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ORIGINAL CONTRIBUTION

Optimal Allocation of FACTS Devices Using Kinetic Gas Molecular Optimization and Cuckoo Search Algorithm

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Abstract Recently, voltage instability is considered as a key issue in the transmission line system due to its dynamic load pattern and increasing load demand. Flexible AC transmission systems (FACTS) devices are exploited to conserve the instability of voltage by controlling real and reactive power over the transmission system. In the transmission network, the size and position of FACTS are important considerations to provide a proper power flow in the system. In this paper, optimal sizing and assignment of FACTS are carried out by combining the kinetic gas molecular optimization (KGMO) and cuckoo search algorithm (CSA). There are three different FACTS devices used, namely Static VAR compensator, Thyristor Controlled Series Compensator and Unified Power Flow Controllers. The major objective functions of the proposed hybrid KGMO-CSA method are minimizing the installation cost, total voltage deviation (TVD), Line Loading and real power loss. Moreover, the optimal placement using the hybrid KGMO-CSA method is validated in MATLAB software by analyzing IEEE 14-, 30- and 57-bus system. Finally, the hybrid KGMO-CSA achieved 3.6442 MW power loss and 0.1007 p.u. TVD which is less when compared to existing quasi-oppositional chemical reaction optimization (QOCRO).

Keywords Cuckoo search algorithm · Flexible AC transmission systems · Kinetic gas molecular optimization · Static VAR compensator · Thyristor controlled series compensator · Unified power flow controllers

Abbreviations

ABC	Artificial Bee Colony
BFA	Bacteria foraging algorithm
CRO	Chemical reaction optimization
CSA	Cuckoo search algorithm
FACTS	Flexible AC transmission systems
GA	Genetic algorithm
GSA	Gravitational search algorithm
GWO	Grey wolf optimization
HBA	Honey bee algorithm
KGMO	Kinetic gas molecular optimization
LL	Line loading
PSO	Particle swarm optimization
QOBL	Quasi-oppositional-based learning
QOCRO	Quasi-oppositional chemical reaction optimization
RPD	Reactive power dispatch
SVC	Static VAR compensator
SPMOEA	Strength Pareto multi-objective evolutionary algorithm
TLBO	Teaching learning-based optimization
TCSC	Thyristor controlled series compensator
TVD	Total voltage deviation
UPFC	Unified power flow controllers

Nomenclature

P_{gi}	Active power generation
Q_{gi}	Reactive power generation
$\mathrm{Cost}_{\mathrm{a}}$	Cost of active power
$\mathrm{Cost}_{\mathrm{r}}$	Cost of reactive power

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a_i, b_i and c_i	Cost Coefficients
N_{L}	Amount of load bus
V_{i}	Load bus voltage
V_{ref}	Reference voltage
P_{ij}	Power flow at each line
P_{ijmax}	Maximum power flow limit
L	Total amount of transmission lines
G_{ij}	Conductance of line i–j
δ_i and δ_j	Voltage angle of ith and jth bus
ΔQ	Size of SVC
s	Functional limit of the FACTS device
X_{Line}	Transmission line reactance
r_{TCSC}	Degree of composition by TCSC
P	Amount of particles
k	Location of the agent
z_j^p	Specifies the kth agent position at dth dimension
T_j^d	kTh agent temperature at dimension d
b	Boltzmann constant
$pbest_j$	Best previous location of jth gas molecule
$gbest_j$	Best previous location of jth gas molecules
E_1 and E_2	Acceleration coefficients
w	Inertia weight
$rand_j$	Uniform random variable
z_{r+1}^j	Position of the molecule
a_j^d	Acceleration of agent k in dimension d
fit_q	Fitness value of the solution.
q	Proportionality index of the quality of an egg
$nest_q$	New nest
S_{pq}	Step size
$p\&q$	Randomly chosen indexes
λ	Levy Coefficient
α	Random number generated between $[-1, 1]$
Γ	Gamma function
X_{pq}^{gen+1}	Nest Location
pa	Discovery rate

Introduction

Nowadays, the constraints in the power system have increased due to the high demand for electrical power. This leads to maximized power flow instability, difficulty in power system operation and huge losses [1]. If a transmission line reaches the thermal limits, it affects the energy security and also causes voltage collapse leading to blackout events. The consequences of huge blackouts result in impacting the cost that depends on the interval of the outage and load types [2]. Moreover, the generation units in the power system provide active power but fail to provide reactive power. Thus, the absence of reactive power disturbs the performance of transmission system [3]. The aforesaid problems are minimized by using the FACTS devices in the transmission line system. The FACTS devices are generally power electronics-based converters that can control different constraints in the transmission system [4]. The FACTS device improves the voltage profile, minimizes the line losses and line loadings, delivers reactive power support in a wide range of operating voltages, and improves the stability of the system [5].

The FACTS devices minimize the losses in high loaded lines by changing the voltage profile, impedance and angle. Additionally, FACTS devices enhance the steadiness and security of system in contingency situations [6]. For different control objectives, the applications of FACTS devices include damping inter-area low-frequency oscillations, optimal power flow and voltage stability [7]. However, the advantages of the FACTS devices are mainly based on device size, type, number and location at the transmission system. The main challenge in the transmission system is the identification of proper FACTS device size, type, number and location [8], 9. The reactive power losses are controlled inside a boundary that enhances the flow of real power at the transmission line when the FACTS devices are placed in the appropriate location [10]. The conventional algorithms that are utilized for the ideal placement of FACTS devices are modified group searcher optimization [11], differential evolution algorithm [12], genetic algorithm [13], 14 and PSO [15]. The main contributions of this research are given as follows:

- Three different FACTS are used to improve the voltage magnitude by controlling real and reactive power in transmission line system.
- The integration of KGMO and CSA is used for ideal sizing and allocation of FACTS devices. KGMO has less computational complexity for FACTS device placement, and the CSA has better exploration and exploitation probability.
- The reactive power compensation and enhancement in power transfer capability are achieved by ideally allocating the FACTS.

The literature survey about the recent researches related to the ideal position of FACTS is described here.

Dutta et al. [16] presented the Quasi-Oppositional Chemical Reaction Optimization (QOCRO) for identifying the finest deployment of FACTS. The QOCRO is the integration of the Quasi-Oppositional Based Learning (QOBL) in Chemical Reaction Optimization (CRO) which is used to stabilize the voltage magnitude. There are two FACTS devices considered in this QOCRO-based allocation which are SVC and TCSC. This QOCRO algorithm is validated in two different bus systems which are IEEE 14- & 30-bus model. The voltage stability and convergence speed are enhanced by incorporating the QOBL and CRO. This system considers only three objective functions that are minimization of voltage deviation, real power loss and voltage stability index.

Reddy et al. [17] designed the hybrid optimization of KGMO and Particle Swarm Optimization (PSO) for optimum distribution of FACTS to avoid the Reactive Power Dispatch (RPD) problem. In this work, three different FACTS are used that are SVC, TCSC and UPFC. The hybrid KGMO-PSO algorithm is validated in the 30-bus test system. The power loss and voltage deviation are minimized by optimally placing the FACTS devices at proper nodes. The PSO used in this KGMO-PSO easily falls into local optima, when it is used in a large dimensional space.

