advantage of the modified Gray code. A seeker optimization algorithm is proposed in [14] for the solution of reactive power dispatch. A solution of reactive power planning problem is determined by loss sensitivity approach in [15], Teaching learning-based optimization algorithm in [16], hybrid harris hawk particle swarm optimizer in [17] and hybrid forms of particle swarm optimization (PSO) algorithm, oppositional based grey wolf optimization (OGWO) algorithm in [18]. Management of reactive power is proposed in [19] based on fuzzy. RPP problem, along with the voltage stability margin, is evaluated by the differential evolution technique in [20]. Sine Cosine optimization algorithm is introduced in [21]. The concept of oppositional based learning was introduced by Tizhoosh [22].

Transmission expansion planning model along with second-order cone programming (SOCP), has been proposed in [23] for high penetration of wind energy. Optimal reconfiguring of the Algerian distribution electrical system with FACTS devices has been proposed in [24] using a fractal search algorithm. The ameliorated Harris hawk optimizer has been proposed in [25] for the solution of Optimal Reactive Power planning problems. A two-stage strategy like dynamic multiyear transmission expansion planning and transmission expansion planning problem has been developed in [26]. Article [27] proposes a planning strategy based on soft computing techniques to determine the system energy loss and economic benefit for the standard test system. The proposed work in [28] considered variants of PSO to improve the reduction in the total cost of energy loss and real power loss for standard New England 39 bus system. Weak bus detection methods are discussed in [29] and constrained VAr planning using penalty successive conic programming in [30]. A summary of optimization strategies for reactive power planning problems is summarized with its merits and demerits of the various approaches as shown in Table 1.

The unique visage of the sine–cosine algorithm is the ability not to get trapped in local minima, more comfortable to implement and gives the same result even after many trails. The silent features of the proposed QOSCA approach for RPP can be summarized as below:

a) Efficiently allocating reactive power sources during the planning and consequently decreasing the operating cost.
b) Improvement of voltage profile is also obtained on each bus.
c) Sine Cosine optimization algorithm appears to be the best method for minimizing the transmission loss at minimum operating cost.
d) The proposed Quasi-oppositional based Sine Cosine algorithm alleviates the drawbacks of the recently developed optimization algorithms.
e) Applications of standard IEEE 14, IEEE 30 and IEEE 57 bus test systems are carried. Therefore, the capability of the Sine Cosine algorithm is achieved.

In this article, Quasi-oppositional based Sine–Cosine algorithm has been proposed to solve the RPP problems for minimization of the transmission power loss and system operating cost while satisfying all the constraints. The main advantage of the SCA technique is that it does not get trapped in local minima. The proposed QOSCA optimization technique is applied to standard IEEE 14, IEEE 30 and IEEE 57 bus systems of a connected power network. The obtained results are compared with different techniques in the published articles, which states the capability and feasibility of the proposed SCA for the solution of RPP problems.

The organization of the rest of the paper is done in the following way. Section 2 includes a mathematical problem formulation including applicable constraints pertaining to the RPP problem. The description and application of QOSSA and SSA techniques are established in Sect. 3. Section 4 discusses simulation results for both the test system followed by concluding remarks in Sect. 5.

Table 1 Summary of literature

Algorithm	Contribution	Research Gaps	Reference
Interior Point method	• Hybrid-heuristic method has been proposed to solve transmission network expansion and reactive power planning problems • Proposed algorithm is tested on three practical test systems	• Ignored the impact of OLTC which can affect magnitude of transmission voltage	[5]
Genetic Algorithm	• VAr planning under multiple operating scenarios, optimizing sizes and locations of new reactive compensation equipment has been applied	• Methods should be adopted to improve convergence rate • Dependency on mutation rate must be avoided	[31]
Differential Evolution	• Proposed approach is applied on IEEE 30 bus system • Minimizes real power loss and cost of Var sources which includes fixed instalment cost and purchase cost	• Based on Trial-and-error method for parameter tuning which must be avoided	[32]
Particle Swarm Optimization	• Maximization of reactive reserves of the system has been proposed	• Depends learning constants and weight • Large parameter adjustment	[34]
Chemical Reaction Optimization	• Vigorous against initial seeds	• Totally depended on initial kinetic energy which must be avoided	[37]
Harmony search algorithm	• Inequality constraints are handled by penalty coefficients for solving reactive power problems	• Dependent on bandwidth vector, pitch adjustment rate and harmony memory	[14]
Seeker Optimization	• Implemented in optimal reactive power dispatch problems on standard IEEE bus power systems	• Rely on parameters and algorithm structure • Cannot find global optimum for multi modal functions	[14]
Gravitational Search Algorithm	• Minimization of real power loss, total voltage deviation and voltage stability indicator has been performed	• Parameter initialization is not robust • Weak local exploration can be avoided by modification or by hybridization of optimization algorithm	[33]
Water Cycle Algorithm	• Implemented for dropping real power loss in IEEE 30 bus system	• May stuck into local optima • Searching capability must be improved by modification or by hybridization • Ignored the impact of reactive power generated by generator buses	[35]
Teaching Learning Algorithm	• Proposed work is to minimize total harmonic distortion of voltage and current, and maximize total fundamental reactive power compensation	• Need more support in exploration characteristics • Healthy voltage profile is not considered	[36]

Problem Formulation

The prime importance of RPP is to minimize the active power losses and operating costs of the system. This planning is done through a proper organization and control of variables, which are transformer tap setting arrangements, shunt capacitors and generation of reactive power. Different advanced techniques have been developed to reduce the line losses in order to achieve an efficient and economic system while keeping bus voltage within an acceptable limit. The operating cost is minimized by cost due to reduced energy losses and the proper installation of capacitors at weak buses. The following objective functions and constraints are considered for the problem of RPP:

The active power loss in the line can be calculated as:

$$\text{Minimize}, F_1 = \min\left(P_{Loss}\right) = \sum_{k=1}^{N_L} g_k\left(V_i^2 + V_j^2 - 2V_iV_j\cos\left(\delta_i - \delta_j\right)\right) \quad (1)$$

where, P_{loss} represents active power loss, g_k is the conductance of the kth branch connected between i^{th} and j^{th} branch. N_L is the number of transmission lines, V_i and V_j is the voltage magnitude at the ith and jth bus respectively. $(\delta_i - \delta_j)$ is the voltage angle difference between i^{th} and j^{th} bus.

