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Optimal placement of TCSC and SVC for reactive power planning using Whale optimization algorithm

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ABSTRACT

In the present work, Whale optimization algorithm (WOA), Differential evolution (DE), Grey wolf optimization (GWO), Quasi-opposition based Differential Evolution (QODE) and Quasi-opposition based Grey wolf optimization (QOGWO) algorithm has been applied for the solution of reactive power planning with FACTS devices i.e., Thyristor controlled series compensator (TCSC) and Static Var compensator (SVC). WOA is a recently developed nature-inspired meta-heuristic algorithm based on hunting behaviour of Humpback Whales; DE is a stochastic real-parameter optimization technique comprising of genetic parameters namely - mutation & cross-over; and GWO is a nature-inspired meta-heuristic algorithm based on hunting behaviour of Grey wolf. Standard IEEE 30 and IEEE 57 bus test system has been adopted for the testing purposes. Location of TCSC has been determined by the power flow analysis method and location of SVC has been determined by the voltage collapse proximity indication (VCPI) method. Further, WOA, GWO, DE, QODE and QOGWO algorithms have been applied to find the optimal setting of all control variables including TCSC, the series type and SVC, the shunt kind of FACTS device in the test system which minimizes active power loss and system operating cost while maintaining voltage profile within permissible limit. The superiority of the proposed WOA technique has been illustrated by comparing the results obtained with all other techniques discussed in the present problem. ANOVA test has also been conducted to show the statistical analysis between different techniques. The proposed approach shows lesser number of iterations which does not gets trapped in the local minima and offers promising convergence characteristics.

1. Introduction

In the prevailing power system networks, the economic and environmental friendly transfer of electrical energy is a challenging task for the power system operators. Construction of new transmission lines to meet the current electricity demand cannot be considered a feasible option due to many reasons including the cost as one of the prime factor. The need for more efficient and fast responding electrical systems has prompted the use of a new technology based on solid-state devices in transmission system. The new technology includes Flexible AC transmission system (FACTS) devices with existing power system to improve the performance of the power system. In a connected power network, FACTS provides new opportunity for controlling the line power flow and minimizing losses while maintaining the bus voltages within a permissible limit. Effective and co-ordinated reactive power planning at weak buses of power system may help in minimizing active power loss and improve the voltage profile of entire connected power network.

Authors have presented simulated annealing based algorithm in Refs. [1,2] for the optimal placement of capacitors in a connected power network. Modal analysis method to determine the weak buses for the voltage stability improvement is described in Ref. [3]. The concept of flexible AC transmission systems (FACTS) first introduced by Hingorani is discussed in Ref. [4]. Impact of FACTS devices on optimal power flow is discussed in Ref. [5]. Detection of weak buses for the optimal placement of reactive power sources/sink using voltage collapse proximity indicator method is presented in Refs. [6,7]. Application of an analytical approach for the problem of sizing and locating series and shunt compensators in order to increase the steady state power transfer capacity is described in Ref. [9]. Steady state model of FACTS devices is presented in Ref. [10] along with an illustration as to how these FACTS devices can be used in controlling the line power flow. GA (Genetic algorithm) is used in Ref. [11] for the optimal allocation of different types of FACTS devices. Problem of active and reactive congestion management using FACTS devices is solved in Ref. [12]. A novel power flow control approach with FACTS devices based on power-injection model of FACTS devices is described in Ref. [13]. Determination of optimal location and sizing of

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Table 1
Limits of control variables in different test system.

Control variables	IEEE 30 bus		IEEE 57 bus	
	Minimum	Maximum	Minimum	Maximum
Transformer taps	0.9	1.0	0.9	1.05
TCSC	0.0	0.08	0.0	0.11
SVC	0.0	0.20	0.0	0.20

Table 2
Cost Coefficients values of different FACTS devices.

FACTS device	α	β	γ
TCSC	0.0015	−0.7130	153.75
SVC	0.0003	−0.3051	127.38

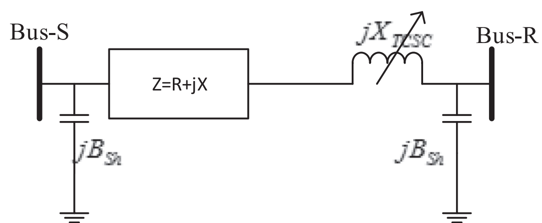

Fig. 1. Static model of TCSC

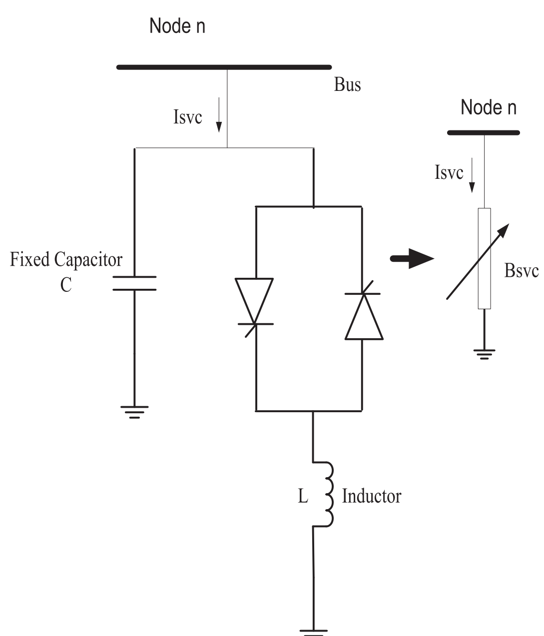

Fig. 2. Static model of SVC.

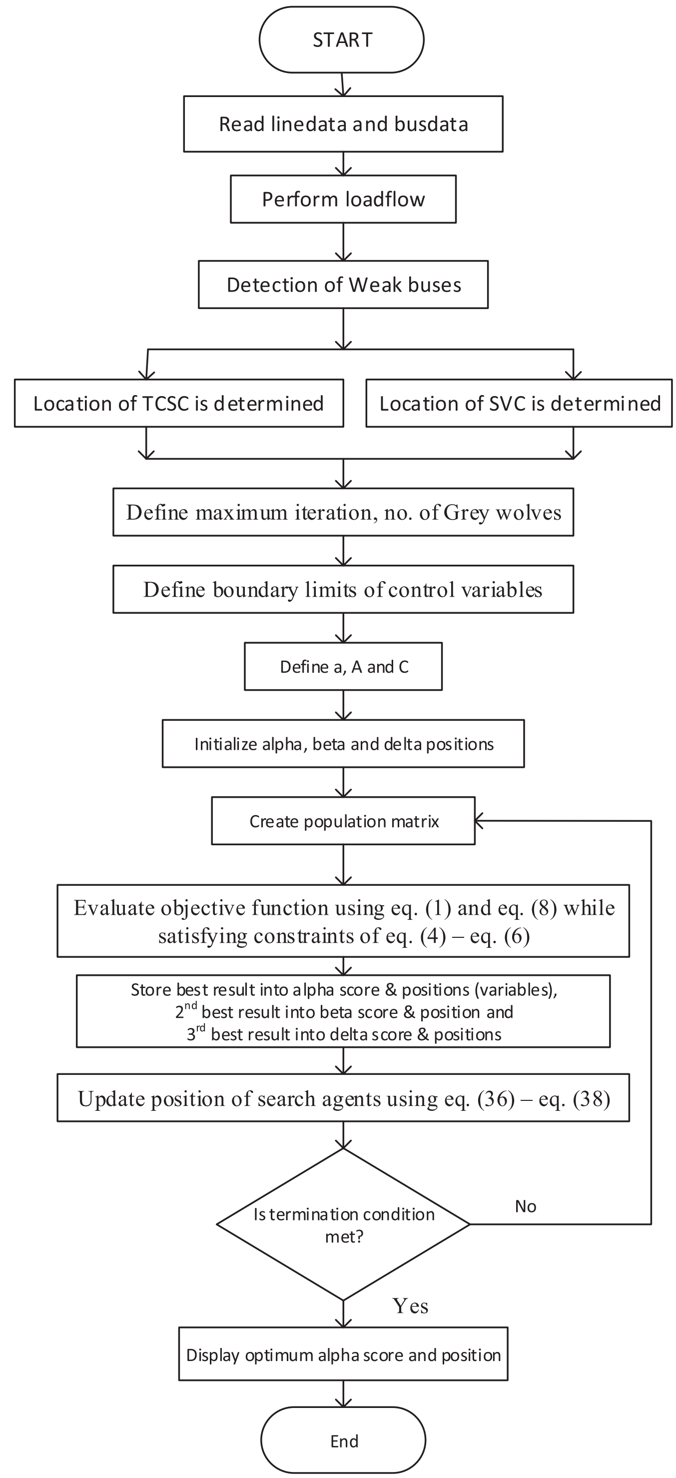

Fig. 3. Flowchart of the proposed work using GWO.