Maru and Padma [18] presented the Multi Population-Based Modified Jaya (MPMJ) algorithm for optimal placement of STATCOM. This algorithm considers three different objective functions that are reduction of power loss, deviation of voltage and expansion of the static voltage stability margin. Here, two different bus systems are utilized to validate the MPMJ in IEEE 30-bus test systems. The loss and voltage values are improved by using this MPMJ with three objective functions. But, MPMJ-based optimal allocation fails to consider the generation cost of FACTS devices in its objective functions.

Sen et al. [19] designed the hybrid algorithm by combining the CRO and Cuckoo Search Algorithm (CSA) to optimally allocate the SVC in the transmission system. There are various aspects considered for placing the SVC such as line loss reduction, voltage stability, generation minimization, Return-On-Investment (ROI) time period and the annual cost of power generation. This hybrid CSA-CRO-based optimal placement of FACTS devices is analyzed in three bus systems, namely IEEE 14-, 30- and 57-bus under various environment. The total voltage deviation is not considered during the optimal allocation of SVC using the hybrid CSA-CRO technique. For an effective transmission system, the voltage deviation should be considered to avoid losses in the bus system.

Nadeem et al. [20] has demonstrated Whale Optimization Algorithm (WOA) for ideal sizing and allocation of FACTS, namely the SVCs, TCSCs and UPFCs. Here, the main intention was the decrement of functional price of network which comprises of devices cost and active power losses. At that time, the suggested WOA was employed to discover some ideal evaluations for the specified devices and for optimal management of FACTS through the reactive power which previously existed in the system (transformers and generators). On the other hand, once the reactive power loading was altered, its outcomes can be incorrect.

Problem Formulation

The hybrid KGMO-CSA is used for the ideal distribution of three FACTS to solve the multi-objective functions. The multi-objective functions include generation cost, total voltage deviation, line loading and real power loss. The description of the multiple objective functions is given as follows.

Generation Cost

The generation cost is mainly dependent on the power generation cost of system. The active and reactive power generation cost is stated in the following Eq. (1) and (2), respectively.

$$Cost_a = \sum_{i=1}^{N_G} a_i\, P_{gi}^2 + b_i P_{gi} + c_i \tag{1}$$

$$Cost_r = \sum_{i=1}^{N_G} a_i Q_{gi}^2 + b_i Q_{gi} + c_i \tag{2}$$

where $Cost_a$ and $Cost_r$ are the generation cost of active and reactive power correspondingly; P_{gi} and Q_{gi} are the real and reactive power correspondingly; N_G states the number of generators. The cost coefficients are represented as a_i, b_i and c_i, respectively.

Total Voltage Deviation

The total voltage deviation is normally a voltage gap between the reference voltage and bus voltage. If the system has less voltage gap, then it results in less voltage deviation. The TVD is expressed in the following Eq. (3):

$$\mathrm{TVD} = \sum_{i=1}^{N_L} (V_i - V_{\mathrm{ref}}) \tag{3}$$

where the amount of load bus is N_L; V_i and V_{ref} specify the load bus voltage and reference voltage, respectively.

Line Loading

The minimization of line loading is utilized to optimize the power flow within a limit and also to decrease the line overload in the transmission system. The line loading decreases the power flow gap between the actual value and limit value. Line loading is expressed in Eq. (4):

$$\mathrm{LL} = \sum\nolimits_{i=1}^{N_\mathrm{L}} (P_{ij}(t) - P_{ijmax})^2 \tag{4}$$

where P_{ij} and P_{ijmax} represent the power flow at each line and maximum power flow limit, respectively; and t represents the time duration.

Real Power Loss

The real and reactive powers are generated at the transmission line due to the transaction between the generator and demand node. The objective of reduction in real power loss (P_{loss}) at transmission line is expressed in the following Eq. (5):

$$P_{\mathrm{loss}} = \sum\nolimits_{i=1}^{L} G_{ij}\left(V_i^2 + V_j^2 - 2V_iV_j\cos(\delta_i - \delta_j)\right) \tag{5}$$

where L specifies the total amount of transmission lines; the voltage magnitude in ith and jth bus is V_i and V_j, respectively; the conductance of line i–j is G_{ij}; voltage angle of ith and jth bus is δ_i and δ_j, respectively;

Modeling of FACTS

FACTS are installed in IEEE system to ensure that the electricity system is dependable, consistent, and reliable. As a result, appropriate size and position of FACTS must be determined throughout the deployment.

SVC Modeling

Here, SVC is employed for controlling the terminal voltage by inject the reactive power. The stability problem of the generator mainly depends on the reactive power limits. So, in this research, the range of reactive power is represented by -100 MVAR $\le Q_{\mathrm{SVC}} \le 100$ MVAR, and the voltage level is maintained between 0.95 and 1.05 pu. So, the evaluated 100 MVAR will provide 90 MVAR once the voltage drops to 0.95; however, it will provide 110 MVAR once the voltage increases to 1.05 pu. These measurements are supportive once inductors are involved to find the voltage deviation. Whenever generator reactive power qualities are simulated by steady Q limits, the reactive power capability value is 1.795 that correlates to the network rated load restriction, i.e., overall loads can increase up to 1.795 times the base loading. Since the generator's active emissions are lower than their evaluations, their reactive powers are higher than that of the desired voltage.

SVC position is stated by Eq. (6):

$$\Delta Q = Q_{\mathrm{SVC}} \tag{6}$$

where ΔQ is stated as SVC's size.

The cost function of SVC:

The SVC cost function is specified in Eq. (7):

$$\mathrm{Cost} - \mathrm{svc} = 0.0003 \times s^2 - 0.305 \times s + 127.38 \tag{7}$$

where the functional limit of the FACTS device is represented as s.

TCSC modeling

TCSC includes capacitive or inductive reactance to change the distribution line's effective series characteristic impedance. Furthermore, TCSC enhances transient stability by reducing inter-area power fluctuations. TCSC position is stated as Eq. (8):

$$X_{\mathrm{TCSC}} = r_{\mathrm{TCSC}}.X_{\mathrm{Line}} \tag{8}$$

where X_{Line} is stated as line reactance; TCSC coefficient is stated as r_{TCSC}. The functioning value is chosen among -0.8 X_{Line} and 0.2 X_{Line} for avoiding overcompensation.

The cost function of TCSC:

The TCSC cost function is specified in Eq. (9):

$$\mathrm{Cost} - \mathrm{TCSC} = 0.0015 \times s^2 - 0.7130 \times s + 153.75 \tag{9}$$

UPFC modeling

UPFC modelling is expressed in Eq. (10):

$$P_{ij} = \frac{V_iV_j}{X_{ij}}\sin(\delta_i - \delta_j) \tag{10}$$

UPFC is positioned among nodes i and j; admittance matrix between i and j is denoted as X_{ij} which adjusts the reactance. That reactance value leads to change in the Jacobian matrix.