The operating cost of the system can be evaluated as:

The cost due to energy losses and the cost of the shunt capacitors is minimized to have an economical operation.

Cost of installing capacitor = 1000\$,
Energy rate = 0.06\$/kWh,
capacitor cost/kVar = 3\$

$$\text{Energyrate} = 0.06 \times 10000 \times 8760 \quad (2)$$

Total operating $\cos t$ *of system* $= P_{Loss} \times Energy$ Cost
$$+ \text{Cost } of \; shunt \; capacitor \quad (3)$$

It is a conflicting objective to minimize both real power loss and maintaining voltage within permissible limits simultaneously. Hence, it is done by proper controlling of different control variables represented by a vector U, consisting of reactive power generator Q_g^i, shunt capacitor value Q_c^i and tap setting T_t^i as:

$$U = \left[Q_g^1, \ldots., Q_g^{npv}, Q_c^1, \ldots., Q_c^{nc}, T_t^1, \ldots., T_t^{nt}\right]$$

where, *npv* is the total number of generator buses, *nc* is the total number of shunt capacitors and *nt* is the total number of tap changing transformers.

A dependent variable X associated with active power loss consisting of slack bus power P_g, the voltage of the load bus V_l^i, reactive power of a generator Q_g^i and transmission line loads can be represented as:

$$X = \left[P_g, V_l^1, \ldots., V_l^{npq}, Q_g^1, \ldots., Q_g^{npv}\right] \quad (4)$$

where, *npq* is the number of load buses, *npv* is the number of PV buses.

Equality constraints:

These are load flow equations, active and reactive power constraints for any i^{th} bus.

$$P_g^i - P_d^i = \sum_{j=1}^{N_b} V_iV_j\left(G_{ij}cos\theta_{ij} + B_{ij}sin\theta_{ij}\right) \quad (5)$$

$$Q_g^i - Q_d^i = \sum_{j=1}^{N_b} V_iV_j\left(G_{ij}sin\theta_{ij} - B_{ij}cos\theta_{ij}\right) \quad (6)$$

where, N_b is the number of buses. P_g^i and P_d^i are the active power generation and demand of the ith bus whereas, Q_g^i and Q_d^i are the reactive power generation and demand at the ith bus. G_{ij} and B_{ij} are the real and the imaginary admittance values respectively.

Inequality constraints-Generator constraints:

$$Q_{g_{min}}^i \leq Q_g^i \leq Q_{g_{max}}^i, i = 1, 2, 3, \ldots., N_g \quad (7)$$

$$V_{g_{min}}^i \leq V_g^i \leq V_{g_{max}}^i, i = 1, 2, 3, \ldots., N_g \quad (8)$$

where, N_g is the number of generator buses, $Q_{g_{min}}^i$ and $Q_{g_{max}}^i$ are minimum and maximum reactive power generation, $V_{g_{min}}^i$ and $V_{g_{max}}^i$ are the upper and lower limits of all the particular generator buses.

Limitation on reactive power injections:

$$Q_{c_{min}}^i \leq Q_c^i \leq Q_{c_{max}}^i \quad (9)$$

where, $Q_{c_{min}}^i$ and $Q_{c_{max}}^i$ are the reactive power injection limit by the shunt capacitors.

Transformer tap setting constraints:

$$T_{min}^k \leq T_p^k \leq T_{max}^k \quad (10)$$

k = 1,2,3,…,ntap.where, ntap is the number of taps changing transformer branches.

Line flow limits:

$$S_l^i \leq S_{l_{max}}^i \quad (11)$$

where, $S_{l_{max}}^i$ is the maximum load on the ith line.

Limitation on bus voltage:

$$V_{l_{min}}^i \leq V_l^i \leq V_{l_{max}}^i \quad (12)$$

i = 1,2,3………nb.
$V_{l_{min}}^i$ and $V_{l_{max}}^i$ are the minimum and maximum voltage limits, nb is the total number of load buses.

Sine Cosine Optimization Algorithm

Sine cosine optimization algorithm is a population-based optimization algorithm that is based on the mathematical function of Sine & Cosine. This algorithm has been proposed by Mirjalili [21] in 2016. In the present work, SCA is used as the optimization algorithm for reactive power planning. Initially, SCA creates multiple random solutions and these solutions then fluctuate towards or outwards the best solution on sine cosine functions given by the mathematical model of SCA.