FACTS devices are illustrated using GA in Refs. [14,15]. In Ref. [16], Authors have proposed a new generalized current injection model for the desired power transfer with FACTS devices that can be easily converted into power injection models without change of original admittance and Jacobian matrices. Enhancement of system security against single contingency via optimal placement of TCSC is presented in Ref. [17]. Optimal allocation of SVC and TCSC to reduce active power loss, voltage deviation and security margin against voltage collapse are presented in Ref. [18]. Mathematical model for determining the power losses and application of classical optimization technique to minimize the loss of power in transmission is developed in Ref. [19]. Congestion management problem by using static synchronous compensator (STATCOM) and static synchronous series compensator (SSSC) is discussed in Ref. [20]. Genetic algorithm (GA) to determine the optimal settings of control variables for the solution of optimal power flow is proposed in Ref. [21]. An AC model of transmission expansion planning problem associated with reactive power planning is described in Ref. [22]. Application of improved particle swarm optimization (PSO) for sizing and allocation of STATCOM to minimize voltage deviation in all the buses is discussed in Ref. [23]. Fuzzy based approach for reactive power control is presented in Ref. [24] where fuzzy membership values plays deciding factor for the placement

Table 3
Best control variable setting by different techniques for IEEE 30 bus system.

Control variables	SGA [24]	Fuzzy-GA [24]	SDE [24]	Fuzzy-DE [24]	SPSO [30]	APSO [30]	EPSO [30]	DE [Studied]	QODE [Studied]	GWO [Studied]	QOGWO [Studied]	Proposed WOA
Q_g (2)	0.3409	0.2876	0.4287	0.0	0.6	0.0	0.6	−0.5090	0.3535	−0.0108	0.0339	0.6
Q_g (5)	0.1815	0.2764	0.0093	0.6	0.0	0.0	0.0	−0.1307	0.2365	−0.1151	−0.0027	0.6250
Q_g (8)	0.1911	0.0729	0.5	0.25	0.0	0.0	0.0	0.3955	0.4462	0.1228	0.2907	0.5
Q_g (11)	0.1975	0.1865	0.1995	0.0416	0.4	0.4	0.4	0.3031	0.3497	0.0797	0.0515	0.0029
Q_g (13)	0.1023	0.0812	0.0	0.0	0.0	0.0	0.0	0.0474	0.2460	0.2117	0.2342	0.0177
T (11)	0.9099	0.9290	0.9133	0.9787	0.9	0.9	0.9439	0.9021	0.9012	0.9	0.9	0.9
T (12)	0.9859	0.9136	0.9	0.9	0.9	0.9501	0.9	0.9658	0.9514	0.9295	0.9452	0.9448
T (15)	0.9133	0.9501	0.9	0.9370	0.9	0.9180	0.9	0.9007	0.9004	0.9	0.9	0.9
T (36)	0.9344	0.9217	0.9283	0.9157	0.9223	0.9330	0.9326	0.9211	0.9278	0.9289	0.9271	0.9285
TCSC (1)	0.0001	0.0185	0.0195	0.0	0.1463(25)	0.1463(25)	0.1463(25)	0.08(25)	0.0618(25)	0.08(25)	0.08(25)	0.08(25)
TCSC (2)	0.0419	0.0002	0.0419	0.0	0.0419(41)	0.0419(41)	0.0419(41)	0.08(41)	0.1588(41)	0.08(41)	0.08(41)	0.08(41)
TCSC (3)	0.0002	0.0016	0.0	0.0	0.1049(28)	0.1049(28)	0.1049(28)	0.0797(28)	0.1999(28)	0.08(28)	0.08(28)	0.08(28)
TCSC (4)	0.0515	0.0009	0.0080	0.0	0.1388(5)	0.1388(5)	0.1368(5)	0.08(5)	0.0116(5)	0.08(5)	0.08(5)	0.08(5)
SVC (1)	0.0892	0.1906	0.1097	0.0	0.0(7)	0.0(7)	0.0(7)	0.0663(22)	0.0797(22)	0.0368(22)	0.0589(22)	0.0524(22)
SVC (2)	0.0511	0.0051	0.0427	0.0	0.0(15)	0.0(15)	0.0(15)	0.1492(04)	0.08(04)	0.1707(04)	0.12(04)	0.1544(04)
SVC (3)	0.0398	0.0486	0.0480	0.0	0.0(17)	0.0(17)	0.0(17)	0.1498(28)	0.0789(28)	0.20(28)	0.20(28)	0.2(28)
SVC (4)	0.0521	–	0.0958	–	0.0840(21)	0.0768(21)	0.0(21)	0.0225(20)	0.08(20)	0.0049(20)	0.0091(20)	0.0145(20)
P_{Loss}	0.0406	0.0399	0.0406	0.0403	0.0435	0.0434	0.0438	0.0393	0.0393	0.0393	0.0393	**0.0393**
C_{Total}	2.1786×10^6	2.1297×10^6	2.1770×10^6	2.1171×10^6	2.3622×10^6	2.3558×10^6	2.3671×10^6	2.0984×10^6	2.0681×10^6	2.0985×10^6	2.0676×10^6	2.0669×10^6

of FACTS devices. Principle of grey wolf optimization algorithm is discussed in Ref. [25]. Location of SVC and TCSC's are determined by fuzzy membership function and application of GA for reactive power planning is discussed in Ref. [26]. In Ref. [27], Hybrid UPFC model is designed where series side of UPFC is represented by ideal voltage source and shunt side as current source model. Reactive power planning problem under different loading condition is handled using FACTS devices in Ref. [28]. Equivalent impedance model obtained from sensitivity analysis to optimize the allocation of FACTS devices is introduced in Ref. [29]. Different hybrid forms of PSO algorithm for proper coordination of reactive power planning using FACTS devices is presented in Ref. [30]. In Ref. [31], the Gravitational search algorithm (GSA) based optimization algorithm is applied for the optimal allocation of FACTS devices along with an observation of effect of FACTS devices on the power transfer capacity of the individual generator of the test system while varying the active and reactive loading. Principle of Whale optimization algorithm is discussed in Ref. [32]. Differential evolution algorithm is a population based technique - is presented in Ref. [33] and its applicability in the different solution domain is described in Refs. [34–36]. The concept of quasi-opposition based learning introduced by Tizhoosh is applied successfully in differential evolution algorithm and described in Ref. [38].

In some of the above mentioned research work FACTS devices are used for the minimization of operating cost and active power loss where detection for the placement location of FACTS devices is an important aspect. Here, voltage collapse proximity indication method and power flow analysis method is used for the determination of weak nodes of the connected power network. The weak buses provide significant information regarding voltage collapse in severe contingency cases and candidate location for the optimal placement of FACTS devices.

For the assessment of reactive power planning with FACTS devices, the pool and hybrid model needs an optimization algorithm with following features:

- ➢ Lesser number of control parameters.
- ➢ Faster convergence characteristics.
- ➢ Lesser computational time.
- ➢ Same parameter settings for different problems.
- ➢ Must give same accurate result consistently even after several trials.
- ➢ Its ability not to be trapped in local minima thus exploring wider search area.
- ➢ Algorithm must be simple and straightforward to implement.

From the previous references, it is observed that various evolutionary algorithms applied for reactive power planning lacks some of the above features.

In the present work, the standard IEEE 30 and IEEE 57 bus test system has been tested for the optimal placement of FACTS devices like SVC and TCSC. Initially the placement positions of TCSC and SVC has been determined by the power flow analysis and voltage collapse proximity indication technique and then WOA and other optimization algorithm is applied for the optimal setting of TCSC and SVC along with other control variables.

2. Objective and problem formulation

2.1. Objective of the work

The main objective of this work is to propose the use of optimal placement of series and shunt types of FACTS devices at suitable locations in the connected power network for the reduction of active power loss and overall operational cost of the system. The main purpose of this article is to minimize active power loss and total operating cost of the system by installing TCSC and SVC at the optimal locations in the transmission system. Installation costs of FACTS devices and the cost due to energy loss have been combined to form the total operating cost.

Table 4
Comparison of active power loss and operating cost in IEEE 30 bus test system.

Active power loss without planning in p.u (A)	Operating cost due to energy loss without planning in $ (B)	Methods using FACTS	Active power loss after RPP in p.u(A_1)	Total operating cost after RPP in $ (B_1)	Decrease in active power loss in p.u (A_1-A)	Decrease in operating cost in $ (B_1-B)
0.0711	3737016	SGA [24]	0.0406	2.1786×10^6	0.0305	1.55841×10^6
		Fuzzy-GA [24]	0.0399	2.1297×10^6	0.0312	1.60731×10^6
		SDE [24]	0.0406	2.1770×10^6	0.0305	1.560016×10^6
		Fuzzy-DE [24]	0.0403	2.1171×10^6	0.0308	1.619916×10^6
		SPSO [30]	0.0435	2.3622×10^6	0.0276	1.374816×10^6
		APSO [30]	0.0434	2.3558×10^6	0.0277	1.381216×10^6
		EPSO [30]	0.0438	2.3671×10^6	0.0273	1.369916×10^6
		DE [Studied]	0.0393	2.0984×10^6	0.0318	1.638616×10^6
		QODE [Studied]	0.0393	2.0681×10^6	0.0318	1.668916×10^6
		GWO [Studied]	0.0393	2.0985×10^6	0.0318	1.638516×10^6
		QOGWO [Studied]	0.0393	2.0676×10^6	0.0318	1.669416×10^6
		Proposed WOA	0.0393	2.0669×10^6	0.0318	1.67026×10^6

