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TECHNICAL PAPER

Optimal location and parametric settings of FACTS devices based on JAYA blended moth flame optimization for transmission loss minimization in power systems

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Abstract

This paper presents a novel hybrid algorithm that includes the superior properties of strong algorithms which have been developed in recent past. The study involves minimization of transmission loss in IEEE networks through the efficient placement of flexible alternating current transmission system (FACTS) devices. In this work two types of devices namely thyristor controlled series compensator (TCSC) and static VAR compensator (SVC) are used in IEEE 14 bus and IEEE 30 bus systems. The main objective of active power loss reduction is achieved through the minimization of installation cost of these devices which is considered as the fitness function for the optimization algorithms. In this paper Moth flame optimization (MFO) in its natural form as well as in hybrid form called JAYA blended MFO (JMFO) is applied for the study. The results obtained are compared with existing technique like particle swarm optimization (PSO).

1 Introduction

With the increase in the electrical power demand, the stress on the power system conditions is also rising. This results in the increase in difficulty in the power system operation, instability in the power flow and higher losses. Apart from this the untapped sectors in the transmission system due to environmental and economic issues is a major concern of power network designers and policy framers. The rapid progress in the self-commutated power electronic devices has led to the proposition of flexible alternating current transmission system (FACTS) devices. FACTS devices have been introduced and experimented for power system areas in detail by Hingorani et al. (2000). FACTS controllers are linked to more than one improvements in the power system networks. They can be implemented for enhancement of system loadability (Duan et al. 2015), improve the system security (Vaidya and Rajderkar 2011), reduce transmission losses (Jumaat et al. 2011), elevate the voltage stability (Sundareswaran et al. 2009) and manage congestion in complex grids (Singh and David 2001; Sute and Rajderkar 2012). However in order to make proper utilization of FACTS, the type of FACTS devices to be used, their ratings and their location must be decided appropriately.

The power system experts have shown keen interest in exploring various types of FACTS devices like the series connected thyristor controlled series compensator (TCSC) and static synchronous series compensator (SSSC), or the shunt connected static VAR compensator (SVC) and static compensator (STATCOM), or the shunt-series devices like unified power flow controller (UPFC). However, as discussed earlier their location, type and size play a major role in their operation and its effect on the network operation. Therefore in the last few decades numerous attempts have been made towards the optimal placement of such FACTS devices in different IEEE bus systems through various classical optimization techniques which can be named as linear programming methods, non-linear programming methods and mixed integer non-linear programming methods (Sharma 2006). Apart from these methods fuzzy application has also been made for achieving the above mentioned objectives (Phadke et al. 2012; Ushasurendra and Parathasarthy 2012; Bhattacharyya and Gupta 2014; Gitizadeh and Kalantar 2009). In spite of having desirable convergence these classical methods suffer some set-backs like trapping in local solutions and mandatory assumptions like differentiability, continuity and convexity of the mathematical problem.

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These drawbacks can be avoided through the algorithms that are meta-heuristic in nature such as genetic algorithm (GA), differential evolution (DE), particle swarm optimization (PSO), gravitational search algorithm (GSA) and the like. These are nature inspired algorithms which ascertain the convergence to global solutions (minima or maxima as the problem requires) and can be easily applied to problem irrespective of the number of variables and nature of the problem. The techniques generate a random set of possible solutions and find the best possible among them which ensures evaluation of each and every possible solutions existing in the search space.