The optimization process is divided into two-phase that is, exploration and exploitation. In exploration, promising regions of search space are obtained, as the optimization algorithm combines with the random solutions in the set of solutions precipitously with a high rate of randomness. In exploitation, there is a gradual change in random solutions, and random variations are less as compared to exploration. Mathematically, exploration and exploitation of updating positions can be expressed as:

$$X_{t+1}^i = X_t^i + r_0 \times \sin(r_1) \times \left| r_2 P_t^i - X_t^i \right| \tag{13}$$

$$X_{t+1}^i = X_t^i + r_0 \times \cos(r_1) \times \left| r_2 P_t^i - X_t^i \right| \tag{14}$$

The two equations can be used depending on the factor r_3 as:

$$X_{t+1}^i = \begin{cases} X_t^i + r_0 \sin(r_1) \times \left| r_2 P_t^i - X_t^i \right|, r_3 < 0.5 \\ X_t^i + r_0 \cos(r_1) \times \left| r_2 P_t^i - X_t^i \right|, r_3 \geq 0.5 \end{cases} \tag{15}$$

where, X_t^i is the position of the present solution in i[th] dimension at i[th] iteration. r_0, r_1, r_2, r_3 are random numbers. P is the position of the destination point in i[th] dimension, ‖ is the absolute value. In order to achieve a balance between the exploration and exploitation phase, the dynamic fine-tune of r_0 during the search process is carried out using Eq. (16).

$$r_0 = a - (a \times iter)/itermax \tag{16}$$

where, a is a constant, *iter* is the current iteration and *itermax* is the maximum number of iterations.

$r_1 \in [0, 2\pi]$
$r_2 \in [0, a]$
$r_3 \in [0, 1]$

r_0 determines the movement direction, either in the region between the solution and the destination or outside it. r_1 determines the depth of movement, towards or outwards the destination. r_2 brings a random weight for the destination in order to stochastically emphasize ($r_2 > 1$) or de-emphasize ($r_2 < 1$) the effect of destination in defining the distance. r_2 equally shift between sine and cosine components.

Opposition-based learning

Opposition based learning (OBL) was first instituted by Tizhoosh [22], which can potentially accelerate the convergence of optimization techniques and has proved immensely beneficial for computational intelligence. Any evolutionary or swarm optimization methods begin with the initial solution (initial population generation) which improves and updates to reach some optimal solution finally. Termination is based on setting up predefined criteria and computation time is a critical component to evaluate the robustness and effectiveness of a given algorithm depends on the distance between the initial guess and optimal solution. Fitness evaluation or the chances to arrive at the optimal solution enhances by checking the opposite guesses. This forms the basic framework of opposition-based learning.

So, the fitter one whether the guess or different guess, can be applied to the initial solution and subsequently to each solution in the current population to intensify convergence. Opposition based learning primarily benefits by increasing the probability of even visiting the unproductive regions. Also, it has been established through research that the different solution has a higher possibility to inch towards global optima as compared to a random solution [23]. Mathematically, OBL can be described as follows:

Quasi-oppositional SCA

In this section, the author proposes a hybrid optimization technique of QOSCA by introducing an opposition-based learning concept in the SCA technique. All swarm optimization techniques commence with some initial solution or initialization, upgrading by fitness evaluation and terminating at an optimal solution.

In the proposed novel hybrid technique of QOSCA, SCA is considered as the parent algorithm and Quasi-oppositional optimization is embedded in SCA to accelerate the speed of convergence. QOSCA engages opposite points for initializing the population and generation jumping and incorporates fitter candidate solutions from the start of the optimization. The mathematical model of a quasi-opposite point is discussed below:

(i). Opposite point

Let X_j^o be any control variable $\in \left[X^{\max}, X^{\min} \right]$, then any opposition variable can be obtained as

$$OX_j = X_j^{\max} + X_j^{\min} - X_j^0 \tag{17}$$

In this work, the maximum and minimum opposition variables are reactive power generation limits, transformer tap settings and shunt compensation limits as described below:

$$X_j^{\max} = \left[\begin{array}{cccccccc} Q_{G1}^{\max} & \dots & Q_{Gj}^{\max} & T_1^{\max} & \dots & T_j^{\max} & QC_1^{\max} & \dots & QC_j^{\max} \end{array} \right]$$

$$X_j^{\min} = \left[\begin{array}{cccccccc} Q_{G1}^{\min} & \dots & Q_{Gj}^{\min} & T_1^{\min} & \dots & T_j^{\min} & QC_1^{\min} & \dots & QC_j^{\min} \end{array} \right]$$

Therefore, the opposition matrix and quasi-opposition matrix are given by Eq. (18) and (19) respectively.

$$OX = \begin{bmatrix} X_{11}^{\max} + X_{11}^{\min} - X_{11}^0 & \dots & X_{1j}^{\max} + X_{1j}^{\min} - X_{1j}^0 \\ \dots & \dots & \dots \\ X_{i1}^{\max} + X_{i1}^{\min} - X_{i1}^0 & \dots & X_{ij}^{\max} + X_{ij}^{\min} - X_{ij}^0 \end{bmatrix} \quad (18)$$

where, i = Number of population and j = Number of variables.

$$QOX = \begin{bmatrix} QOX_{11} & \dots & QOX_{1j} \\ \dots & \dots & \dots \\ QOX_{i1} & \dots & QOX_{ij} \end{bmatrix} \quad (19)$$

The convergence speed is accelerated by selecting a quasi-opposite population matrix as the initial population. The generation of the next population is guided by jumping rate and this is incorporated in SCA optimization to increase the effectiveness and robustness of the algorithm. The computational steps followed in the new technique of QOSCA are given as follows:

Algorithmic perspective for the proposed work using Sine–Cosine optimization algorithm is given below:

Step 1. Define test system data.
Step 2. Define maximum iteration and agents.
Step 3. Set the upper and lower boundary limits of control variables like reactive power generation, transformer tap settings.
Step 4. Generate population matrix.
Step 5. Check the inequality constraint limits for the position of population matrix, if they are satisfied, then go to the next step; otherwise again generate population matrix and until all the inequality constraints of Eq. (7) to Eq. (12) are satisfied.