2.2. Proposed methodology

The main purpose of the work is to minimize the overall system operating cost and active power loss by optimal co-ordination of FACTS devices with the existing reactive Var sources. As Var generations of the generators and controlling transformer tap settings within their defined limits do not contribute any cost to the operating cost of the system; the same approach has been proposed in this work for the setting of transformer tap positions and reactive generations of generators as such these have been included as controlling parameters along with the TCSC and

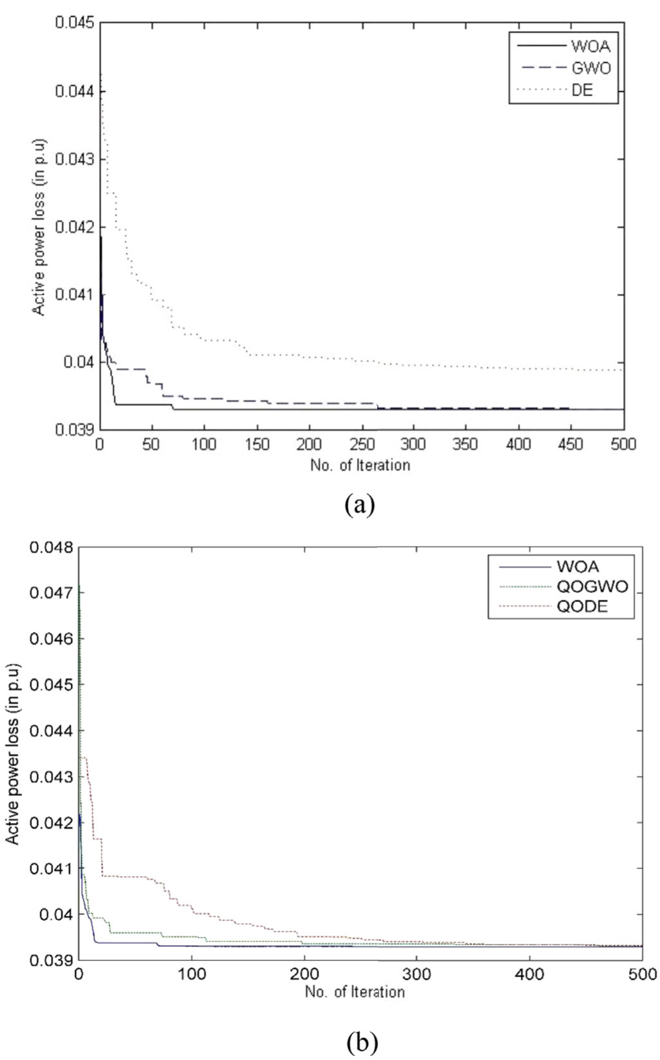

Fig. 4. (a): Variation of active power loss with FACTS device in IEEE 30 bus system (b): Variation of active power loss with FACTS device in IEEE 30 bus system.

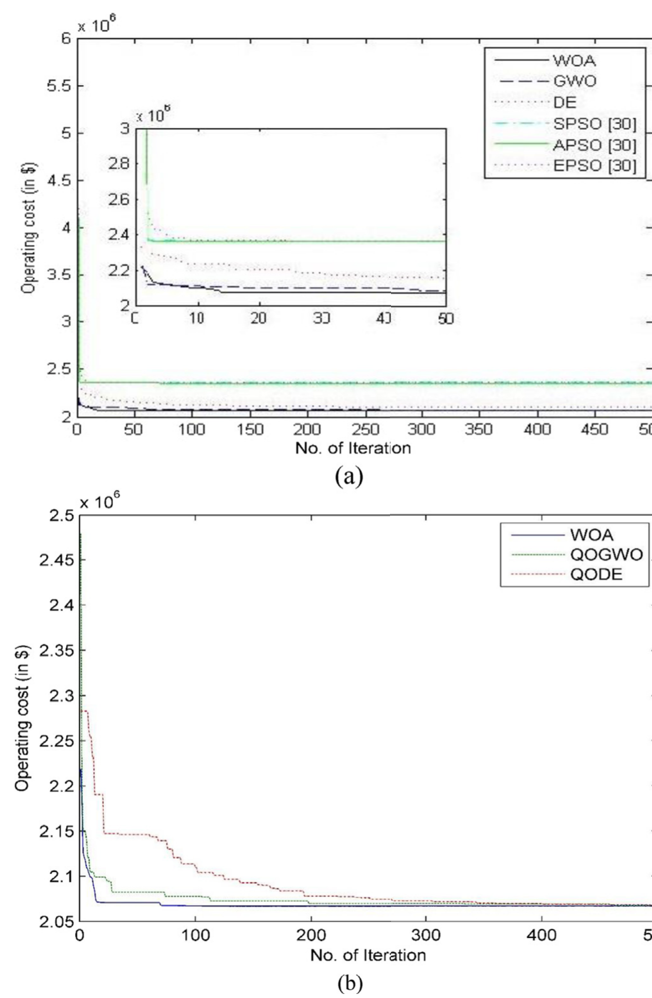

Fig. 5. (a): Variation of operating cost with FACTS device in IEEE 30 bus system (b): Variation of operating cost with FACTS device in IEEE 30 bus system.

Table 5
Best control variable setting by different techniques for IEEE 57 bus system.

Control variables	SPSO [30]	APSO [30]	EPSO [30]	DE [Studied]	QODE [Studied]	GWO [Studied]
Q_g (2)	0.5	0.1213	0.5	0.1504	−0.0011	−0.1258
Q_g (3)	0.6	0.5754	0.6	0.2954	0.0348	0.1785
Q_g (6)	0.25	0.25	0.25	0.2239	0.1377	0.1926
Q_g (8)	0.2	0.2	0.2	1.8451	0.1816	−0.1030
Q_g (9)	0.09	0.09	0.09	−0.0129	0.0364	0.0049
Q_g (12)	0.0	0.0	0.0	1.3528	1.2359	0.0026
T (19)	0.9	0.9	1.1	0.92	0.9030	0.9145
T (20)	0.9	0.9152	0.9	0.9109	0.9135	0.9041
T (31)	1.0128	1.0892	1.1	1.0080	1.0203	1.0385
T(35)	0.9	0.9	1.1	0.9893	1.0161	0.9197
T(36)	0.9	0.9474	0.9	0.9391	0.9531	0.9263
T(37)	1.0203	1.0281	1.0109	1.0498	1.0090	1.0336
T(41)	0.9	0.9021	0.9	0.9019	0.9037	0.9
T(46)	0.9	0.9	1.1	0.9152	0.9871	0.9058
T(54)	0.9	0.9558	0.9	0.9281	0.9481	0.9109
T(58)	0.9	0.9	0.9	0.9003	0.9008	0.9002
T(59)	0.9	0.9	0.9	1.0483	1.0496	1.05
T(65)	0.9	0.9456	0.9	0.9095	0.9004	0.9
T(66)	0.9	0.9	0.9	0.9012	0.9008	0.9
T(71)	0.9	0.9274	1.1	0.9156	0.9123	0.9051
T(73)	1.1	1.1	1.1	1.0446	1.0394	1.0371
T(76)	0.9	1.0357	0.9	0.9673	1.0488	0.9905
T(80)	0.9	0.9	0.9	0.9044	0.9245	0.9024
TCSC (1)	0.0331(37)	0.0331(37)	0.0331(37)	0.0888(37)	0.0941(37)	0.0242(37)
TCSC (2)	0.0304(13)	0.0304(13)	0.0334(13)	0.0710(13)	0.940(13)	0.0115(13)
TCSC (3)	0.0163(61)	0.0163(61)	0.0163(61)	0.1098(61)	0.11(61)	0.11(61)
TCSC (4)	0.0410(57)	0.0410(57)	0.0410(57)	0.1073(57)	0.1090(57)	0.11(57)
SVC (1)	0.0(49)	0.0(49)	0.0(49)	0.1982(23)	0.1794(23)	0.2(23)
SVC (2)	0.0(25)	0.0(25)	0.0(25)	0.1939(48)	0.1995(48)	0.2(48)
SVC (3)	0.3945(28)	0.5099(28)	0.4397(28)	0.1981(38)	0.1954(38)	0.1999(38)
SVC (4)	–	–	–	0.1792(39)	0.1930(39)	0.1986(39)
P_{Loss}	0.2210	0.2231	0.2275	**0.2097**	**0.2097**	**0.2097**
C_{Total}	1.168×10^7	1.179×10^7	1.203×10^7	1.1021×10^7	1.1024×10^7	1.102×10^7