The cost function of UPFC:

The UPFC cost function is specified in Eq. (11):

$$\mathrm{Cost} - \mathrm{UPFC} = 0.0003 \times s^2 - 0.2691 \times s + 188.22 \tag{11}$$

Hybrid KGMO-CSA Method

Initially, FACTS devices are located in the various positions of the system and its behavior is observed with and without FACTS devices. The position where the FACTS devices to be allocated is defined by evaluating power flows in the system. After that, hybrid KGMO-CSA is exploited to discover the magnitudes of FACTS devices. Hybrid KGMO-CSA-based allocation of FACTS devices is tremendous beneficial both in terms of losses, stability and cost which are clearly observed from the result attained. The proposed

KGMO-CSA accomplishes substantial power losses and voltage stability in all the cases when related to existing methods. In this hybrid KGMO-CSA method, the combination of KGMO and CSA algorithms is exploited for the ideal placement of FACTS devices. A detailed description of FACTS is already given in Sect. 3. Additionally, the multi-objectives are evaluated based on the optimum placement by the hybrid KGMO-CSA method.

Figure 1 displays the block diagram for the overall system. The multi objectives include TVD, power loss, line loading and cost of FACTS devices. In the first stage, the input requirements for the standard bus data from 14, 30 and 57 are given. Then, randomly allocate the FATCS devices in a random placement to check the power loss and voltage stability. In the next stage, hybrid KGMO-CSA is introduced for optimal placement of FACTS devices. By using this KGMO-CSA, finest places for the devices have been found. Then, optimally place the FACTS in particular bus to enhance the voltage and reduce the losses.

Data Collection from IEEE 30 Bus System

In this hybrid KGMO-CSA method, the line and bus data are collected from the IEEE 30-bus system. The line data contain resistance, impedance, susceptance and tap changing transformer. Additionally, the bus data have voltage, angle, real power, reactive power and its types (e.g., generator bus, load bus and slack bus). Based on this line and bus data, the optimal allocation of FACTS devices is optimized from the hybrid optimization method.

Optimal Allocation of FACTS Using KGMO-CSA

Three different FACTS devices are used in the hybrid KGMO-CSA to improve the constancy of arrangements. The ideal specifications and price for the components are

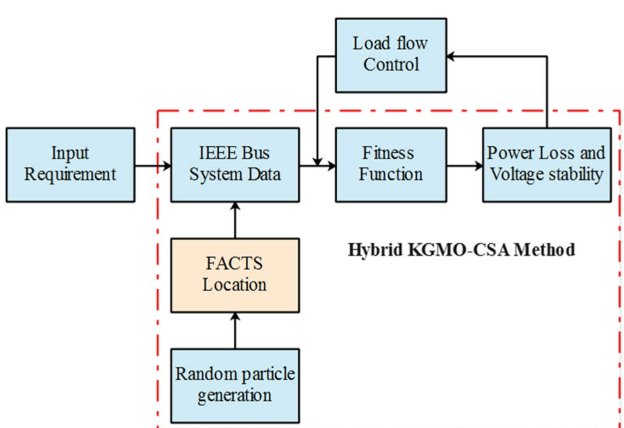

Fig. 1 Block diagram of overall system

discovered for IEEE 14, 30 and 57 bus utilizing KGMO-CSA, with the goals of improving transmission line voltage regulation and lowering power losses. Managing the power factor of series compensators solves line congestions, while controlling the reactive power of shunt compensators solves low voltages. Unstable buses and connections are identified by combining the load buses and line outage index to locate the best places for these devices. The suggested KGMO-CSA is then used to determine not only an optimum value for these devices, but also the appropriate synchronization of FACTS with and without the reactive sources currently in the system. In this hybrid KGMO-CSA method, two different optimization algorithms, namely KGMO and CSA, are used for optimizing the location of the FACTS devices. Then, the FACTS devices are placed in various test buses based on the optimized locations derived from the hybrid optimization algorithm.

Kinetic Gas Molecular Optimization Algorithm

KGMO is generally a metaheuristic optimization algorithm that was developed based on the behavior of gas molecules. The inputs given to the KGMO are reactive power, real power, power loss and bus voltage. Moreover, the initial location and size of the FACTS devices are given along with the inputs that are randomly selected in the bus system. In this hybrid KGMO-CSA method, the inputs are considered as gas molecules.

Consider, the KGMO has P amount of particles and the location of the agent k in KGMO is specified in the following Eq. (12):

$$Z_j = \left(z_j^1, \ldots .z_j^d\right) \, for \; (j = 1, 2, \ldots .d) \tag{12}$$

where z_j^d specifies the k^{th} agent position at d^{th} dimension. Equation (13) provides the velocity of the agent k.

$$V_j = \left(v_j^1, \ldots .v_j^d\right) \, for \; (j = 1, 2, \ldots .d) \tag{13}$$

where v_j^d specifies the k^{th} agent velocity at d^{th} dimension.

The motion of the gas molecules depends upon the Boltzmann distribution that specifies the velocity which is directly proportional to energy of molecule and Eq. (14) expresses the kinetic energy of the gas molecule.

$$k_j^d(r) = \frac{3}{2} \, Pb \; T_j^d \, (r), \;\; K_j = \left(k_j^1, \ldots .k_j^d, \ldots .k_j^m\right) for \; (j = 1, 2, \ldots .P) \tag{14}$$

where K_j represents the kinetic energy at jth agent; b is the Boltzmann constant, T_j^d specifies the kth agent's temperature at dimension d and time r.

Equation (15) expresses the velocity of the gas molecule updated in each iteration.

$$v_j^d(r+1) = T_j^d(r) w v_j^d(r) + E_1 rand_j(r)\left(gbest_j^d - z_j^d(r)\right) + E_2 rand_j(r)\left(pbest_j^d(r) - z_j^d(r)\right) \quad (15)$$

where the best previous location of jth gas molecule is $pbest_j = (pbest_j^1, pbest_j^2, \ldots ..pbest_j^p)$ and best previous location for all the gas molecules is $gbest_j = (gbest_j^1, gbest_j^2, \ldots ..gbest_j^p)$. The inertia weight is w, a uniform random variable is $rand_j$, and the two acceleration coefficients are E_1 and E_2.

Additionally, the position of the molecule is obtained based on the motion that is given in Eq. (16):

$$z_{r+1}^j = \frac{1}{2} a_j^d(r+1) r^2 + v_j^d(r+1) r + z_j^d(r) \quad (16)$$

where the acceleration of agent k in dimension d is a_j^d. The following Eq. (17) is used for determining the minimum fitness function.

$$\begin{aligned} pbest_j &= f(z_j),\ if\ f(z_j) < f(pbest_j) \\ gbest_j &= f(z_j),\ if\ f(z_j) < f(gbest_j) \end{aligned} \quad (17)$$

Cuckoo Search Algorithm

The constraints present in the CSA are described as follows: pa is specified as the discovery rate of alien eggs/solutions, n is expressed as amount of nests or various solutions, and λ is stated as levy coefficient.

The cuckoo arbitrarily selects the nest location to place the eggs by means of Eq. (18) and (19).

$$X_{pq}^{gen+1} = X_{pq}^{gen} + S_{pq} \times Levy(\lambda) \times \alpha \quad (18)$$

$$Levy(\lambda) = \left| \frac{\Gamma(1+\lambda) \times \sin\left(\frac{\pi \times \lambda}{2}\right)}{\Gamma\left(\frac{1+\lambda}{2}\right) \times \lambda \times S^{(\lambda-1)/2}} \right|^{1/\lambda} \quad (19)$$

where X_{pq}^{gen+1} is the newly generated nest; X_{pq}^{gen} is the present nest location; λ is stated as constant value $(1 < \lambda \leq 3)$; arbitrary number created between $[-1, 1]$ is stated as α; gamma function is stated as Γ; step size $(S > 0)$ is represented as S.