Table 3 Boundary of transformer tap setting and shunt capacitor

| Variables	Test system	Minimum Value (p.u)	Maximum Value (p.u)
Shunt capacitor [19]	IEEE 14	0.0	0.15
	IEEE 30	0.0	0.15
	IEEE 57	0.0	0.30
Transformer tap setting [19]	IEEE 14	0.9	1.0
	IEEE 30	0.9	1.0
	IEEE 57	0.9	1.0

Step 6. Initialize r_1, r_2 and r_3. Then by using the Eq. (16), determine moment direction for the current iteration.
Step 7. Update the position of search agents by exploration and exploitation phase from Eq. (13) to Eq. (15).
Step 8. Update the test system data with a new population string.
Step 9. Y-bus is formed.
Step 10. Newton Raphson program is executed and the objective function is determined using Eq. (1) and Eq. (3) while satisfying equality and inequality constraints of Eq. (5) and Eq. (12).
Step 11. Repeat Step-(6) to step-(10) for all the search agents. Now compare the optimum result value with all the search agent solutions. Store the minimum value of the optimum result and the corresponding position of search agents.
Step 12. Set the iteration number equal to 1.
Step 13. Repeat step 4 to step 11. Then increase the current iteration by 1.
Step 14. Now repeat step 4 to step 11 until the maximum number of iteration it has reached.
Step 15. If the current iteration is equal to the maximum number of iteration, then terminate the iterative process. Save as the best solution to optimization problems.

Table 2 Boundary of reactive power generation at the generator bus

IEEE 14 BUS SYSTEM					
Generator Bus	2	3	6		8
Minimum Value (in p.u) [19]	-0.40	0.0	-0.06		-0.06
Maximum Value (in p.u) [19]	0.50	0.40	0.24		0.24
IEEE 30 BUS SYSTEM					
Generator Bus	2	5	8	11	13
Minimum Value (in p.u) [19]	-0.20	-0.15	-0.15	-0.10	-0.15
Maximum Value (in p.u) [19]	0.60	0.625	0.50	0.40	0.45
IEEE 57 BUS SYSTEM					
Generator Bus	2	3	6	8	9	12
Minimum Value (in p.u)	-0.17	-0.10	-0.08	-1.40	-0.03	-0.50
Maximum Value (in p.u)	0.50	0.60	0.25	2.0	0.09	1.55

Table 4 Optimal control parameters for minimum transmission loss and total operating cost when tested on different algorithms on the IEEE-14 bus system

| Control Variable	Sens-GA [15]	Sens-DE [15]	Sens-PSO [15]	SPSO [18]	APSO [18]	EPSO [18]	GWO [18]	OGWO [18]	SCA	QOSCA
Reactive power generation of generators (in p.u)										
$Q_G(2)$	0.3120	0.2815	0.3125	0.3081	0.3078	0.3077	0.2919	0.3232	0.3078	0.3124
$Q_G(3)$	0.2507	0.2589	0.2516	0.2486	0.2501	0.2485	0.2502	0.2550	0.2440	0.2498
$Q_G(6)$	0.2302	0.24	0.24	0.24	0.2257	0.24	0.1542	0.1549	0.1872	0.1869
$Q_G(8)$	0.0897	0.1197	0.0888	0.1016	0.0990	0.1012	0.0204	-0.0030	0.305	0.0007
Transformer tap setting (in p.u)										
Tap (8)	0.95	0.9531	0.9573	0.95	0.9542	0.9542	0.9688	0.9661	0.9	0.9
Tap (9)	0.95	0.95	0.95	0.95	0.9518	0.9518	0.9712	0.9500	0.9	0.9
Tap (11)	0.9502	0.95	0.95	0.95	0.9513	0.9513	0.9004	0.9500	0.9	0.9
Shunt Capacitors (in p.u)										
Q_{C1}	0.0473	0.0344	0.0478	0.0478	0.0485	0.0472	0.0498	0.0612	0.0468	0.0571
Q_{C2}	0.0526	0.0539	0.0580	0.0515	0.0523	0.0530	0.0704	0.0563	0.0423	0.0520
Q_{C3}	0.0147	0.0082	0.0	0.0	0.0121	0.0	0.0332	0.0441	0.0409	0.0394
Active power loss (p.u)	NR	NR	NR	0.1321	0.1321	0.1321	0.1320	0.1320	0.1315	0.1315
Operating cost $\times 10^6$ ($)	6.9470	6.9439	6.9472	6.9477	6.9481	6.9477	6.9369	6.9361	6.9109	6.9097
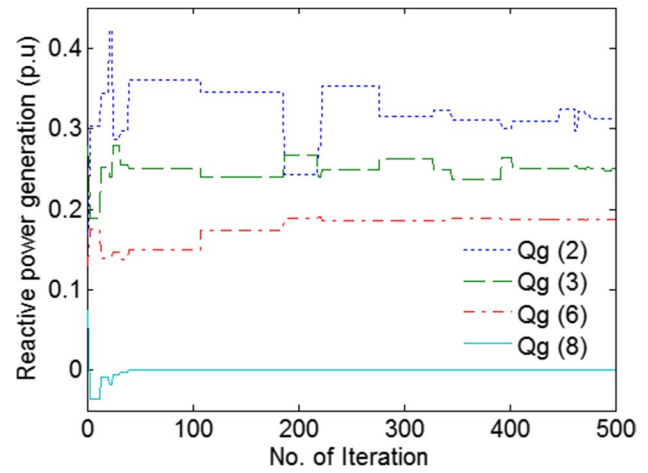
**Fig. 1** Variation of Reactive power generation profile

Result and discussion

In order to demonstrate the applicability and validity of the proposed Quasi-oppositional based Sine Cosine optimization and Sine Cosine optimization algorithm technique for the solution of reactive power planning, standard IEEE 14, IEEE 30 and IEEE 57 bus test system has been considered for the testing purpose. Boundary limits of control variables of these test systems are shown in Tables 2 and 3. In order to validate the proposed optimization algorithm, it has been made to run for 500 iterations and 40 number of search agents in each of the given test systems.