Control variables	GWO [Studied]	QOGWO [Studied]	Proposed WOA
Q_g (2)	−0.1258	−0.0402	0.5
Q_g (3)	0.1785	0.5682	0.1257
Q_g (6)	0.1926	0.0731	−0.08
Q_g (8)	−0.1030	1.0292	0.8128
Q_g (9)	0.0049	−0.0014	0.0295
Q_g (12)	0.0026	1.1004	1.5500
T (19)	0.9145	0.9068	0.9
T (20)	0.9041	0.9026	0.9
T (31)	1.0385	0.9840	1.0240
T(35)	0.9197	0.9066	0.9139
T(36)	0.9263	0.9069	0.9
T(37)	1.0336	1.05	1.05
T(41)	0.9	0.9	0.9
T(46)	0.9058	0.9012	0.9
T(54)	0.9109	0.9519	0.9
T(58)	0.9002	0.9	0.9
T(59)	1.05	1.05	1.05
T(65)	0.9	0.9	0.9
T(66)	0.9	0.9	0.9
T(71)	0.9051	0.9	0.9
T(73)	1.0371	1.05	1.05
T(76)	0.9905	1.05	0.9
T(80)	0.9024	0.9068	0.9
TCSC (1)	0.0242(37)	0.0391(37)	0.1100(37)
TCSC (2)	0.0115(13)	0.0411(13)	0.0837(13)
TCSC (3)	0.11(61)	0.11(61)	0.1100(61)
TCSC (4)	0.11(57)	0.11(57)	0.1100(57)
SVC (1)	0.2(23)	0.1949(23)	0.2(23)
SVC (2)	0.2(48)	0.20(48)	0.2(48)
SVC (3)	0.1999(38)	0.20(38)	0.2(38)
SVC (4)	0.1986(39)	0.1991(39)	0.2(39)
P_{Loss}	**0.2097**	**0.2072**	**0.2050**
C_{Total}	1.102×10^7	1.0893×10^7	1.0775×10^7

SVC. The locations of TCSC has been determined by the power flow analysis and locations of SVC by voltage collapse proximity indication (VCPI) method. Different optimization algorithms including WOA have been used to optimize not only the size of the FACTS devices but also the setting of the transformer tap setting arrangements and reactive power generations of the generators. As the settings of transformer tap positions and reactive generations of the generators within the specified limit are independent on the system cost, only the cost of the TCSC and SVC have

Table 6
Comparison of active power loss and operating cost in IEEE 57 bus test system.

Active power loss without planning in p.u (A)	Operating cost due to energy loss without planning in $ (B)	Methods using FACTS	Active power loss after RPP in p.u (A_1)	Total operating cost after RPP in $ (B_1)	Decrease in active power loss in p.u (A-A_1)	Decrease in operating cost in $ (B-B_1)
0.2799	1.471×10^7	SPSO [30]	0.2210	1.168×10^7	0.0589	3.03×10^6
		APSO [30]	0.2231	1.179×10^7	0.0568	2.92×10^6
		EPSO [30]	0.2275	1.203×10^7	0.0524	2.68×10^6
		DE [Studied]	0.2097	1.1021×10^7	0.0702	3.68×10^6
		QODE [Studied]	0.2097	1.1024×10^7	0.0702	3.68×10^6
		GWO [Studied]	0.2097	1.102×10^7	0.0702	3.69×10^6
		QOGWO [Studied]	0.2072	1.0893×10^7	0.0727	3.62×10^6
		Proposed WOA	0.2050	1.0775×10^7	0.0749	3.93×10^6

been considered. The objective function is to minimize the overall operating cost which has mainly two parts. One is the cost due to energy loss attributed by active power loss of the system and the other is the cost of the FACTS devices. The description of objective function and various constraints are explained below:

(i) Minimization of active power loss

$$\text{Minimize } F_1(x_1, x_2) = P_{Loss} = \sum_{k=1}^{N_L} \left[G_k\left(V_s^2 + V_r^2 - 2V_sV_rCos\delta_{sr}\right)\right] \tag{1}$$

Here x_1 and x_2 may be expressed by the following equations:

$$x_1 = \left[Q_{G1}, \cdots, Q_{GN_{PV}}, V_{L1}, \cdots, V_{LN_{PQ}}, S_{L1}, \cdots, S_{LN_L}\right] \tag{2}$$

$$x_2 = \left[T_1, \cdots, T_{N_T}, V_{G1}, \cdots, V_{GN_{PV}}, Q_{C_1}, \cdots, Q_{CN_C}, SVC_1, \cdots, SVC_{NSVC}, TCSC_1, \cdots, TCSC_{NTCSC}\right] \tag{3}$$

where $F_1(x_1, x_2)$ is the function of minimization of active power loss. G_k is the conductance of branch k. V_s and V_r are the magnitude of voltages at sending bus and receiving bus respectively. δ_{sr} is the phase angle difference between sth and rth bus.

x_1 is the vector of dependent variables consisting of reactive power generation of generator $(Q_{G1}, \cdots, Q_{GN_{PV}})$, load voltages $(V_{L1}, \cdots, _{LN_{PQ}})$, and transmission line loadings $(S_{L1}, \cdots, S_{LN_L})$. x_2 is vector of control variables consisting of transformer tap settings $(T_1, \cdots, T_{N_T})$, magnitude of generator voltages $(V_{G1}, \cdots, V_{GN_{PV}})$, reactive power injections $(Q_{C1}, \cdots, Q_{CN_C})$, static var compensator $(SVC_1, \cdots, SVC_{N_{SVC}})$, and $(TCSC_1, \cdots, TCSC_{N_{TCSC}})$. Limits of TCSC, SVC and transformer tap positions is given in Table 1.

The equality and inequality constraints must be satisfied while searching optimal solution. The equality constraints can be defined as:

$$P_{Gs} - P_{Ds} - V_s \sum_{N=1}^{N_B} V_r[G_{sr}Cos(\delta_{sr}) + B_{sr}Sin(\delta_{sr})] = 0 \tag{4}$$

$$Q_{Gs} - Q_{Ds} - V_s \sum_{N=1}^{N_B} V_r[G_{sr}Sin(\delta_{sr}) - B_{sr}Cos(\delta_{sr})] = 0 \tag{5}$$

The inequality constraints can be defined as:

$$\left.\begin{array}{l} V_i^{\min} \le V \le V_i^{\max}, i \in N_B \\ T_i^{\min} \le T \le T_i^{\max}, i \in N_T \\ Q_{G_i}^{\min} \le Q_{G_i} \le Q_{G_i}^{\max}, i \in N_{PV} \\ Q_{C_i}^{\min} \le Q_{C_i} \le Q_{C_i}^{\max}, i \in N_C \\ SVC_i^{\min} \le SVC_i \le SVC_i^{\max}, i \in N_{SVC} \\ TCSC_i^{\min} \le TCSC_i \le TCSC_i^{\max}, i \in N_{TCSC} \end{array}\right\} \tag{6}$$

where,

V_s = Transfer conductance between bus “s” and “r”.
G_{sr}, B_{sr} = Transfer conductance & susceptance between bus “s” and “r”.
P_{Gs}, P_{Ds} = Active power injected & demanded at bus “s”.
Q_{Gs}, Q_{Ds} = Reactive power injected & demanded at bus “s”.
δ_{sr} = Voltage angle difference between bus “s” and “r”.
N_{PV} = Number of generator buses.
N_{PQ} = Number of load buses.
N_L = Number of transmission line.
N_B = Number of buses.
N_T = Number of transformer tap settings.
N_C = Number of shunt capacitors.
N_{SVC} = Number of SVC.
N_{TCSC} = Number of TCSC.

(ii) Minimization of voltage deviation

For secured operation of the power systems, maintaining a steady voltage profile is one of the challenging task. The minimization of voltage deviation can be expressed as:

Table 7
Comparative analysis of operating cost after 30 trials by different algorithms.

Algorithm	Total operating cost (in $)		
	Best	Worst	Mean
IEEE 30 BUS SYSTEM			
DE	2.0984×10^6	2.0992×10^6	2.0987×10^6
QODE	2.0681×10^6	2.0889×10^6	2.0767×10^6
GWO	2.0985×10^6	2.1062×10^6	2.0998×10^6
QOGWO	2.0676×10^6	2.0849×10^6	2.0715×10^6
WOA	2.0669×10^6	2.0805×10^6	2.0690×10^6
IEEE 57 BUS SYSTEM			
DE	1.1021×10^7	1.1073×10^7	1.1029×10^7
QODE	1.1024×10^7	1.1068×10^7	1.1030×10^7
GWO	1.1020×10^7	1.1240×10^7	1.1056×10^7
QOGWO	1.0893×10^7	1.0989×10^7	1.0899×10^7
WOA	1.0775×10^7	1.0984×10^7	1.0781×10^7