The modified equation is obtained by using Eq. (20):

$$S_{pq} = X_{pq}^{gen} - X_{fq}^{gen} \quad (20)$$

where S_{pq} represents the step size $p, f \epsilon \{1, 2, \ldots ., m\}$ and $q \epsilon \{1, 2, \ldots ., D\}$ are randomly selected indexes, f is selected randomly, and it is dissimilar from p. The host bird chooses the high-quality egg based on the probability which is expressed in Eq. (21):

$$pro_q = \left(\frac{0.9 \times fit_q}{max(fit)}\right) + 0.1 \quad (21)$$

where fitness value is represented as fit_q; proportionality index of egg is stated as q. The expression for building a new nest is given at Eq. (22).

$$nest_q = X_{q,min} + rand(0,1) \times (X_{q,max} - X_{q,min}) \quad (22)$$

where the minimum and maximum values of the new nest distances are stated as $X_{q,max} and X_{q,min}$. Table 1 shows the parameter specification of hybrid KGMO-CSA. The following parameters such as population count (P_i), weighting factor (w), maximum iteration $(iter_{Max})$ and temperature value (T) are decreased exponentially from 0.95 to 0.1 which are tabulated in Table 1.

Process of Optimal Allocation of FACTS Devices Using KGMO and CSA

In this hybrid KGMO-CSA method, the CSA is integrated into the KGMO because of the appropriate exploration and exploitation probability of CSA. Moreover, the KGMO offers less computational complexity in large-dimensional

Table 1 Parameter specification of KGMO-CSA

Parameter	Values
Population count (P_i)	50
Weighting factor (w)	1.3
Number of gas molecules	5
Temperature (T)	0.95 to 0.1
Discovery rate (pa)	3
Number of nest (n)	20
Step size (S)	0.1
Levy coefficient (λ)	1.5
Maximum iteration $(iter_{Max})$	200
Probability coefficient (pro)	0.1
Proportionality index (q)	1

space. This hybrid KGMO-CSA results in an optimal location and size for FACTS devices in IEEE bus system. The flowchart for the hybrid KGMO-CSA is given in Fig. 1. The pseudocode for the hybrid KGMO-CSA is shown below.

PSEUDOCODE

Consider every molecule {
Repeat and modify every molecule till it fulfills entire parameters}
Do {
For every element {
Evaluate the fitness function
If the estimated fitness is improved over the previous best
Fix the recent assessment as new best value
}
}
For every element {
If the estimated fitness is improved over the global value
Fix the recent value as new global best
}
Evaluate the kinetic energy for every molecule present in the system
Update the position and velocity of each particle
}
} while the conditions of limited error measure or more iterations count not accomplished
Objective function (), = (1,2.......)
Produce preliminary population count of n host nests (P_i = 1, 2...n)
While t < Generation count
Randomly develop a cuckoo through Lévy dissemination;
Calculate its worth;
Randomly select a nest between n;
Calculate its worth;
Substitute j through new result;
End
A portion of poorer nests are neglected and fresh nest is made at
Find fresh position with the help of Lévy flights;
Save the finest result;
Order the results and discover the new best value;
End while

Figure 2 displays the flowchart for hybrid KGMO-CSA. The optimal FACTS position depends on hybrid

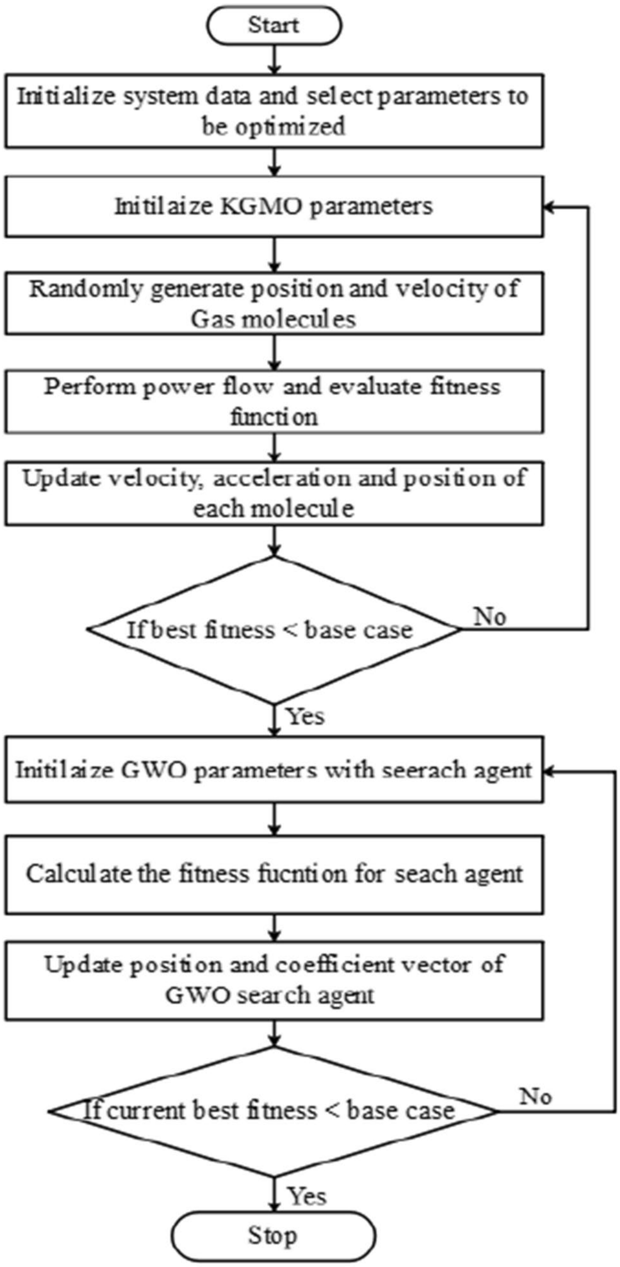

Fig. 2 Flowchart of hybrid KGMO-CSA

KGMO-CSA to eliminate the RPD issues and is given in the following steps.

Step 1: Initially, select the constraints for optimal allocation of FACTS devices. The five cases considered in this hybrid KGMO-CSA method are given in the below sections.

Step 2: Determine the search space by selecting *P* amount of molecules.

Step 3: Initialize the KGMO specifications such as iteration count, inertia weight, temperature, mass, Boltzmann constant and acceleration coefficients.

Table 2 Specifications of IEEE 14- and 30-bus system

Particular	Details	
	30 bus	14 bus
Transmission lines	41	20
Transformers	4 locations	3 locations
Shunt compensators	9 locations {	2 locations
Generators	6 buses {1, 2, 5, 8, 11, 13}	5 buses (1,2,5,8,11)

Table 3 Population Count for Optimization Methods

Methods	Population count
Particle swarm Optimization	20
Harmony search algorithm	25
Grey wolf optimization	18
Whale optimization	30
Hybrid KGMO-CSA	50

Step 4: Set the initial velocity and position of the gas molecule for the KGMO algorithm.

Step 5: Compute the kinetic energy, velocity and acceleration for each molecule. Based on the aforementioned values, update the velocity of the gas molecules.

Step 6: For the updated position of gas molecules, calculate the fitness functions that are described in the following section. Subsequently, define the personal and global best values of each gas molecule.