In IEEE 14 bus test system, there are four generator buses with interconnected 20 transmission lines. Three branches are equipped with tap changing transformer and one shunt capacitor. Initially, active power loss without reactive power planning is 13.99 MW and its operating cost is 7.3531×10^6\$. The search space of this test system has 10 dimension that includes four reactive power generators, three transformer tap settings
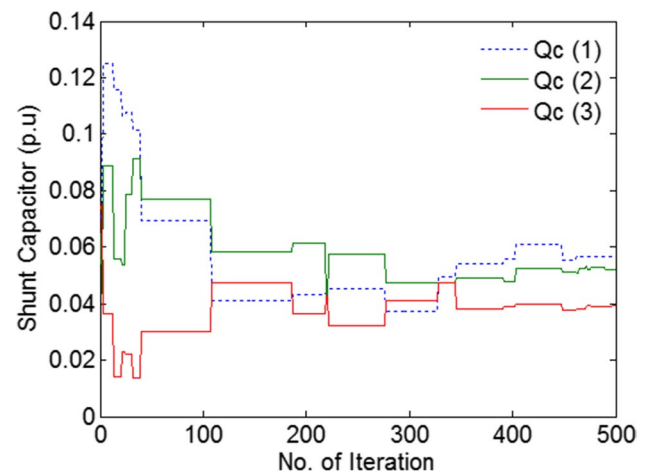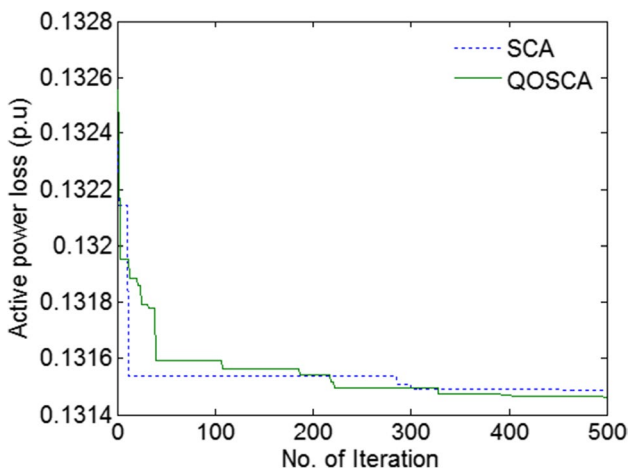

Fig. 2 Variation of Shunt capacitors for Q_c (1), Q_c (2) and Q_c (3)
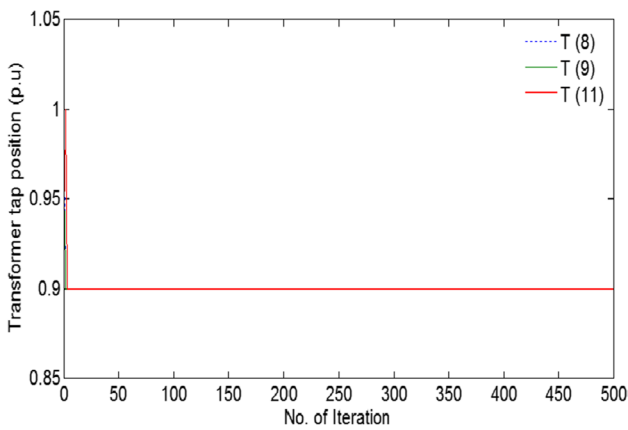
Fig. 3 Variation of Transformer Tap settings for T (6–9), T (6–10) and T (28–27)

and shunt capacitors are placed at weak buses, where a large amount of reactive power is present. Table 4 represents the control parameters obtained by the proposed SCA. The results of proposed SCA are also compared with other optimization algorithm like Sens-GA [15], Sens-DE [15], Sens-PSO [15], SPSO [18], APSO [18], EPSO [18], GWO [19] and OGWO [19]. The variation of reactive power generation profile is shown in Fig. 1. The variation of shunt capacitors for Qc (1), Qc (2) and Qc (3) is shown in Fig. 2. With the application of the proposed approach, total active power loss is reduced to 0.1315 p.u and system operating cost is also reduced to 6.9234×10^6\$. Figure 3 depicts the reactive power generation variation at the generator buses during every iteration. Figures 4 and 5 displays the transformer tap setting condition and reactive power variation of shunt capacitors respectively. The minimization of the active power loss curve is shown in Fig. 6 and the convergence characteristics curve of the system operating cost is shown in Fig. 7. The convergence curve
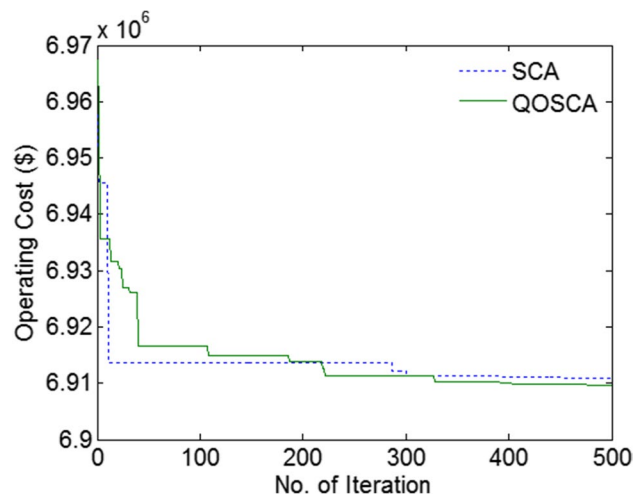

Fig. 5 Convergence curve of operating cost using SCA and QOSCA technique

candidly reveals the superiority of the proposed algorithm and the influence of QOSCA to avoid premature convergence and yield solutions with accuracy.