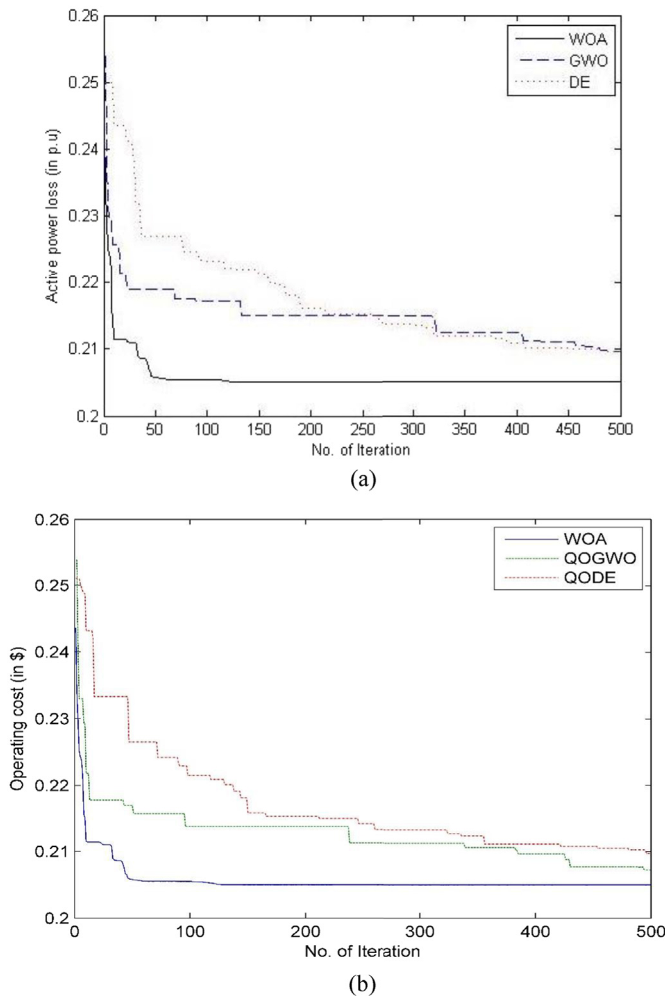

Fig. 6. (a): Variation of active power loss with FACTS devices in IEEE 57 bus (b): Variation of active power loss with FACTS devices in IEEE 57 bus.

$$VD = \sum_{i=1}^{N_b} |V_b - 1.0| \tag{7}$$

where N_b is total number of buses and V_b is bus voltage.

(iii) Minimization of operating cost

It consists of two parts, first part is cost due to energy loss and second part is cost due to investment cost of FACTS devices. So the objective function requires not only to reduce the cost of energy loss by minimizing the active power loss with TCSC and SVC but also to minimize the investment costs of TCSC and SVC. Hence the objective function is minimization of total operating cost and can be expressed as:

$$Cost_{Total} = C_{Energy} + C_{FACTS} \tag{8}$$

where,

$C_{Energy} = P_{Loss} \times 0.06 \times 100000 \times 365 \times 24.$
Cost due to energy loss = 0.06 $/KWhr
Fixed installed cost of shunt capacitor = 1000 $
Number days in a year = 365
Number of hours in a day = 24

The above cost data related to C_{Energy} is taken from Refs. [1,2]. Based on Siemens AG database [14,15], the cost of FACTS devices (C_{FACTS}) may be formulated as:

$$C_{FACTS} = \alpha s^2 + \beta s + \gamma \tag{9}$$

where, S is the operating range of the FACTS devices in MVAR. α, β and γ are the cost coefficients of the FACTS devices and they depend on the types of the FACTS devices. Table 2 shows cost coefficient values of different FACTS devices.

3. Steady state models of FACTS devices

The FACTS controller provides a new concept in controlling line power flow, minimizing losses, reduction of faults and maintaining healthy voltages at desired level. This can be achieved by controlling one or more of the interrelated system parameters including current, voltage, phase angle, series impedance and shunt impedance with the insertion of FACTS controllers in a power system network. There are many types of FACTS devices out of which TCSC is a series and SVC is a shunt kind of FACTS devices. Modelling of TCSC and SVC are discussed below:

3.1. Modelling of TCSC

Transmission lines are represented by lumped π equivalent parame-

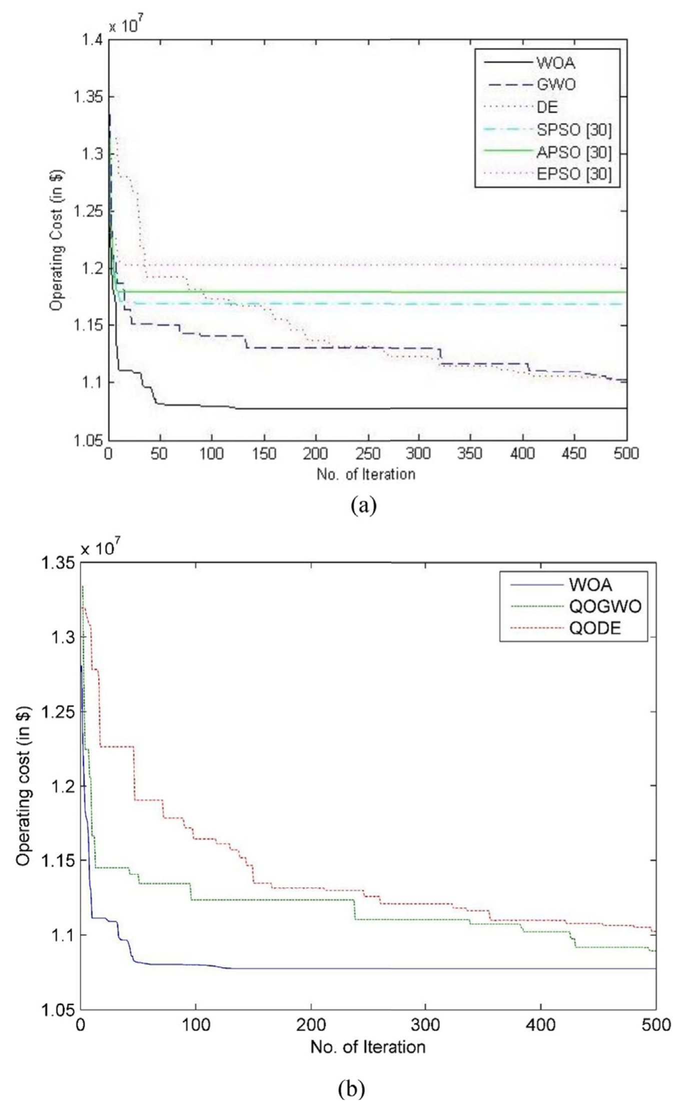

Fig. 7. (a): Variation of operating cost with FACTS devices in IEEE 57 bus (b): Variation of operating cost with FACTS devices in IEEE 57 bus.

Table 8
ANOVA test for IEEE 30 and IEEE 57 bus test system.

Source of variation	Sum of square	degrees of freedom	Mean square	F-ratio	5% F-limit [37]
IEEE 30 BUS SYSTEM					
Between techniques	0.0257	(5–1) = 4	6.425×10^{-3}	13.7286	F(4,25) = 2.7587
Within techniques	0.0117	(30–5) = 25	4.68×10^{-4}		
IEEE 57 BUS SYSTEM					
Between techniques	0.0146	(5–1) = 4	3.65×10^{-3}	21.7261	F(4,25) = 2.7587
Within techniques	0.0042	(30–5) = 25	1.68×10^{-4}		

ters. The series compensator TCSC is a static capacitor/reactor with impedance jX_c. Hence it can vary the impedance to below or above the line natural impedance. The static model of the network with TCSC connected between branches (sth to rth bus) is presented in Fig. 1. The active and reactive power flow equations of the branch (from sth to rth bus) after installing TCSC are given by Eqs. (10) and (11) respectively.

$$P_{sr} = V_s^2 G_{sr} - V_s V_r G_{sr} Cos(\delta_s - \delta_r) - V_s V_r B_{sr} Sin(\delta_s - \delta_r) \tag{10}$$

$$Q_{sr} = -V_s^2 B_{sr} - V_s V_r G_{sr} Sin(\delta_s - \delta_r) + V_s V_r B_{sr} Cos(\delta_s - \delta_r) \tag{11}$$

Similarly, the real and reactive power flows from rth bus to sth bus may be expressed by Eqs (12) and (13) respectively.

$$P_{rs} = V_r^2 G_{rs} - V_r V_s G_{rs} Cos(\delta_r - \delta_s) - V_r V_s B_{rs} Sin(\delta_r - \delta_s) \tag{12}$$

$$Q_{rs} = -V_r^2 B_{rs} - V_r V_s G_{rs} Sin(\delta_r - \delta_s) + V_r V_s B_{rs} Cos(\delta_r - \delta_s) \tag{13}$$

where, Conductance of transmission line $G_{sr} = \frac{R}{R^2 + (X - X_{TCSC})^2}$

And, susceptance of transmission line $B_{sr} = \frac{-X - X_{TCSC}}{R^2 + (X - X_{TCSC})^2}$

Ybus matrix is modified with the new value of the line reactance considering the presence of TCSC in the line in Ref. [24] following manner:

for j = 1:*ntcsc*
Linedata(*TCSC_pop*(*j*)) = *Linedata*(*TCSC_pop*(*j*))-*sqrt*(-*1*)**tcsc_value*;
end

where, ntcsc = Number of TCSC elements

tcsc_value = Value of TCSC in MVAR.

After adding TCSC on the line between sth and rth bus of connected power network, the new admittance (Y_{bus}^{TCSC}) matrix can be updated as:

$$Y_{bus}^{TCSC} = Y_{bus} + \begin{array}{cc} \begin{bmatrix} 0 & 0 & 0 & .... & 0 & 0 \\ 0 & \Delta y_{sr} & 0 & .... & -\Delta y_{sr} & 0 \\ 0 & 0 & 0 & .... & 0 & 0 \\ .... & .... & .... & .... & .... & 0 \\ 0 & -\Delta y_{sr} & 0 & .... & \Delta y_{sr} & 0 \\ 0 & 0 & 0 & .... & 0 & 0 \end{bmatrix} & \begin{matrix} \\ row - s \\ \\ \\ row - r \\ \\ \end{matrix} \end{array} \tag{14}$$

3.2. Modelling of static VAR compensator

SVC is a solid-state controller that absorbs or injects reactive power to the buses where it is connected along the transmission line by switching various combination of capacitors and inductors in parallel with the lines. It uses thyristor valves to rapidly add or remove shunt connected reactors and capacitors. Fig. 2 shows equivalent circuit of SVC that can be modelled as shunt-connected variable susceptance B_{SVC} at bus-n.