Genetic algorithm (GA) was the foremost algorithm to be tested for the objective of optimal placement of FACTS devices to improve the transfer capability of a system by Gerbex et al. (2001). The optimal locations of FACTS have been selected using GA (Cai et al. 2004) for efficient operation of generators in a deregulated electricity supply system. UPFC has been used for the improvement in power security of the system through appropriate placement using DE algorithm (Shaheen et al. 2011). DE has been implemented for the placement of TCSC and SVC in an IEEE 30 bus network to increase its loadability to 200% of the base load (Bhattacharyya and Goswami 2012) and a comparison with PSO is done. The loadability of a system has been improved with the minimum cost for the installation of FACTS devices through a standard PSO technique (Saravanan et al. 2007) where multiple types of devices like TCSC, SVC and UPFC are chosen. The well established PSO technique have been modified to non-dominated sorting particle swarm optimization (NSPSO) (Benabid et al. 2009) and this technique has been used for the optimal placement of SVCs and TCSCs in order to improve the voltage stability, minimize the real power losses and to reduce the voltage deviation. Similarly, PSO has been improvised to improved particle swarm, optimization (IPSO) (Ravi and Rajaram 2013) for the optimization of the location, rating and control settings of a STATCOM so that the voltage deviations are minimized in an IEEE 30 bus network. Adaptive form of PSO has been hybridized with simulated annealing (APSO-SA) (Tabatabaei et al. 2011) to determine the optimal location and ratings of TCSC and SVC which can increase the voltage stability index and loading factor of the system along with reducing the active power losses and cost of investment in an standard IEEE 14 bus network. Apart from this a modified form of PSO (MPSO) is applied to IEEE 30 bus system for the maximization of the load delivering capacity of the network (Parastar et al. 2007). Similarly, the real power losses in various IEEE networks have been reduced through TCSC by appropriate placement using PSO and GA (Rashed et al. 2007). The optimal location and rating for appropriate placement of FACTS devices has been hunted through various optimization techniques discussed like ant colony optimization (ACO) (Fughar and Nwohu 2014), artificial bee colony (ABC) (Sumpavakup et al. 2010), gravitational search algorithm (GSA) (Rashedi et al. 2007), bees algorithm (BA) (Idris et al. 2010). Cuckoo search (CS) (Nguyen et al. 2016) in its virgin and modified form known as modified cuckoo search (MCS) (Akumalla et al. 2016) and adaptive form as adaptive cuckoo search (ACS) (Taleb et al. 2016) has also been tested for the optimal placement of FACTS. The available transfer capacity of a system is enhanced using cat swarm optimization (CSO) (Nireekshana et al. 2016) in contingency condition through FACTS devices. There has been remarkable work where meta-heuristic algorithms have been efficiently applied for improving the power system operations by optimization of more than one objective which are framed as multi-objective functions (Ranganathan and Kalavathi 2016; Ara et al. 2012). FACTS devices like TCSC and SVC have been employed for the optimal power flow (OPF) problem also using different optimization techniques like novel symbiotic organisms search (SOS) algorithm (Prasad and Mukherjee 2016) and touring ant colony optimization (TACO) technique among a few to be named. Teaching learning based optimization (TLBO) has been applied for the loss minimization in a network through efficient us e of SVC in the system.

In this paper, a recently developed algorithm named as Moth flame optimization (MFO) (Mirjalili 2015) has been examined through application in various standard IEEE bus systems for the minimization of loss in the network. The devices under consideration in this work are TCSC and SVC which are placed optimally in the networks to reduce the active power loss occurring in the lines. The results are compared with PSO and a hybrid concept using the strengths of both these algorithms is implemented for the fore-mentioned objective of loss minimization as well.

2 Allocation of FACTS devices

The main aim of this work is to locate FACTS devices in the best possible sections of the network to reduce the power loss occurring in the lines to minimum. In order to achieve this, MFO in its natural form as well as MFO blended with JAYA algorithm and PSO are tested separately as independent algorithms as well as in a hybrid manner. The placement of FACTS devices needs an overview on the modeling of the devices to be placed and the mathematical analysis of the problem which has been covered in this section.

2.1 FACTS device modeling

In this paper two FACTS devices namely TCSC and SVC have been considered for the minimization of real power loss in the lines. A schematic model of both these devices in shown below in Fig. 1 taken from Jumaat et al. (2012).