Similarly, In IEEE 30 bus test system, there are five generator buses with interconnected 41 transmission lines. Three branches are equipped with tap changing transformer and two shunt capacitors. Initially, active power loss without reactive power planning is 7.11 MW and its operating cost is 3.737016×10^7\$. The search space of this test system has 13 dimension that includes five reactive power generators, three transformer tap settings and four shunt capacitors are placed at weak buses where a large amount of reactive power is present.

Table 5 represents the control parameters obtained by the proposed SCA. The results of proposed SCA are also compared with other optimization algorithm like Sens-GA [15], Sens-DE [15], Sens-PSO [15], SPSO [18], APSO

Fig. 4 Convergence curve of active power loss using SCA and QOSCA technique
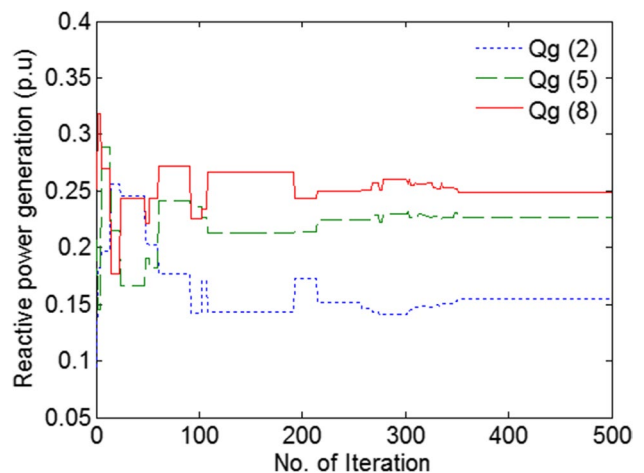
Fig. 6 Variation of Reactive power generation profile

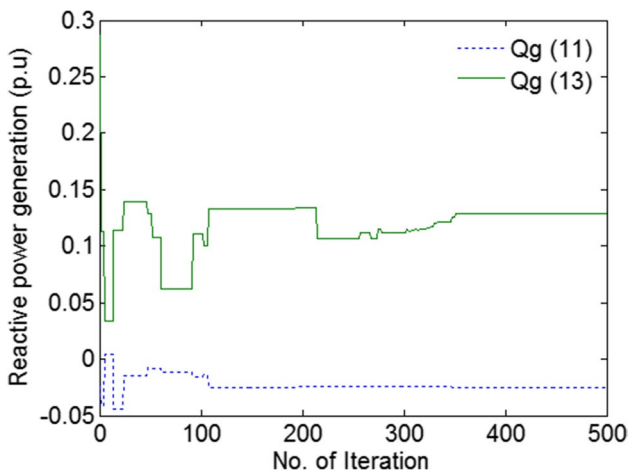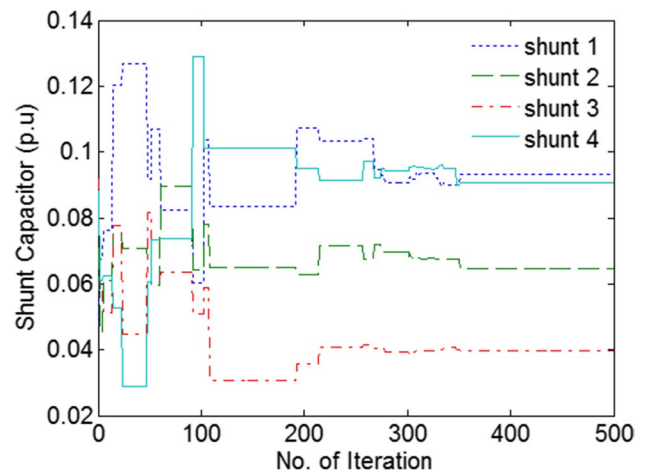**Fig. 7** Variation of Reactive power generation profile

Fig. 8 Variation of Shunt capacitors for Q_c (1), Q_c (2) and Q_c (3)

Table 5 Optimal control parameters for minimum transmission loss and total operating cost when tested on the IEEE-57 bus system

Variable	SCA	QOSCA
Reactive generation of generators (in p.u)		
Q_G (2)	0.1575	0.4942
Q_G (3)	0.4028	0.3094
Q_G (6)	0.0137	0.1013
Q_G (8)	-0.4394	0.8443
Q_G (9)	0.0201	0.0599
Q_G (12)	-0.0109	0.0759
Transformer tap positions (in p.u)		
T (19)	0.9114	0.9342
T (20)	0.9123	0.9080
T (31)	0.9958	0.9973
T (35)	0.9152	0.9218
T (36)	0.9000	0.9196
T (37)	0.9979	0.9788
T (41)	0.9000	0.9000
T (46)	0.9000	0.9225
T (54)	0.9016	0.9065
T (58)	0.9021	0.9016
T (59)	0.9348	0.9293
T (65)	0.9044	0.9001
T (66)	0.9000	0.9000
T (71)	0.9000	0.9025
T (73)	0.9980	0.9957
T (76)	0.9721	0.9924
T (80)	0.9028	0.9012
Shunt capacitors (in p.u)		
Q_{C1}	0.2971	0.2970
Q_{C2}	0.2772	0.1573
Q_{C3}	0.1393	0.2691
Q_{C4}	0.1119	0.1800
Active power loss (p.u)	0.2509	0.2482
Operating cost ($)	1.3188×10^7	1.3044×10^7