The reactive power injected into the bus due to SVC can be expressed as:

$$Q_{SVC} = B_{SVC} V^2 \tag{15}$$

where V is the magnitude of voltage of the bus at which SVC is connected.

Ybus matrix is modified with the values considering the presence of SVC in that bus in Ref. [24] by the following manner:

for j = 1:*nsvc*
Shunt(*svc_pop*(*j*)) = *sqrt*(-1)**svc_value*;
end

where, nsvc = Number of SVC elements

svc_value = Value of SVC.

After adding SVC at bus-I of connected power network, the new admittance matrix (Y_{bus}^{SVC}) is formed as:

$$Y_{bus}^{SVC} = Y_{bus} + \begin{array}{cc} \begin{bmatrix} 0 & 0 & 0 & .... & 0 & 0 \\ 0 & Y_{shunt} & 0 & .... & 0 & 0 \\ 0 & 0 & 0 & .... & 0 & 0 \\ .... & .... & .... & .... & .... & 0 \\ 0 & 0 & 0 & .... & 0 & 0 \\ 0 & 0 & 0 & .... & 0 & 0 \end{bmatrix} & \begin{matrix} \\ row - i \\ \\ \\ row - j \\ \\ \end{matrix} \end{array} \tag{16}$$

4. Detection of weak buses for the placement of series and shunt FACTS devices

The main purpose of detection of weak buses is to find the optimal locations of FACTS devices because FACTS devices can influence the natural electrical characteristics of transmission lines; increase the steady-state transmittable power; and controls the voltage profile along the lines. By providing adequate reactive power support at the appropriate locations, not only leads to a reduction in power loss and improvement in the voltage profile; but also solves voltage instability problem. These methods are based on concept of power flow through a single line.

4.1. Power flow analysis

In the power flow analysis, reactive power flowing in all the branches are calculated and the branches carrying those high reactive power are identified. The end point of that branch or the bus where the branch meets is treated as weak buses and at these weak buses TCSC's are placed.

The location of TCSC's are determined by using following steps:

Step 1: Read linedata and busdata of test system.
Step 2: Create Y-bus matrix.
Step 3: Calculate Voltage and angle using Newton Raphson method.
Step 4: Calculate active and reactive power in each branch using loadflow method.
Step 5: Select the branch with maximum reactive power.
Step 6: Check if selected branch is connected to generator or slack bus. If yes, then go To step 5 otherwise move to next step.
Step 7: End point of branch or bus is selected for the location of TCSC.

4.2. Voltage collapse proximity indication

Voltage collapse proximity indication [7,8] method is based on the maximum power transfer theory of a line. Let the load impedance $Z_L \angle \phi$

be fed by a constant voltage source V_s of internal impedance $Z_s\angle\theta$. The maximum power can be transferred to the load only when the ratio of Z_L/Z_s is equal to 1.0. This ratio is used as voltage collapse predictor for that bus after generalising the network into a single line.

Consider load impedance to be varied while ϕ remains constant. Due to this assumption not only the accuracy will be maintained; but also will simplify the problem. With increase of demand in load, Z_L decreases and current increases. This leads to voltage drop at receiving end.

$$V_r = Z_L I \tag{17}$$

where $I = \frac{V_s}{\sqrt{[(Z_s Cos\theta + Z_L Cos\phi)^2 + (Z_s Sin\theta + Z_L Sin\phi)^2]}}$

$$V_r = \frac{Z_r}{Z_s}\frac{V_s}{\sqrt{\left[1+\left(\frac{Z_r}{Z_s}\right)^2 + 2\left(\frac{Z_r}{Z_s}\right)Cos(\theta-\phi)\right]}} \tag{18}$$

Active power at receiving end,

$$P_r = V_r I Cos\phi \tag{19}$$

$$P_r = \frac{V_s^2/Z_s}{1+\left(\frac{Z_r}{Z_s}\right)^2 + 2\left(\frac{Z_r}{Z_s}\right)Cos(\theta-\phi)}\frac{Z_r}{Z_s}Cos\phi \tag{20}$$

Similarly, power loss in the line is

$$P_l = \frac{V_s^2/Z_s}{1+\left(\frac{Z_L}{Z_s}\right)^2 + 2\left(\frac{Z_L}{Z_s}\right)Cos(\theta-\phi)}Cos\theta \tag{21}$$

Maximum real power that can be transferred to the receiving end can be obtained using boundary condition $\frac{\partial P_r}{\partial Z_L} = 0$ that leads into $\frac{Z_L}{Z_s} = 1$. Substituting it in Eq. (20),

$$\text{Maximum transferable power } P_{r(\max)} = \frac{V_s^2}{Z_s}\frac{Cos\phi}{4Cos^2\left(\frac{\theta-\phi}{2}\right)} \tag{22}$$

Since VCPI is based on the concept of maximum power transferred through a line. Hence VCPI can be defined as,

$$VCPI = \frac{P_r}{P_{r(\max)}} \tag{23}$$

For voltage stability system, VCPI should have value less than unity. If the value exhibits close to 1.0, it implies that it is approaching its instability point. Buses approaching to instability point are considered as weak buses. These buses are selected for the candidate locations of SVC.

5. Whale optimization algorithm

This algorithm is motivated by Humpback whale for capturing prey and bubble-net hunting strategy and was first proposed by Mirjalini and Lewis [32] in 2016. The key features and methodology of WOA are described in the following subsection.

5.1. Features

Whales are the biggest mammals in the world and are considered as highly intelligent animal with emotion. The most interesting fact of this mammal is that they never sleep because they have to breathe from surface of the oceans. They have twice the number of spindle cells than an adult human and that is the main reason of their smartness. It has been proved that whales can think, learn, judge, communicate and exhibit emotion. One of the biggest baleen whale is Humpback whale (*Megaptera movaeangliae*) and they have a unique hunting method known as bubble-net feeding method.

5.2. Methodology

The whales have a specific encircling prey pattern. They use bubble-net strategy while searching and attacking their prey. The mathematical models of these behaviours are discussed below:

(i) Search for the prey (Exploration phase)

In the exploration phase, the position of a search agent is updated according to a randomly chosen search agent instead of best search agent obtained. This behaviour can be represented as follows:

$$\vec{D} = \left|\vec{C}\cdot\overrightarrow{X_{rand}} - \vec{X}\right| \tag{24}$$

$$\vec{X}(iter+1) = \overrightarrow{X_{rand}} - \vec{A}\cdot\vec{D} \tag{25}$$

where, $\overrightarrow{X_{rand}}$ = Random position vector of whale chosen from current population.

(ii) Encircling prey

The whales have the ability to recognize the location of prey and encircle them. This encircling behaviour is represented by the following equations:

$$\vec{D} = \left|\vec{C}\times\overrightarrow{X_P}(iter) - \vec{X}(iter)\right| \tag{26}$$

$$\vec{X}(iter+1) = \overrightarrow{X_P}(iter) - \vec{A}\times\vec{D} \tag{27}$$

where iter indicates current iteration, A and C are coefficient vectors.

X_P specifies position vector of the prey and X specifies position vector of Whale.

The vector A and C are calculated as follows:

$$\vec{A} = 2\vec{a}\times\vec{r_1} - \vec{a} \tag{28}$$

$$\vec{C} = 2\times\vec{r_2} \tag{29}$$

where component of $\vec{a}$ are linearly decreased from 2 to 0 over the course of iteration (in both exploration and exploitation phases) and r_1 and r_2 are random vectors in range [0,1].

(iii) Bubble-net attacking method (Exploitation phase)

There are two approaches for bubble-net behaviour of the whales which are described below:

- Shrinking encircling mechanism

This ability is achieved by decreasing the value of ‘a’ in Eq. (28). Hence fluctuation range of $\vec{A}$ is also decreased by $\vec{a}$, $\vec{A}$. is the random value in the interval [-a,a] where a is decreased from 2 to 0 over the course of iterations.

- Spiral updating positions

This behaviour is achieved by calculating the distance between the whale and the location of its prey. A spiral equation has been created to mimic the helix-shaped movement of humpback whales which is as follows:

$$\vec{X}(iter+1) = \vec{D}\cdot e^{bl}\cdot Cos\left(2\prod l\right) + \vec{X}(iter) \tag{30}$$

where, $\vec{D} = \left|\vec{X_P}(iter) - \vec{X}(iter)\right|$ signifies the distance between ith whale to its prey (best solution).where, b = Constant for defining the shape of logarithmic spiral.

l = Random number in [-1, 1].
= Element-by-element multiplication.