Step 7: Input the processed values that contain the size and position of FACTS from the KGMO to the CSA algorithm. Then CSA updates its behavior of encircling prey and hunting.

Step 8: Evaluate the optimum value based on the fitness function derived for this hybrid optimization.

Step 9: Validate the solution from the hybrid optimization with the base case value. The base case has two different values which are power loss and total voltage deviation. If the values from the optimization are less than the base case value, it is considered as an optimal solution. Otherwise, the process of hybrid optimization starts again from Step 1.

Step 10: Terminate the hybrid optimization algorithm once the optimal solution is achieved for adequate placement of FACTS devices.

Results and Discussion

The experimental results and discussion of the hybrid KGMO-CSA method-based optimal allocation of FACTS

Table 4 Performance analysis for Scenario 1

Control variables	Initial values	Optimal values
V1	1.0500	1.0439
V2	1.0400	1.0198
V5	1.0100	1.0099
V8	1.0100	1.0262
V11	1.0500	1.0296
V13	1.0500	1.0323
T11	1.0780	0.9541
T12	1.0690	1.0247
T15	1.0320	0.9943
T36	1.0680	0.9615
Qc10	0.0000	3.5583
Qc12	0.0000	2.8731
Qc13	0.0000	2.2694
Qc17	0.0000	2.6702
Qc20	0.0000	2.8385
Qc21	0.0000	2.7782
Qc23	0.0000	3.0416
Qc24	0.0000	3.1675
Qc29	0.0000	1.2411
TVD (p.u)	1.47	0.1915
Ploss (MW)	5.74	5.2343
LL	6.42	5.353

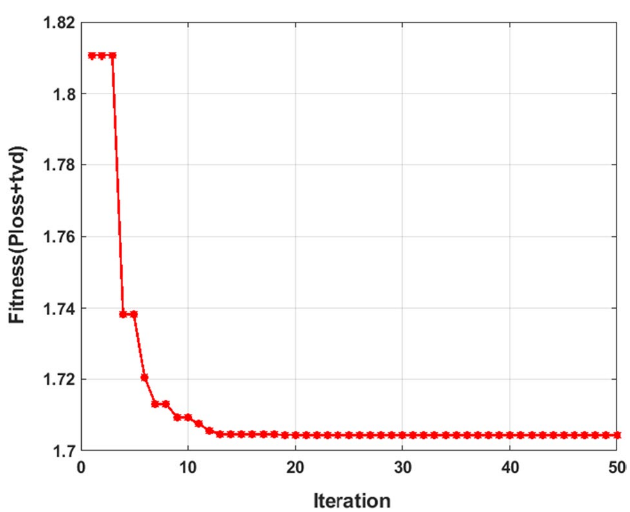

Fig. 3 Fitness function for scenario 1

devices are explained in this section. The simulation of this hybrid KGMO-CSA method is carried out using MATLAB R2020a software that runs on a Windows 10 OS with i5 processor. The FACTS device placement for resolving the multi-objective problem is performed in the IEEE 30 bus. The rating of IEEE 30 and 14 bus is mentioned in Table 2.

Table 5 Performance analysis for Scenario 2

Control variables	Initial values	Optimal values
V1	1.0500	1.0299
V2	1.0400	1.0390
V5	1.0100	1.0331
V8	1.0100	1.0087
V11	1.0500	1.0292
V13	1.0500	0.9909
T11	1.0780	0.9982
T12	1.0690	0.9928
T15	1.0320	0.9537
T36	1.0680	0.9801
Qc10	0.0000	2.1377
Qc12	0.0000	1.5403
Qc13	0.0000	2.2657
Qc17	0.0000	3.5854
Qc20	0.0000	3.0387
Qc21	0.0000	2.4162
Qc23	0.0000	3.1345
Qc24	0.0000	2.6004
Qc29	0.0000	2.4739
SVC location	15.0000	15.0000
SVC size	0.0000	0.2557
SVC cost ($/MVAR)	–	127.365
TVD (p.u)	1.47	0.1274
Ploss (MW)	5.74	4.5435
LL	6.42	3.9129

Table 3 shows the population values for different optimization techniques.

Performance Analysis

30 Bus System

The behavior of hybrid KGMO-CSA is analyzed by TVD, power loss, line loading and cost of the devices. The performance analysis is carried out for five different scenarios that are mentioned in the previous section:

Table 4 shows the performance of scenario 1 for 30-bus system. Here, there are no FACTS devices considered for resolving the RPD problem. The values of TVD, Ploss and LL for the transmission system without FACTS devices are 0.1915 p.u, 5.2343 MW and 5.353, respectively. The fitness graph for scenario 1 is illustrated in Fig. 3.

The scenario 2 performance analysis is given in Table 5. The results of Table 5 are taken for 30 bus with only SVC. The values of TVD, Ploss and LL for scenario 2 are 0.1274 p.u, 4.5435 MW, and 3.9129, respectively. The location and size of the SVC are 15 and 0.2557, respectively. Additionally, the cost of the SVC used in this scenario 2 is 127.365

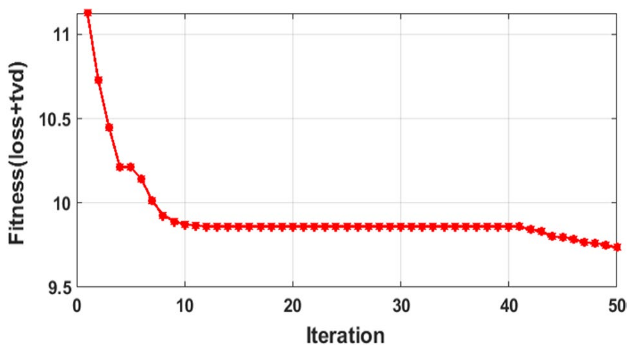

Fig. 4 Fitness function for scenario 2

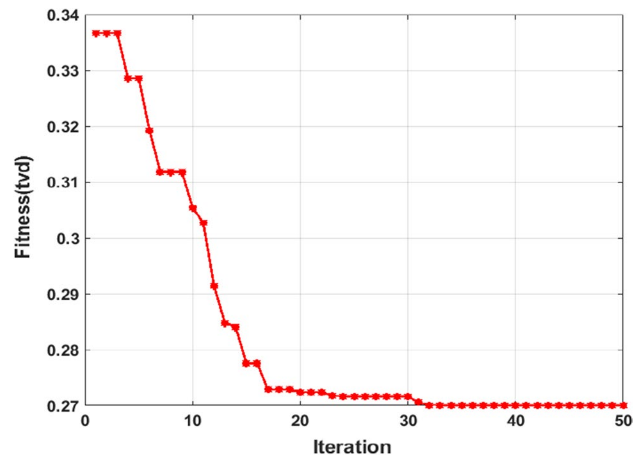

Fig. 5 Fitness function for scenario 3

Table 6 Performance analysis for Scenario 3

Control variables	Initial values	Optimal values
V1	1.0500	0.9862
V2	1.0400	1.0644
V5	1.0100	1.0676
V8	1.0100	1.0289
V11	1.0500	1.0653
V13	1.0500	0.9691
T11	1.0780	1.0550
T12	1.0690	0.9000
T15	1.0320	0.9683
T36	1.0680	0.9690
Qc10	0.0000	2.9367
Qc12	0.0000	2.3654
Qc13	0.0000	5.0000
Qc17	0.0000	4.0393
Qc20	0.0000	2.4885
Qc21	0.0000	4.4321
Qc23	0.0000	0.0992
Qc24	0.0000	3.2304
Qc29	0.0000	2.4741
TCSC location	15.0000	16.0000
TCSC size	0.0000	0.137
TCSC cost ($/MVAR)	–	154.3736
TVD (p.u)	1.47	0.1077
Ploss (MW)	5.74	4.217
LL	6.42	4.9755

$/MVAR. Table 4 concludes that the TVD, Ploss and LL values for scenario 2 are lesser than scenario 1. Figure 4 illustrates the fitness function graph for Scenario 2.