[18], EPSO [18], GWO [19] and OGWO [19]. With the application of the proposed approach, total active power loss is reduced to 0.0679 p.u and system operating cost is also reduced to 6.9097×10^6\$. Figures 6 and 7 depicts the reactive power generation variation at the generator buses during every iteration. Figures 8 and 9 displays the reactive power variation of shunt capacitors and transformer tap setting conditions respectively. The minimization of the active power loss curve is shown in Fig. 10 and the convergence characteristics curve of the system operating cost is shown in Fig. 11. From obtained tables and figures, it can be observed that the proposed QOSCA and SCA techniques are able to reduce real power loss to a large extent; hence, the capability of the transmission lines improves. It can also be observed that QOSCA
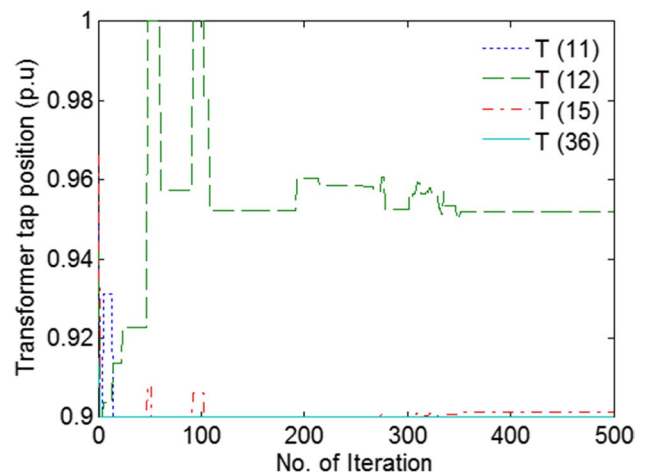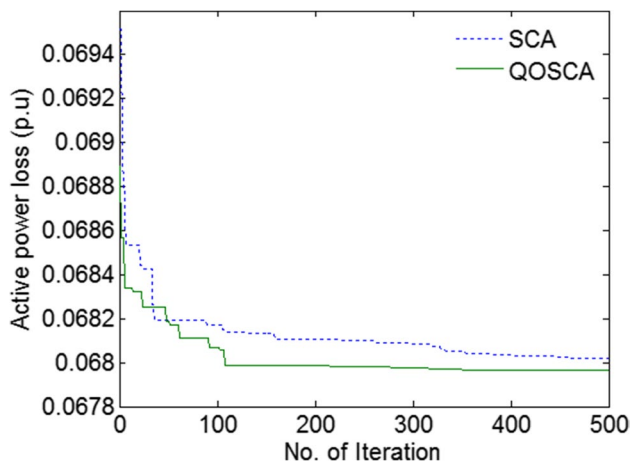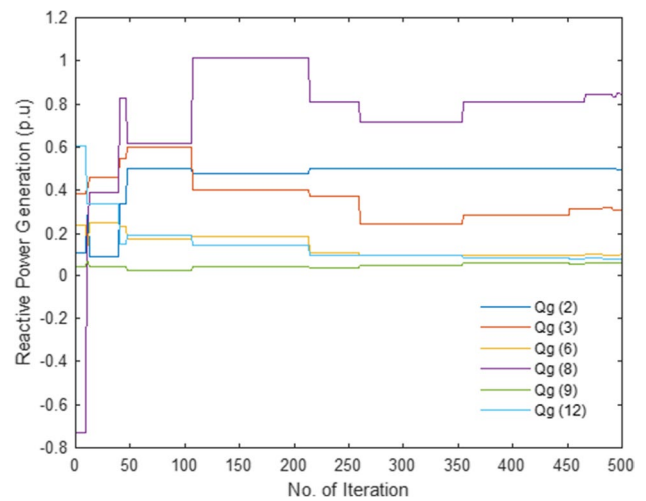

Fig. 9 Variation of Transformer Tap settings for T (6–9), T (6–10) and T (28–27)

Fig. 10 Convergence curve of active power loss using SCA and QOSCA technique

Fig. 12 Variation of Reactive power generation profile

optimization gives the better results as compared to the other optimization techniques.

The standard IEEE 57 bus test system consists of seven generating units at buses 1, 2, 3, 6, 8, 9 and 12 interconnected with 80 transmission lines and seventeen branches are equipped with tap changing transformer. In addition, there are shunt capacitors at buses 18, 25 and 53. Bus 1 is selected as slack bus. The total active power demand is 1251.70 MW and reactive power demand is 335.70 MVAr at 100 MVA. Initially, active power loss without reactive power planning is 27.99 MW and its operating cost is 1.471×10^7\$. The search space of this test system has 13 dimension that includes six reactive power generators, seventeen transformers tap settings and three shunt capacitors are placed at weak buses where

a large amount of reactive power support is required. Table 5 shown best control parameter setting obtained by proposed SCA and QOSCA. With the application of the proposed approach, total active power loss is reduced to 0.2482 p.u and system operating cost is also reduced to 1.3044×10^7\$. Figure 12 depicts the reactive power generation variation at the generator buses during every iteration. Figures 13 and 14 displays the reactive power variation of shunt capacitors and transformer tap setting conditions respectively.