In fact, the whales swim around its prey within a shrinking circular as well as a spiral-shaped path simultaneously. Due to this behaviour, we assume that there is a probability of 50% in choosing either the shrinking encircling mechanism or the spiral model to update the position of whales during optimization. Mathematical model for this behaviour is as follows:

$$\vec{X}(iter+1) = \begin{cases} \vec{X_P}(iter) - \vec{A}\cdot\vec{D} & if \quad p < 0.5 \\ \vec{D}\cdot e^{bl}\cdot Cos\left(2\prod l\right) + \vec{X_P}(iter) & if \quad p \geq 0.5 \end{cases} \tag{31}$$

where, p = Random number in [0,1].

At the starting of WOA, initial search space is created randomly where each search agent represents position of a whale. After every iteration, search agents update their positions with respect to either a randomly selected search agent or the best solution obtained till then. The parameter of 'a' is decreased in order to provide exploration and exploitation. For updating the position of the search agents, $|\vec{A}| > 1$ is selected whenever random search agent is selected; while $|\vec{A}| < 1$ is selected whenever the best solution is selected. WOA is able to switch between either a spiral or circular movement depending on the value of 'p'. Finally WOA comes to end by satisfying all the termination conditions which was given initially. Algorithmic procedure for the complete execution of the proposed work using WOA is given below:

Step 1. Define line data and bus data of the test system.
Step 2. Determine the locations for the placement of TCSC by power flow analysis.
Step 3. Determine the locations for the placement of SVC by voltage collapse proximity index (VCPI) method using the Eq. (23).
Step 4. Set the number of search agents and the maximum number of iterations.
Step 5. Define the boundary limits of control variables such as reactive generation of generators, transformer tap positions, TCSC and SVC.
Step 6. Initialize the population matrix for 'n' number of search agents.

$$\begin{bmatrix} Q_{g11} \ldots Q_{g1n}\, T_{11} \ldots T_{1n}\, SVC_{11} \ldots SVC_{1n}\, TCSC_{11} \ldots TCSC_{1n} \\ \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \\ Q_{gn1} \ldots Q_{gnn}\, T_{n1} \ldots T_{nn}\, SVC_{n1} \ldots SVC_{nn}\, TCSC_{n1} \ldots TCSC_{nn} \end{bmatrix}$$

Step 7. If the inequality constraint limits for the position of each search agent of the whale population matrix are satisfied, then go to the next step; otherwise again generate the initial population matrix and repeat the step 6, until all the inequality constraints of Eq. (6) are satisfied.
Step 8. Initialize *a, A* and *C* using the Eqs. (28) and (29).
Step 9. Update line data and bus data of the test system with new population string.
Step 10. Y-bus is modified and updated by using Eqs. (14) and (16).
Step 11. Newton Raphson program is executed and fitness function is evaluated using Eqs. (1) and (8) while satisfying equality and inequality constraints of Eqs. (4) and (5).
Step 12. Repeat Step-(9) to step-(11) for all the search agents. Now compare the fitness solution value with all the search agent solution. Store the minimum value of fitness function and the corresponding position of search agents.
Step 13. Set the iteration number equal to 1.
Step 14. The new prey is searched (exploration phase) by using Eq. (24).
Step 15. After new prey is searched then encircling of prey is done using Eq. (26).
Step 16. Update the position of search agents for attacking the prey with bubble-net strategy using Eq. (28).
Step 17. Update the value of *a, A* and *C* using Eqs. (28) and (29) with new position of search agent.
Step 18. Check all the equality and the inequality constraints mentioned in Eqs. (4)–(6) with the new position of each search agent.
Step 19. Repeat the step-(9) to step-(12).
Step 20. Increase the iteration number by 1, i.e., $iter = iter + 1$.
Step 21. If the maximum number of iteration has reached then terminate the iterative process and store the fitness value as the best solution of optimization problem otherwise repeat the steps-(14) to steps-(20).

6. Grey wolf optimization

Grey wolf (*Canis lupus*) optimization algorithm was first given by Ref. [25] in 2014 as a new swarm intelligence technique. The key features and methodology of GWO are described in the following subsection.

6.1. Features

GWO algorithm is based on the leadership and hunting behaviour of Grey wolf. They prefer to live in a pack. They live in an average sized group of 5–12 members under a strict dominant hierarchy. The leader of the group is Alpha. Alpha is responsible for making decisions about hunting, sleeping place, time to wake up, etc. The Alpha wolf is also known as dominant wolf because his/her orders must be followed by the pack. Alpha may not be the strongest member but is the best in terms of managing the pack. Alpha is followed by Beta. It is the best candidate to become the Alpha if Alpha passes away or becomes old. It acts as an adviser to Alpha; discipliner of the pack and gives feedback to the Alpha. The lowest ranking grey wolf is Omega. It plays the role of a scapegoat. If a wolf is not Alpha, Beta or Omega then it is known as Delta. They dominate Omega. Scouts, sentinels, elders, hunters and caretakers belong to this category.

6.2. Methodology

In GWO algorithm, the fittest solution is known as Alpha (α), the second best solution is Beta (β) and the third best solution is Delta (δ). Rest of the solution is assumed to be Omega (ω). The ω wolves just follow these three wolves. The mathematical model of encircling prey, hunting and attacking the prey are discussed below:

(i) Encircling prey

Grey wolves tend to encircle prey. A mathematical depiction of their encircling behaviour can be represented as the below equation:

$$\vec{D} = \left|\vec{C}\cdot\vec{X_P}(iter) - \vec{X}(iter)\right| \tag{32}$$

$$\vec{X}(iter+1) = \vec{X_P}(iter) - \vec{A}\cdot\vec{D} \tag{33}$$

where, $\vec{X}$ and $\vec{X_P}$ are the position vectors of grey wolf and prey respectively and iter is the present iteration.

The $\vec{A}$ and $\vec{C}$ are coefficient vectors and they are calculated as per the below equations:

$$\overrightarrow{A} = 2\overrightarrow{a}\cdot\overrightarrow{r_1} - \overrightarrow{a} \tag{34}$$

$$\overrightarrow{C} = 2\cdot\overrightarrow{r_2} \tag{35}$$

where, $\overrightarrow{r_1}$ and $\overrightarrow{r_2}$ are random vectors between 0 and 1. The components of $\overrightarrow{a}$ are linearly decreased from 2 to 0 over the course of iterations. Grey wolves update their position around the prey in any random location by using Eqs. (32) and (33).

(ii) Hunting

In order to mathematically simulate the hunting behaviour of grey wolves, we suppose that the alpha (best candidate solution), beta and delta have better knowledge of the location of the prey. We choose the first three best solutions obtained and indicate the other search agents to update their positions accordingly and so on to ultimately find the best solution.

$$\left.\begin{aligned}\overrightarrow{D_\alpha} &= \left|\overrightarrow{C_1}\cdot\overrightarrow{X_\alpha} - \overrightarrow{X}\right|\\ \overrightarrow{D_\beta} &= \left|\overrightarrow{C_2}\cdot\overrightarrow{X_\beta} - \overrightarrow{X}\right|\\ \overrightarrow{D_\delta} &= \left|\overrightarrow{C_3}\cdot\overrightarrow{X_\delta} - \overrightarrow{X}\right|\end{aligned}\right\} \tag{36}$$

Following equations can be used to define the position of the Grey wolf during hunting.

$$\left.\begin{aligned}\overrightarrow{X_1} &= \overrightarrow{A_1}\cdot\left(\overrightarrow{D_\alpha}\right)\\ \overrightarrow{X_2} &= \overrightarrow{A_2}\cdot\left(\overrightarrow{D_\beta}\right)\\ \overrightarrow{X_3} &= \overrightarrow{A_3}\cdot\left(\overrightarrow{D_\delta}\right)\end{aligned}\right\} \tag{37}$$

The position of the Grey wolf is updated in the manner as shown in Eq. (38)

$$\overrightarrow{X}(iter+1) = \frac{\overrightarrow{X_1} + \overrightarrow{X_2} + \overrightarrow{X_3}}{3} \tag{38}$$

(iii) Attacking the prey

If $\left|\overrightarrow{A}\right| > 1$, then the best candidate solution are diverged from the prey to find a fitter prey; and if $\left|\overrightarrow{A}\right| < 1$, then it forces the wolves to go after the prey. After every iteration α, β and δ wolves updates their positions towards the probable positions of the prey. Grey wolves finish the hunt by attacking the prey when it stops moving. Finally, GWO algorithm comes to an end by satisfying all the conditions. Fig. 3 shows complete execution of the proposed work using GWO.

7. Differential evolution optimization in brief

Differential evolution algorithm is one of the most powerful stochastic real-parameter optimization algorithm and it does not use the gradient of the problem being optimized. This algorithm was first introduced by Storn and Price [33]. The performance of this algorithm depends on three variables – population size, mutation scaling factor and crossover rate. The population is generated by population size real valued and n-dimensional vector whose parameter values are selected at random within the boundaries set by the user. Each vector is also known as chromosome and forms a candidate solution. A parent vector from current generation is known as target vector and mutation vector obtained through differential mutation operation is called as donar vector. A trial vector is formed by recombining the donar with target vector. If the cost of the trial vector is less than that of the target vector, the target vector is replaced by trial vector in the next generation.