The fitness graph for scenario 3 is illustrated in Fig. 5. Table 6 shows the performance of scenario 3 for 30 bus. The value of TVD, Ploss and LL for transmission systems with TCSC is 0.1077 p.u, 4.217 MW and 4.9755, respectively. The location and size of the TCSC are 16 and 0.137, respectively. Furthermore, the cost of TCSC used in the bus system is 154.3736 $/MVAR.

Table 7 Performance analysis for Scenario 4

Control variables	Initial values	Optimal values
V1	1.0500	1.0534
V2	1.0400	1.0650
V5	1.0100	1.0196
V8	1.0100	1.0479
V11	1.0500	1.0503
V13	1.0500	0.9788
T11	1.0780	0.9567
T12	1.0690	1.0540
T15	1.0320	0.9861
T36	1.0680	0.9970
Qc10	0.0000	1.9261
Qc12	0.0000	0.7125
Qc13	0.0000	0.2863
Qc17	0.0000	0.7656
Qc20	0.0000	3.2344
Qc21	0.0000	2.7643
Qc23	0.0000	2.3348
Qc24	0.0000	1.6346
Qc29	0.0000	3.0487
UPFC location	0.0000	27.0000
UPFC size	0.0000	0.9866
UPFC degree	0.0000	0.558
UPFC impedance	0.0000	0.1021
UPFC cost ($/MVAR)	–	187.7069
TVD (p.u)	1.47	0.1014
Ploss (MW)	5.74	3.940
LL	6.42	3.6168

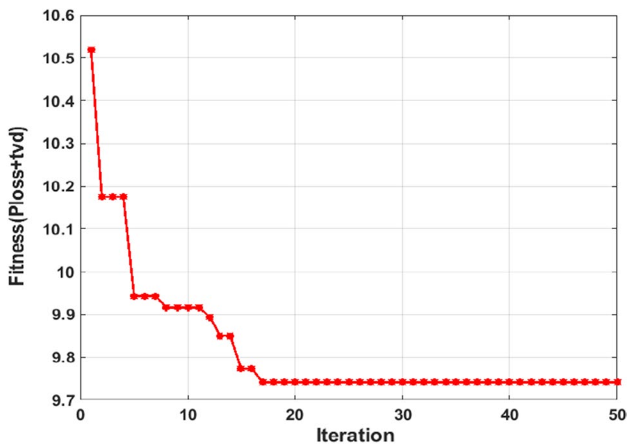

Fig. 6 Fitness function for scenario 4

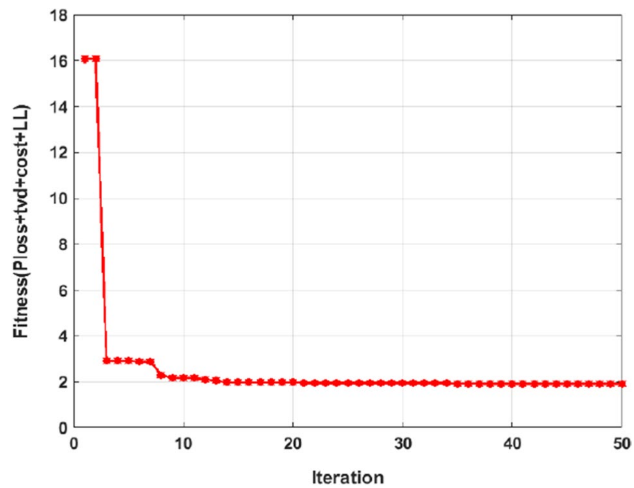

Fig. 7 Fitness function for scenario 5

Table 8 Performance analysis for Scenario 5

Control variables	Initial values	Optimal values
V1	1.0500	0.9564
V2	1.0400	0.9770
V5	1.0100	1.0706
V8	1.0100	1.0251
V11	1.0500	0.9574
V13	1.0500	0.9951
T11	1.0780	0.9515
T12	1.0690	0.9684
T15	1.0320	1.0076
T36	1.0680	1.0236
Qc10	0.0000	0.6943
Qc12	0.0000	4.0131
Qc13	0.0000	2.6516
Qc17	0.0000	3.1690
Qc20	0.0000	1.4142
Qc21	0.0000	3.6634
Qc23	0.0000	2.1248
Qc24	0.0000	2.9427
Qc29	0.0000	1.9355
SVC location	0.0000	16.0000
SVC size	0.0000	41.2602
TCSC location	0.0000	25.0000
TCSC size	0.0000	0.974
UPFC location	0.0000	6.0000
UPFC size	0.0000	0.9943
UPFC degree	0.0000	0.3352
UPFC impedance	0.0000	0.64
SVC cost ($/MVAR)	–	129.1645
TCSC cost ($/MVAR)	–	152.7372
UPFC cost ($/MVAR)	–	187.8794
TVD (p.u)	1.47	0.1007
Ploss (MW)	5.74	3.6442
LL	6.42	4.1659

Table 9 Performance analysis of TVD and PLOSS of SVC for IEEE 14-bus system

Symbol	Without SVC	KGMO_CSA_SVC
V1	1.0677	1.0742
V2	1.0659	1.0364
V5	0.9777	0.9856
V8	1.0528	1.0346
V11	1.0611	0.9901
T11	0.9798	0.9913
T12	1.0629	1.0100
T15	0.9354	0.9716
Qc10	1.2431	1.7566
Qc12	4.6983	1.0945
SVC location	–	2.000
Size	–	5.2833
TVD(P.U)	13.3822	13.1275
PLOSS (MW)	0.3407	0.2759

Table 10 Bus voltage for each line

Bus voltage at each bus	
Without FACTS	With FACTS
1	1.0014
0.997013516	0.9993
0.982830187	0.9903
0.975301886	0.9866
0.96785835	0.9831
0.949340982	0.9731
0.945849362	0.9697
0.93215167	0.9563
0.925803365	0.9502
0.919931487	0.9444
0.919055081	0.9436
0.917527092	0.9421
0.911347548	0.9361
0.909073448	0.9338

Table 11 Performance analysis of SVC and TCSC for IEEE 14-bus system

Symbol	Initial	TVD, PLOSS and COST comparison		
		KGMO_CSA_SVC	KGMO_CSA_TCSC	KGMO_CSA_SVC_TCSC
V1	1.0500	1.0512	1.0421	1.0976
V2	1.0400	1.0240	1.0354	1.0893
V5	1.0100	1.0423	1.0131	1.0385
V8	1.0100	1.0243	1.0510	1.0369
V11	1.0500	1.0335	1.0012	0.9999
T11	1.05	0.9820	0.9982	0.9751
T12	1.078	0.9934	0.9758	0.9816
T15	1.069	0.9798	0.9885	0.9188
Qc10	1.032	2.2181	2.1545	2.0307
Qc12	1.068	1.1679	2.1983	3.0980
SVC location	–	12	–	2.0000
SVC size	–	41.4525	–	31.25
SVC cost	–	115.2525	–	98.3626
TCSC location	–	–	10	3.0000
TCSC size	–	–	8.1524	9.0660
TCSC cost	–	–	143.2637	149.6199
Total cost	–	115.2525	143.2637	247.982
TVD		0.1321	0.1970	0.1195
PLOSS	13.49	12.5924	12.9923	12.4163