2.1.1 Thyristor controlled series compensator (TCSC)

A TCSC comprises of a capacitor bank in parallel with the pair of thyristor controlled inductive branch in anti-parallel manner. the schematic diagram of a TCSC is shown in Fig. 1a. The complete unit shown below is connected in series with the transmission line. The effective reactance of the unit can be given as Eq. 2.1 in Jumaat et al. (2012):

$$x_{TCSC} = \frac{x_C \times x_L}{\frac{x_C}{\pi}[2(\pi - \alpha) + sin(2\alpha)] - x_L}, \tag{2.1}$$

where x_C and x_L are the reactance offered by the capacitor and reactor respectively and α is the firing angle of the thyristors. The rating of TCSC to be installed is treated as one of the independent variables to be optimized can be written as:

$$x_{TCSC} = r_{TCSC} \times x_{Line}, \tag{2.2}$$

where x_{Line} is the reactance of the line where TCSC is placed and r_{TCSC} is the degree of compensation provided by the device. The limits of the degree of compensation are predetermined between $[-0.8, 0.2]$ in order to avoid any situation of over and under compensation. The reactance of TCSC can be varied by variation in the firing angle and it changes the line reactance where it is connected as per the equation:

$$x_{Line}^{new} = x_{Line}^{old} + x_{TCSC}, \tag{2.3}$$

where x_{Line}^{old} and x_{Line}^{new} refer to the reactance of the line before and after placement of TCSC.

2.1.2 Static VAR compensator (SVC)

SVC is modeled as a reactive power injecting device connected in shunt with the bus. A schematic model of SVC is shown in Fig. 1b. SVC consists of a pair of thyristors connected in anti-parallel manner with a capacitor bank in shunt. The unit is connected in shunt at the bus where compensation is desired. SVC is capable of exchanging reactive power at the bus and accordingly it can provide inductive or capacitive compensation. The reactive power exchanged by SVC is given in Eq. 2.4 from Jumaat et al. (2012):

$$Q_i^{SVC} = -V_i^2 \times B_{SVC} \tag{2.4}$$

where V_i is the magnitude of voltage at the ith bus and B_{SVC} is the susceptance of the SVC given as:

$$B_{SVC} = \frac{x_L - \frac{x_C}{\pi}[2(\pi - \alpha) + sin(2\alpha)]}{x_C \times x_L}, \tag{2.5}$$

where x_C and x_L are the reactance offered by the capacitor and reactor respectively and α is the firing angle of the thyristors.

2.2 Objective function

The main frame of any optimization problem depends on the objective function based on certain pre-defined equality and inequality constraints. The problem can be mathematically framed as:

$$Minimize\ F_{obj}(x, u), \tag{2.6}$$

subject to:

$$g(x, u) = 0 \tag{2.7}$$

$$h(x, u) \leq 0, \tag{2.8}$$

where F_{obj} represents the objective function to be optimized, x stands for the dependent variables of the optimization problem like the real and reactive power