The convergence curve of active power loss using SCA and QOSCA technique is shown in Fig. 15. The convergence curve of operating cost using SCA and QOSCA technique is shown in Fig. 16.
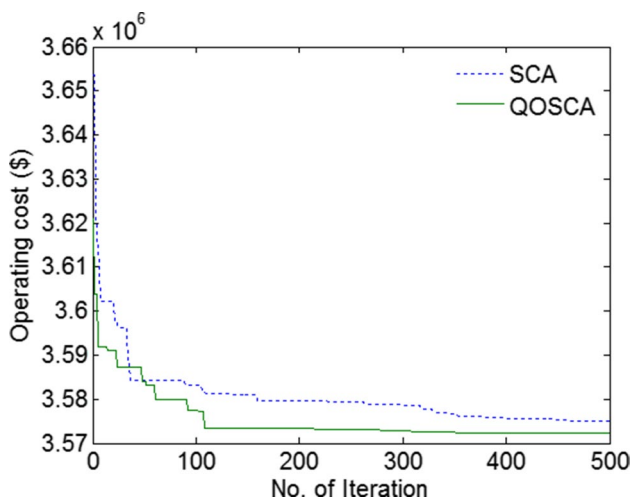
Fig. 11 Convergence curve of operating cost using SCA and QOSCA technique
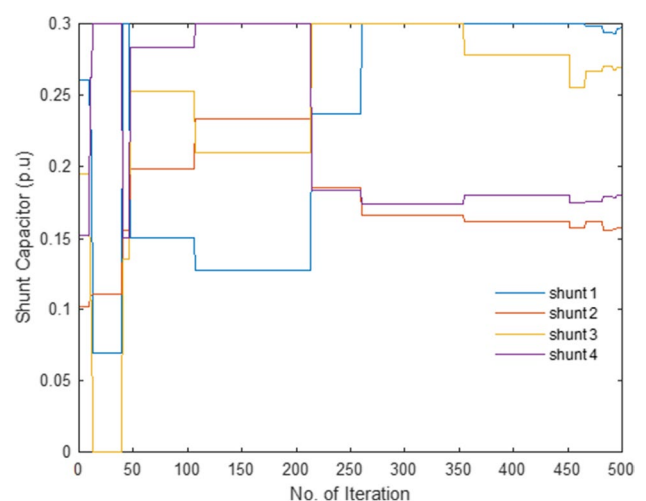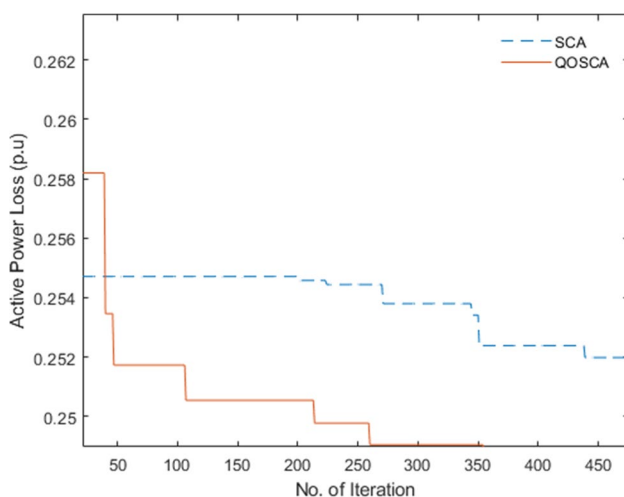

Fig. 13 Variation of Shunt capacitors for Q_c (1), Q_c (2), Q_c (3) and Q_c (4)
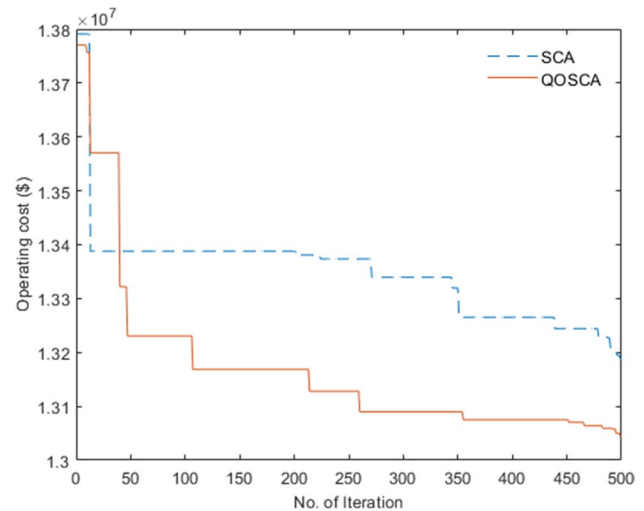
Fig. 14 Variation of Transformer Tap settings

Fig. 16 Convergence curve of operating cost using SCA and QOSCA technique
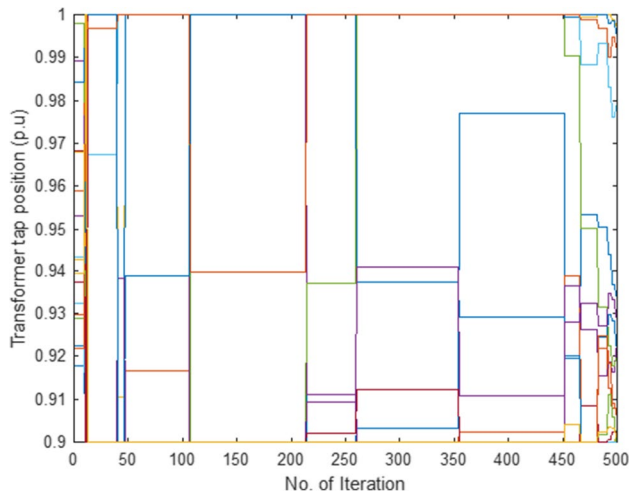
Conclusion

Reactive power planning has been a crucial problem for power system operators. The prime importance of RPP is to minimize the active power losses and operating costs of the system. This planning is done through proper co-ordination of control variables, which are transformer tap setting arrangements, shunt capacitors and generation of reactive power by generators. Different state-of-the-art methods have been developed to reduce line losses in order to achieve an efficient and economical system. In this work, SSA and QOSSA techniques have been successfully implemented on standard IEEE 14 and IEEE 30 bus system of the connected power network. The proposed QOSCA reduces the transmission losses by 6.38% in IEEE 14, 4.56% in IEEE 30 and 12.77% in IEEE 57 bus system. The outcomes are compared with other techniques used in the literature. It is observed that the QOSCA algorithm provides much better results than the other techniques used in recent state-of-literature. It can be concluded that the Sine cosine algorithm may be considered as an effective optimization technique for solving RPP problems and can be considered as a promising candidate for future researches.

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Fig. 15 Convergence curve of active power loss using SCA and QOSCA technique

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