8. Quasi-opposition based learning in brief

Quasi-oppositional search technique was first introduced by Tighoosh [38] in order to accelerate the convergence rate of different optimization techniques in the field of computational intelligence. Swarm intelligence based optimization algorithm starts with some initial population and try to converge to the best optimal solution. As the termination conditions are satisfied, the process of searching optimal solution is stopped. This method considers current population as well as its opposite population at the same time in order to get better solution. The mathematical model of quasi-opposite point is discussed below:

(i) Opposite point

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

$$OX_j = X_j^{\max} + X_j^{\min} - X_j^0 \tag{39}$$

$$X_j^{\max} = \left[Q_{g1}^{\max} \;....\; Q_{gj}^{\max}\; T_1^{\max} \;...\; T_j^{\max}\; TCSC_1^{\max} .... \;TCSC_j^{\max}\; SVC_1^{\max} \;...\; SVC_j^{\max}\right]$$

$$X_j^{\min} = \left[Q_{g1}^{\min} \;....\; Q_{gj}^{\min}\; T_1^{\min} \;...\; T_j^{\min}\; TCSC_1^{\min} .... \;TCSC_j^{\min}\; SVC_1^{\min} \;...\; SVC_j^{\min}\right]$$

Therefore opposition matrix may be expressed as

$$OX = \begin{bmatrix} X_{11}^{\max} + X_{11}^{\min} - X_{11}^0 & \dots & X_{1j}^{\max} + X_{1j}^{\min} - X_{1j}^0 \\ \dots & \dots & \dots \\ X_{i1}^{\max} + X_{i1}^{\min} - X_{i1}^0 & \dots & X_{ij}^{\max} + X_{ij}^{\min} - X_{ij}^0 \end{bmatrix} \tag{40}$$

where, i = Number of population

j = Number of variable.

The algorithm for Quasi –opposition point used in QOBL is given below:

Algorithm 1: Pseudo code for the calculation of QO point

$M_j = (X_{\max}^j + X_{\min}^j)/2$
If $(OX_{ij} > M_j)$
  $QOX_{ij} = OX_{ij} + (M_j - OX_{ij}) \times r_1 \cdot (\%\quad r_1 \quad \varepsilon \quad [0,1])$
  else
  $QOX_{ij} = M_j + (OX_{ij} - M_j) \times r_1$
end

And Quasi-opposition matrix is formed accordingly

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

The Quasi-opposite population matrix QOX is used to accelerate its convergence speed. The fittest candidate solution is selected from QOXas initial population. Based on the jumping rate, new population is generated by the procedure of optimization algorithm. Quasi-opposite population is generated by using Algorithm-1.

9. Result and discussion

In order to demonstrate the applicability and validity of the proposed Whale optimization algorithm for reactive power planning with TCSC and SVC devices located at weak buses, standard IEEE 30 and IEEE 57 bus test system has been taken for the testing purpose. To indicate the optimization capability of the proposed Whale optimization algorithm, it has been made to run for 500 iterations in each of the given test system and the results of interest have been **bold face**d in the respective tables.

9.1. Test system 1: IEEE 30 bus system

The standard IEEE 30 bus test system consists of six generating units at buses 1, 2, 5, 8, 11 and 13 interconnected with 41 transmission lines. Their four branches (i.e., 6–9, 6–10, 4–12, 28–27) are equipped with tap changing transformer and the two branches have shunt capacitors at buses 10th and 24th. Bus 1 is selected as slack bus. The total active power demand is 2.834 MW and reactive power demand is 1.262 MVAR at 100 MVA. Initially, active power loss without reactive power planning is 7.11 MW and its operating cost is 3.737016×10^6\$. TCSC's are placed in 25th, 41st, 28th and 5th lines which are detected as the weak lines by the power flow analysis method whereas SVC's are placed in 22nd, 4th, 28th and 20th buses by voltage collapse proximity indication (VCPI) method. With this configuration, WOA, GWO, DE, QOGWO and QODE algorithms are applied for the minimization of active power loss and system operating cost consisting of cost due to energy loss & cost of the FACTS devices. Here, the number of search agents have been taken as 40. Control variable setting for this test system using different optimization techniques are tabulated in Table 3. Comparative analysis of studied techniques like SGA [24], Fuzzy-GA [24], SDE [24], Fuzzy-DE [24], SPSO [30], APSO [30], EPSO [30], DE, QODE, GWO and QOGWO is shown in Table 4. The proposed approach yields active power loss as 0.0393 p.u and operating cost as 2.0669×10^6\$. The comparative convergence curve for active power loss is shown in Fig. 4. Fig. 4(a) shows comparative analysis between WOA, GWO and DE algorithm. Fig. 4(b) compares the convergence characteristics obtained using WOA, QOGWO and QODE algorithm. Similarly, the comparative convergence curve for the system operating cost is shown in Fig. 5. Fig. 5(a) shows comparative analysis between WOA, GWO, DE, SPSO [30], APSO [30] and EPSO [30] algorithm. Fig. 5(b) compares the convergence characteristics obtained using WOA, QOGWO and QODE algorithm. From these figures, it is observed that active power loss and system operating cost converges smoothly at lesser number of iteration for WOA compared to other optimization algorithms. It is also observed that WOA provides faster and better solution than any other optimization techniques.

9.2. Test system 2: IEEE 57 bus system

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. Their seventeen branches are equipped with tap changing transformers and the three branches having shunt capacitors. Bus 1 is selected as slack bus. The total active power demand is 12.5170 MW and reactive power demand is 3.3570 MVAR at 100 MVA base for this system. Initially, active power loss without reactive power planning is 27.99 MW and its operating cost is 1.471×10^7 \$. TCSC's are placed in 37th, 13th, 61st and 57th lines detected as weak lines by the power flow analysis method whereas SVC's are placed in 23rd, 48th, 38th and 39th buses detected as weak buses by voltage collapse proximity indication (VCPI) method. With this configuration WOA, GWO, DE, QOGWO and QODE optimization algorithms are applied for the minimization of active power loss and system operating cost consisting of cost due to energy loss & cost of the FACTS devices. Here number of search agents taken as 80 for all the optimization algorithm. Control variable setting for this test system using different optimization techniques are shown in Table 5. Comparative analysis of active power loss and system operating cost using different techniques are shown in Table 6. The active power loss and total system operating cost in WOA method for this system is much less than other optimization methods as observed from Table 6. The comparative convergence curve for active power loss is shown in Fig. 6. Fig. 6(a) shows comparative analysis between WOA, GWO and DE. Fig. 6(b) compares the convergence characteristics obtained using WOA, QOGWO and QODE algorithm. Similarly, comparative convergence curve for system operating cost are shown in Fig. 7. Fig. 7(a) shows comparative analysis between WOA, GWO and DE. Fig. 7(b) compares the convergence characteristics obtained using WOA, QOGWO and QODE algorithm. From these figures, it is observed that active power loss and system operating cost converges smoothly at lesser number of iteration for WOA than any other optimization algorithm. It is also be observed that WOA provides faster and better solution than the other optimization algorithm (see Table 7).

10. ANOVA test

ANOVA test result is taken for all the optimization methods. This test is conducted to get idea of variance of the mean of the system operating cost with different optimization methods. Finally test result is shown in Table 8. Here ANOVA test is performed by the coding method. In the proposed work, ANOVA test is performed between five optimization techniques namely, DE, QODE, GWO, QOGWO and WOA (i.e., $k = 5$) and each optimization algorithm has been executed for 30 times (i.e., $n = 30$). Table 8 also shows that the calculated value of F [37] for both the systems are less than the tabulated value of F at 5% level of significance with degrees of freedom being 4 and 25. These analysis contradicts the null hypothesis advocating no differences in minimize cost by the techniques. We may therefore conclude that the difference in the minimized cost by the techniques is significant and is not just a matter of chance. Hence the ANOVA test by the virtue of its nature supports the fact that one among the three techniques used gives better result.

11. Conclusion

A recently developed WOA has been successfully implemented to solve the reactive power planning problem of power systems using series and shunt types of FACTS devices. The optimal location of TCSC, series type FACTS device is determined by the power flow analysis where the location for the SVC, shunt type FACTS device is determined by the VCPI method. Reactive power planning problem is formulated as a nonlinear optimization problem with equality and inequality constraints of the power network. In this study, minimization of both the active power loss and total system operating cost including the cost of the FACTS devices are considered while maintaining voltage profile within the permissible limit. To show the effectiveness of the proposed work, IEEE-30 and IEEE-57 bus test system are analysed. The result obtained by the proposed approach is compared with the results obtained by DE, GWO and WOA. Quasi-oppositional based DE and GWO is also implemented to get better solution. The implementation of quasi-oppositional in DE and GWO is primarily done to expand the search space which in turn increases the exploitability and robustness of the algorithm. It is observed that the proposed WOA provides more accurate and reliable guidance for optimal co-ordination of FACTS devices with other reactive power sources present in the power network. Merit lies with WOA is that its simple structure for implementation and its ability not to be trapped in local minima thus exploring wider search area. It may also be concluded that WOA may be an effective method of optimization in the field of power system engineering. Also a one way ANOVA test is conducted to observe the variance of the mean of the operating cost. The ANOVA test by virtue of its nature supports that WOA gives better result among all the methods.