Table 12 Performance analysis of SVC, TCSC and UPFC for IEEE 14-bus system

Symbol	Initial	PLOSS, TVD, Line Loading Index and COST			
		KGMO_CSA_SVC	KGMO_CSA_TCSC	KGMO_CSA_UPFC	KGMO_CSA_SVC_TCSC_UPFC
V1	1.0500	1.0532	1.0121	1.0823	1.0504
V2	1.0400	1.0218	1.0521	1.1000	1.0385
V5	1.0100	0.9659	0.9962	1.0428	1.0162
V8	1.0100	1.0244	0.9854	0.9791	1.0274
V11	1.0500	1.0245	0.9987	0.9984	1.0302
T11	1.05	0.9824	1.0111	0.9719	1.0136
T12	1.078	0.9900	0.9784	1.0497	1.0483
T15	1.069	0.9775	0.9884	0.9525	0.9954
Qc10	1.032	2.5687	2.1546	1.2911	2.5728
Qc12	1.068	1.8607	2.3651	0.0983	3.0497
SVC location	15.000	6.0000	–	–	5.0000
SVC size	0.0000	39.6186	–	–	19.7086
SVC cost	–	139.9346	–	–	127.3800
TCSC location	15.000	–	11.0000	–	14.0000
TCSC size	0.000	–	5.3621	–	0.0262
TCSC cost	–	–	146.2232	–	153.7500
UPFC location	0.000	–	–	9.0000	1.0000
UPFC size	0.000	–	–	0.9500	0.5135
UPFC cost	–	–	–	188.2244	188.2200
Total cost	–	–	–	–	469.3500
TVD		0.1375	0.1321	0.12792	0.1066
PLOSS	13.49	13.4125	13.2401	13.1306	12.0133
LL	15.968	15.636	16.5599	14.563	14.0121

Table 13 Performance analysis of SVC, TCSC, UPFC and STATCOM for IEEE 57-bus system

Parameters	GWO	QOGWO	Proposed KGMO_CSA
T (59)	1.05	1.05	1.01
T (31)	1.0385	0.984	1.024
T (73)	1.0371	1.05	1.05
T (37)	1.0336	1.05	0.9
T (76)	0.9905	1.05	1.02
T (36)	0.9263	0.9069	1.03
T (35)	0.9197	0.9066	0.9139
T (19)	0.9145	0.9068	1.012
T (54)	0.9109	0.9519	1.021
T (46)	0.9058	0.9012	1.032
T (71)	0.9051	0.9	1.02
T (20)	0.9041	0.9026	0.9
T (80)	0.9024	0.9068	0.9
T (58)	0.9002	0.9	0.8902
T (41)	0.9	0.9	0.8926
T (65)	0.9	0.9	0.8917
T (66)	0.9	0.9	0.8913
Qg (6)	0.1926	0.0731	−0.091
Qg (3)	0.1785	0.5682	0.1257
Qg (9)	0.0049	−0.0014	0.0146
Qg (12)	0.0026	1.1004	1.55
Qg (8)	−0.103	1.0292	0.8128
Qg (2)	−0.1258	−0.0402	0.5
TCSC (1)	0.0123(37)	0.032391(37)	0.154100(27)
SVC (1)	0.20(23)	0.1179(23)	0.3(25)
UPFC (1)	0.725 (41)	0.628 (41)	0.462(41)
STATCOM (1)	0.5 (26)	0.481 (26)	0.331(26)
PLoss	0.2097	0.2086	0.2059
CTotal	1.109×10^7	1.01899×10^7	1.09792×10^7

The performance analysis of scenario 4 is given in Table 7. The values of TVD, Ploss and LL for scenario 4 are 0.1074 p.u, 3.940 MW and 3.6168, respectively. The location and size of the UPFC are 27 and 0.9866, respectively. Additionally, the cost of the UPFC used in this scenario 4 is 187.7069 $/MVAR. Table 6 concludes the TVD, Ploss and LL values for scenario 4 are lesser than those of scenario 1 and scenario 2. Figure 6 illustrates the fitness function graph for Scenario 4.

Table 8 shows the results of the 30 bus with all FACTS that include SVC, TCSC and UPFC. The value of TVD, Ploss and LL for scenario 5 is 0.1007 p.u, 3.6442 MW and 4.1659, respectively. The locations of SVC, TCSC and UPFC are positioned at 16, 25 and 6, respectively. The proposed KGMO-CSA optimizes the sizes of SVC, TCSC and UPFC as 41.2602, 0.974 and 0.9943, respectively. Additionally, the costs of the SVC, TCSC and UPFC used in this scenario 5 are 129.1645, 152.7372 and 187.8794 $/MVAR, respectively.

Table 14 Statistical inference values

Mean	Medium	Mean Deviation	Variance	SD	Best	Worst	Standard error	Convergence	Confidence interval	Length of confidence interval
5.13	3.731	1.402	1.1158	0.622	10.62	8.335	0.017	1.3253	0.52	1

Table 15 Comparative analysis of the hybrid KGMO-CSA method for 30 bus

Parameters	QOCRO [16]	KGMO-PSO [17]	Hybrid KGMO-CSA
TVD (p.u)	0.1039	0.1167	0.1007
Ploss (MW)	–	3.8786	3.6442

From Table 8, it can be concluded that TVD and Ploss for scenario 5 are lesser than those of scenarios 1, 2 and 3. Figure 7 illustrates the fitness function graph for Scenario 5.

14 Bus System

The behavior of the hybrid KGMO-CSA method is analyzed in terms of TVD, power loss, line loading and cost of the devices. The performance analysis is carried out in three different scenarios which are given as follows: 1. With SVC, 2. With SVC and TCSC, 3. With SVC, TCSC and UPFC. The last scenario considers the 14 bus with all FACTS that include SVC, TCSC and UPFC.

Table 17 Performance between proposed and existing methods for real power loss savings [9]

IEEE 57-Bus	Proposed KGMO_CSA Method	PSO-based GSA	GA	HBA	BFA
SVC	1.64	–		0.98	0.93
TCSC	2.19	1.653	1.26	0.19	0.11
UPFC	8.93	–	–	0.75	0.56

From Table 9, the performance of the KGMO for 14 bus is evaluated in terms of PLOSS and TVD. It can be concluded that the PLOSS and TVD of KGMO_CSA_SVC are better than the bus system without SVC. For example, the PLOSS of IEEE 14 bus system with SVC is 0.2759 MW, which is less when compared to the bus system without SVC. From the analysis, it determined that the SVC placement for the reactive power dispatch problem gives better performance in terms of TVD and power loss. Table 10 shows voltage of each bus for FACTS devices.