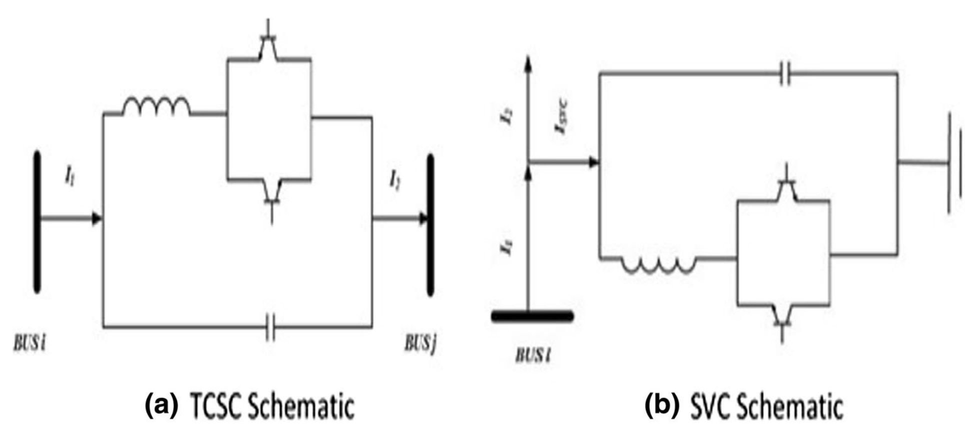

Fig. 1 Schematic diagram of TCSC and SVC

generated at the slack bus, reactive power generation of the generators, voltage magnitudes and angles of the bus voltages and u refers to the independent variables of the optimization problem which include the location, type (in case of multi-type FACTS device installation) and ratings of the FACTS devices to be installed. The objective of this work is to minimize the active power loss in the transmission loss in the network given as:

$$P_{loss} = \sum_{i=1}^{N_3} P_{g,i} - \sum_{i=1}^{N_3} P_{d,i}, \tag{2.9}$$

where $P_{g,i}$ refers to the active power generated at the ith bus and $P_{d,i}$ refers to the active power delivered at the ith.

2.3 Constraints

The real and reactive power balance equations as given in Jumaat et al. (2012) represent the equality constraints $g(x, u)$ are given by the operational limits as follows:

$$\begin{aligned} &P_{g,i} - P_{d,i} - |V_i| \sum_{j=1}^{N_3} |V_j| \big(G_{i,j} cos\big(\delta_i - \delta_j\big) \\ &\quad + B_{i,j} sin\big(\delta_i - \delta_j\big)\big) = 0 \\ &\quad \forall \; i \in [1, N_3] Q_{g,i} - Q_{d,i} - |V_i| \sum_{j=1}^{N_3} |V_j| \big(G_{i,j} sin\big(\delta_i - \delta_j\big) \\ &\quad + B_{i,j} cos\big(\delta_i - \delta_j\big)\big) = 0 \quad \forall \; i \in [1, N_3] \end{aligned} \tag{2.10}$$

and the inequality constraints, $h(x, u)$ are given below in Eq. 2.11 from Jumaat et al. (2012):

$$\begin{aligned} &P_{g,i}^{min} \le P_{g,i} \le P_{g,i}^{max} \quad \forall \; i \in [1, N_1] Q_{g,i}^{min} \le Q_{g,i} \le Q_{g,i}^{max} \\ &\quad \forall \; i \in [1, N_1] V_{l,j}^{min} \le V_{l,j} \le V_{l,j}^{max} \\ &\quad \forall \; j \in [1, N_3] \delta_{l,j}^{min} \le \delta_{l,j} \le \delta_{l,j}^{max} \\ &\quad \forall \; j \in [1, N_3] x_{tcsc}^{min} \le x_{tcsc} \le x_{tcsc}^{max} Q_{SVC}^{min} \le Q_{SVC} \le Q_{SVC}^{max} \end{aligned} \tag{2.11}$$

where N_1 is the total number of generating units, N_2 is the total number of transmission lines, N_3 is the total number of buses, $P_{g,i}$ is the active power at ith generator bus $i \in [1, N_1]$, $Q_{g,i}$ is the reactive power at ith generator bus $i \in [1, N_1]$, V_j is the voltage magnitude at jth bus $j \in [1, N_3]$, δ_i and δ_j is the voltage angle at the ith and jth buses respectively, x_{tcsc} is the reactance of TCSC where $x_{tcsc} \in [-0.8, 0.2]$ (Gerbex et al. 2001), Q_{SVC} is the reactive power rating of SVC where $Q_{SVC} \in [-100, 100]$ (Gerbex et al. 2001).

2.4 Fitness function formulation

The optimal allocation involving the location and rating of FACTS devices is accomplished taking the installation cost of devices into account. The objective of this paper is to minimize the transmission loss without violating the constraints. The minimization is achieved through meta-heuristic techniques where the fitness function plays a key role in selection or rejection of the randomly selected variables.The fitness function can be framed mathematically as per the Eq. 2.12 as given in Saravanan et al. (2007):

$$IC = C \times S \times 1000, \tag{2.12}$$

where IC refers to the installation cost of devices in US\$, C is the cost of FACTS device in US\$/KVar and S is given as Eq. 2.13:

$$S = |Q_2 - Q_1|, \tag{2.13}$$

where Q_1 and Q_2 are the reactive power flowing in the lines before and after the installation of FACTS devices respectively. The cost C depends upon the type of FACTS device installed. The cost for TCSC and SVC can be written as Eq. 2.14 taken from Cai et al. (2004):

$$\begin{aligned} C_{TCSC} &= 0.0015S^2 - 0.7130S + 153.75 \\ C_{SVC} &= 0.0003S^2 - 0.3051S + 127.38. \end{aligned} \tag{2.14}$$

3 Optimization techniques applied to the problem

The problem of optimal allocation of FACTS devices is approached through three different techniques. Firstly a standard swarm based method of particle swarm optimization (PSO) is applied followed by a recently developed technique called Moth flame optimization (MFO) (Mirjalili 2015) and JAYA blended methodology with MFO named as JAYA blended MFO (J-MFO) which has been proposed for the first time by the authors. The concept of JAYA algorithm has been proposed by Rao (2016). The algorithm emphasizes on the elimination of the worst results to reach the best and optimal solution. This technique not only ensures faster results but also the better ones which has been shown in Subhashini and Chinta (2019). This feature has encouraged the authors to take up the existing problem of FACTS allocation and solve it by enhancing the performance of MFO through the incorporation of JAYA algorithm with it.

3.1 Moth flame optimization (MFO)

Moth flame optimization (Mirjalili 2015) is a recently developed swarm algorithm based on the nature of moths where they travel in dark following a light source. Here the moths are treated as the search agents and the flame is the best possible optimum solution where the moths need to reach. The moths are represented as a 2-dimensional matrix comprising of randomly selected values lying in the range pre-defined for the control variables to be optimized:

$$[M] = [[L][T][R]], \tag{3.1}$$

where $[L]$ gives the location for the FACTS devices as:

$$[L] = \begin{bmatrix} L_{11} & L_{12} & .. & L_{1N_d} \\ L_{21} & L_{22} & .. & L_{2N_d} \\ .. & & & \\ .. & & & \\ L_{N_p1} & L_{N_p2} & .. & L_{N_pN_d} \end{bmatrix} \tag{3.2}$$

$[T]$ is the type of each FACTS device whether TCSC or SVC. While TCSC is denoted by a fixed number 1, SVC is represented as 2:

$$[T] = \begin{bmatrix} T_{11} & T_{12} & .. & T_{1N_d} \\ T_{21} & T_{22} & .. & T_{2N_d} \\ .. & & & \\ .. & & & \\ T_{N_p1} & T_{N_p2} & .. & T_{N_pN_d} \end{bmatrix} \tag{3.3}$$

and finally $[R]$ gives the rating of the devices to be installed at the concerned locations. Mathematically it is represented as:

$$[R] = \begin{bmatrix} R_{11} & R_{12} & .. & R_{1N_d} \\ R_{21} & R_{22} & .. & R_{2N_d} \\ .. & & & \\ .. & & & \\ R_{N_p1} & R_{N_p2} & .. & R_{N_pN_d} \end{bmatrix} \tag{3.4}$$

where N_d and N_p are the number of FACTS devices to be placed and population size of the search space respectively. The fitness of each moth is evaluated by substituting the moth positions in Eq. 2.9 which is represented as:

$$[OM] = [OM_1, OM_2, \ldots, OM_{N_p}]^T. \tag{3.5}$$

The flames on the other hand represent the values yielding the best fitness. The acceptance or rejection of the proposed values depends on the value of fitness function evaluated from the moths and flames separately and then compared. The key equation from Mirjalili (2015) which governs the movement of the moths in the search space is given as:

$$M_i^{new} = D_i \times e^{bt} \times cos(2 \times \pi \times t) + F_j, \tag{3.6}$$

where M_i^{new} gives the new updated position of ith moth b is a constant equal to 1 F_j is the position of the jth flame t is a random number in $[-1, 1]$ depending on the distance of moth from the flame D_i is the distance of the ith moth from the jth flame and can be written mathematically as:

$$D_i = |F_j - M_i|. \tag{3.7}$$

3.2 JAYA blended MFO (J-MFO)

In the present work a novel hybrid optimization technique has been developed known as JAYA blended MFO (JMFO) algorithm. The original JAYA algorithm (Rao 2016) is based on the concept of using both the best solution and the worst solution in the position update equation of search agents during the optimization process as given below:

$$\begin{aligned} x_i^j(k+1) = x_i^j(k) + \alpha_i^j(k)\left[x_{best}^j(k) - |x_i^j(k)|\right] \\ - \beta_i^j(k)\left[x_{worst}^j(k) - |x_i^j(k)|\right], \end{aligned} \tag{3.8}$$

where k is the iteration index, i denotes the search agent index, j represents the variable associated with the ith agent and α and β are random numbers lying in the range [0, 1]. $x_{best}^j(k)$ and $x_{worst}^j(k)$ define the position of the jth variable of the ith agent at the kth iteration corresponding to the best and worst individual respectively. The philosophy here is to add the differential position of the best to current positions with the current position and at the same time remove the differential position of the worst to the current position from the current position to avoid the greedy situation generally encountered while only best positions are referred in the position update equation. Thus while attempt has been made to formulate a hybrid strategy considering Moth flame optimization (MFO) (Mirjalili 2015) technique with JAYA algorithm (Rao 2016), it is observed that the original MFO algorithm has already incorporated the best solution (in terms of Flame position F_j referring to Eq. 3.8) in the moth position update equation M_i. So the concept borrowed from JAYA algorithm to be included in the MFO algorithm is the term devoting the differential position of the worst to the current positions. However a spiraling motion is considered instead of a linear MFO between the moth and the flame, the same nature is protected. While worst term is taken into cognizance in the modified MFO algorithm blended with the JAYA algorithm. The moth update position of Eq. 3.9 now transformed to:

$$\begin{aligned} M_i^{new} = & \left(D_i^{best} - D_i^{worst}\right) \times e^{bt} \times cos(2 \times \pi \times t) \\ & + \left(F_j^{best} - F_q^{worst}\right). \end{aligned} \tag{3.9}$$

Here F_j^{best} and F_j^{worst} represent positions corresponding to the jth best individual and qth worst individual. This proposed JMFO algorithm has also been applied to the case studies to highlight its performance enhancement over the original MFO and with other competitors:

$$D_i^{best} = |F_{j^{best}} - M_i| D_i^{worst} = |F_{k^{worst}} - M_i|. \tag{3.10}$$

3.3 Methodology of allocation of FACTS using various algorithms

This section deals with the algorithm for the optimal allocation of FACTS devices using the various meta heuristic techniques mentioned above in Sects. 2.1, 2.2 and 2.3. The purpose of this optimization study is to minimize the active power loss in the transmission lines and keeping the bus voltages within the limits. In order to achieve this two types of FACTS devices namely TCSC and SVC are used. The fitness function for the optimization process is the installation cost of the devices and the variables to be optimized are the location and rating of the devices to be stationed at various points in the network.The steps involve din the process are as follows:

- Step 1: The network data are read and load flow is executed without installation of FACTS devices. The initial voltage and loss constraints are set.
- Step 2: The major parameters of the optimization techniques like w_{max}, w_{min}, c_1, c_2 in case of PSO, b in case of MFO and J-MFO are initialized and stored. The other parameters like population size (here 50), size of each agent (depending upon the number of devices to be installed), maximum number of iterations (here 1000) and number of runs are also initialized
- Step 3: An initial population of search agents (particle sin case of PSO and moths in case of MFO and JMFO) giving the location and rating of devices to be installed is randomly generated within the boundaries predefined for the location and ratings of the devices. Mathematically it is given as:

$$[u] = [[L][T][R]], \tag{3.11}$$

  where $[L]$ represents the set of locations of FACTS devices, $[T]$ gives the type of device (whether TCSC or SVC at each location) and $[R]$ is the rating of each one of the devices those are placed at corresponding locations. The type of device $[T]$ is incorporated as a entity in the control variable only if more than one type of device is placed. The size of each sub matrix $[L]$, $[T]$ and $[R]$ depends on the number of devices to be incorporated.
- Step 4: The network parameters are updated as per the ratings of the devices after placing them at the respective locations. The load flow is executed for the updated configuration of the system and the constraints are checked for boundary conditions as mentioned in Eq. 2.11. The active power loss is also evaluated in the load flow operation. The loss obtained with various search agents are sorted and check for the constraint satisfaction.
- Step 5: The fitness of each search agent is calculated using Eq. 2.9. The search agent with the best fitness is selected and stored. They are denoted as $P_{best,old}$ and $G_{best,old}$ in case of PSO and $M_{best,old}$ and $OM_{best,old}$ in case of MFO and JMFO.
- Step 6: The positions of the agents in the search space are updated as per the update Eqs. 3.6 and 3.9 and Step 4 is repeated again.
- Step 7: The load flow for the updated positions is carried out and
- Step 8: The fitness of each search agent is calculated using Eq. 2.9. The search agent with the best fitness is selected and stored. They are denoted as $P_{best,new}$ and $G_{best,new}$ in case of PSO and $M_{best,new}$ and $OM_{best,new}$ in case of MFO and JMFO.
- Step 9: The process from Step 6 to Step 8 are repeated till the termination criteria is satisfied. The final search agent with best fitness i.e., minimum installation cost and minimum power loss is retained as the final optimum values for the control variables.

4 Results and discussions

The efficacy of the existing technique called MFO and the proposed modification called JMFO has been established through their application to optimal FACTS allocation problem in standard IEEE 14 bus and 30 bus systems (Jumaat et al. 2012). The results obtained thereby are compared with a well known standard technique like PSO. The population size is taken as 50, maximum number of iterations are 1000 and the experiments are carried out for 20 independent runs. The study is carried out in two phases where both single and multiple device placement is done. The computational resources used for the fulfillment of the task are codes written in MATLAB 2016b with additional package of Mat Power and the simulation is done on a 2.60 GHz i5 PC with 8GB RAM. A comparison study of the minimization of power loss and installation cost of devices with TCSC and SVC using various optimization techniques is given below in Table 1.

Table 1 Minimization of active power loss through various optimization techniques using single FACTS device

IEEE systems	Type of device	P_{loss} without FACTS (MW)	PSO		MFO		JMFO	
			P_{loss} (MW)	IC (US$)	P_{loss} (MW)	IC (US$)	P_{loss} (MW)	IC (US$)
14	TCSC	12.75	11.24	155.28	10.89	155.15	**10.44**	**154.62**
	SVC		11.29	128.54	10.54	127.64	**10.15**	**127.17**
30	TCSC	16.21	15.69	154.29	14.54	154.66	**14.01**	**153.54**
	SVC		15.78	128.62	14.29	128.14	**14.00**	**127.80**

The bold numericals signifies the minimum installation cost and minimum power loss values obtained using the proposed technique