The performance analysis of case 2 for 14 bus is tabulated in Table 11, which clearly shows that the KGMO algorithm

Table 16 Comparative analysis for IEEE 14-bus system

Scenario	Objective case	PSO	WIPSO [5]	KGMO_CSA
With SVC	TVD	0.1453	0.1411	0.1321
	Ploss	11.989	12.233	12.59
	LL	18.423	16.986	16.7858
	All + Cost	Tvd = 0.1399 Ploss = 14.018 LL = 15.663 Cost = 178.5896	Tvd = 0.1387 Ploss = 13.764 LL = 15.639 Cost = 166.6414	Tvd = 0.1375 Ploss = 13.4125 LL = 15.6364 Cost = 138.8588
With TCSC	TVD	0.1732	0.1847	0.1970
	Ploss	14.186	13.923	12.9923
	LL	16.279	15.849	15.6539
	All + Cost	Tvd = 0.1365 Ploss = 14.858 LL = 17.384 Cost = 153.7692	Tvd = 0.1381 Ploss = 13.176 LL = 17.0087 Cost = 149.6985	Tvd = 0.1321 Ploss = 13.2401 LL = 16.5599 Cost = 149.3659
With UPFC	TVD	0.1211	0.1223	0.1195
	Ploss	13.987	12.526	12.4163
	LL	13.685	13.778	13.5215
	All + Cost	Tvd = 0.1814 Ploss = 12.654 LL = 15.001 Cost = 188.2348	Tvd = 0.1111 Ploss = 12.391 LL = 14.898 Cost = 182.5484	Tvd = 0.1146 Ploss = 12.1385 LL = 14.563 Cost = 181.4551
With SVC, TCSC, UPFC	TVD	0.1252	0.1148	0.1136
	Ploss	12.589	12.433	12.2133
	LL	15.063	15.012	14.9286
	All + Cost	Tvd = 0.1846 Ploss = 12.386 LL = 15.923 Cost = 496.5987	Tvd = 0.1566 Ploss = 12.125 LL = 14.889 Cost = 487.7889	Tvd = 0.1066 Ploss = 12.0133 LL = 14.0121 Cost = 483.1463

with FACTS devices provides better performance for RPD problem than the KGMO without FACTS devices. It shows that the SVC and TCSC placement using KGMO_CSA is better than other scenarios. For example, the PLOSS of KGMO_CSA using both SVC and TCSC is 12.4163 MW, which is less when compared to other scenarios.

Table 12 shows the performance analysis of minimization of PLOSS, TVD, COST and LL for IEEE 14-bus system. From Table 12, it is observed that the proposed KGMO_CSA touches the optimal point effortlessly at minimum iteration count. It shows that the KGMO_CSA using all three placements of SVC, TCSC and UPFC together is better than other scenarios. For example, the PLOSS of KGMO using SVC, TCSC and UPFC is 12.0133 MW, which is less when compared to the other scenarios such as KGMO_CSA with only SVC or with both SVC and TCSC.

57Bus System

In the STATCOM, the boundary conditions are violated once the STATCOM link is moved from PV bus to PQ bus. The produced or consumed reactive power may then equal to the restriction that had been broken. The STATCOM is presented as a supply voltage for the whole range of operating conditions in this study, allowing for a robust voltage support system. Generally, IEEE 57 bus comprises 50 load buses, 7 generator buses and 80 feeder lines. Bus 1 is deliberated as slack bus and entire load demand is 1195.8 MW and 319.4 MVAR. The optimum position and sizing of four FACTS devices are initiated for IEEE 57 bus using proposed KGMO_CSA technique.

From Table 13, the optimal placement of SVC, TCSC and STATCOM is placed in IEEE 57-bus. Primarily, real power loss excluding planning reactive power is 27.99 MW, and its functioning price is 1.471×10^7. Table 13 indicates that the TCSCs and UPFCs are positioned in 27 and 41 which are perceived as ineffective lines found by the proposed method, while SVC and STATCOM devices are positioned in 25 and 26 buses, respectively. The proposed KGMO_CSA method provides less cost of 1.09792×10^7 and power loss of 0.2059 which is much better than the other existing GWO and QOGWO approaches. Table 14 tabulates the statistical inference values.

Comparative Analysis

The behavior of KGMO-CSA is associated with previous techniques to know the effectiveness of the hybrid KGMO-CSA method. The comparison of the hybrid KGMO-CSA method is validated in terms of TVD and power loss. The existing techniques used in the comparison are QOCRO [16] and hybrid KGMO-PSO [17]. Additionally, the comparative analysis of the hybrid KGMO-CSA method is validated for the IEEE 30-bus system. In [16], QOCRO is developed for obtaining the finest positions of the TCSC and SVC. The hybrid optimization of KGMO and PSO is used to obtain the positions and sizes of SVC, TCSC and UPFC [17].

Table 15 shows the comparative analysis of the hybrid KGMO-CSA method with QOCRO [16] and hybrid KGMO-PSO [17]. From this above obtained table, it determined that the hybrid KGMO-CSA achieves less TVD and power loss as compared to the QOCRO [16] and hybrid KGMO-PSO [17]. For example, the TVD of the KGMO-CSA method is 0.1007 p.u, which is less when compared to that of both QOCRO [16] and hybrid KGMO-PSO [17]. The QOCRO [16] fails to consider the generation cost and line loading during optimal placement of FACTS devices. Additionally, the PSO of hybrid KGMO-PSO [17] is insignificant for large-dimensional space. But, the hybrid KGMO-CSA method considers four different objective functions, namely generation cost, total voltage deviation, line loading and real power loss. Thus, the hybrid KGMO-CSA provides significant results for optimal placement due to less computational complexity.

Table 16 shows the comparative analysis of KGMO_CSA, PSO and WIPSO [5]-based allocations for IEEE 14-bus system, respectively. This comparison is made for four different scenarios that are the bus system with SVC, with TCSC, with UPFC and with all FACTS devices. The comparison concludes that the IEEE 14 bus with the FACTS provides better performance when compared to the system without FACTS devices.

The proposed technique for obtaining power losses and enhancing the voltage profile once the FACTS placement is done and then related through conventional methods, namely Genetic Algorithm (GA), PSO, Honey Bee Algorithm (HBA), as well as Bacteria Foraging Algorithm (BFA) [9], and their outcomes are shown in Table 17. In Table 17, it is observed that KGMO-CSA has less real power loss which is superior to other methods.

Conclusion

Nowadays, security is the primary apprehension of power system due to the liberalized strategy in control production. In this research, security indexes are power flow and voltage profiles. Those indexes are utilized as main intention for security related issues which are recompensed by ideally allocating the FACTS. On the contrary, improper allotment of FACTS produces excessive current and interrupts the load summary that causes security problems. In this research, optimal sizing and position of FACTS are carried out by hybrid KGMO-CSA technique. The TVD and power loss of the hybrid KGMO-CSA method are less when compared to that of QOCRO and hybrid KGMO-PSO. From the results, the power loss of the hybrid KGMO-CSA method is reduced up to 6.04% and TVD is reduced up to 13.71% when compared to the existing KGMO-PSO. From the simulation outcomes, it is clearly observed that hybrid KGMO-CSA is better than the existing QOCRO technique. In the future, optimal placement and sizing of FACTS can be analyzed in large bus systems like IEEE 85 and IEEE 118 by using novel optimization algorithms.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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