4.1 IEEE 14 bus system with single FACTS device

In this section all the three algorithms have been tested with IEEE 14 bus system for investigation of the optimal location and rating of a TCSC and a SVC in order to reduce the transmission loss. Initially the network is tested with single TCSC and SVC separately and remarkable results have been obtained. While a single TCSC minimizes the loss from 12.75 MW in an uncompensated system to 11.24 MW, 10.89 MW, 10.44 MW using PSO, MFO and JMFO respectively. On the other hand SVC could minimize the loss better by reducing it to 11.29 MW, 10.54 MW and 10.15 MW with PSO, MFO and JMFO respectively. The optimal location for TCSC detected using JMFO is at line number 14 between bus 9 and bus 14 of rating -0.004614 p.u and the same for SVC is found to be at bus number 9 with a rating of 54 *MVAR*. The convergence curve for the two devices given in Fig. 2a for TCSC and Fig. 2b for SVC show that JMFO gives better minimization than MFO and PSO. It can be seen in Table 1 that the installation cost of both TCSC and SVC i.e., 154.62 *US*$ and 127.17 *US*$ respectively, are minimum with the optimal locations and ratings found using JMFO.

4.2 IEEE 30 bus system with single FACTS device

The performance of MFO and JMFO has been compared with standard PSO technique for the objective of loss minimization of an IEEE 30 bus network. TCSC and SVC are considered for the same in separate cases. The convergence curves in Fig. 3 establish JMFO better than MFO and PSO by giving lower minimum for the installation cost of the devices. JMFO when applied to the systems, the optimal location of TCSC is found to be at line number 18 running between the buses 1 and 15 with a rating of -0.007254 p.u. Similarly, the bets location for SVC which gives the minimum power loss is found to be bus number 27 with a SVC rating of 36 *MVAR*. While with TCSC, P_{Loss} is minimized to 14.01 MW SVC reduced the power loss to 14.00 MW against 16.21 MW of uncompensated system power loss. The minimum installation cost of TCSC and SVC is obtained as 153.54 *US*$ and 127.80 *US*$ using JMFO as the optimization technique

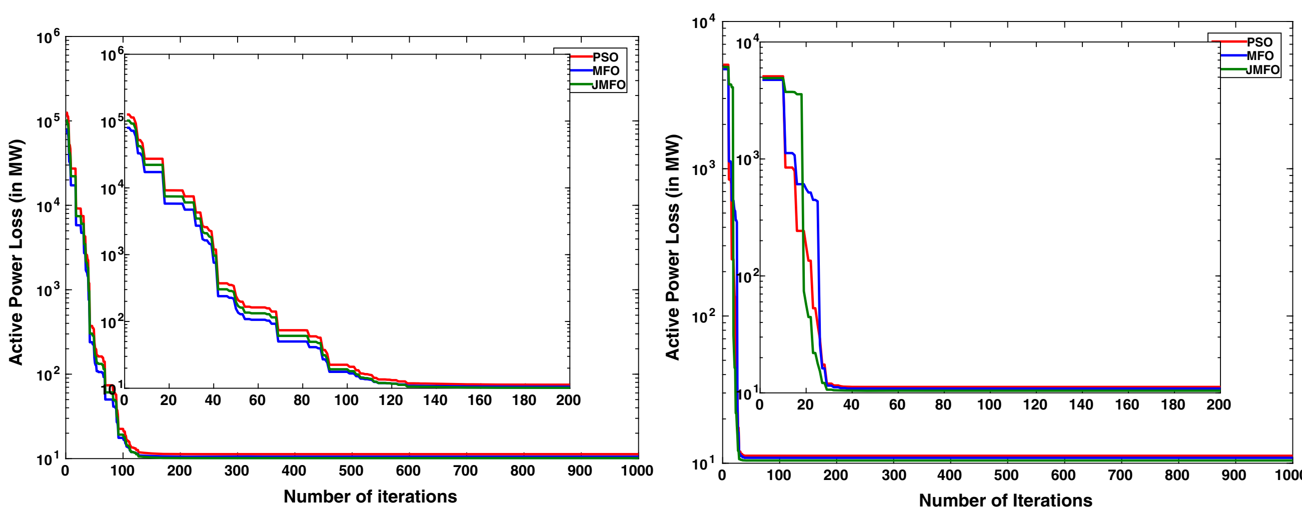

Fig. 2 Convergence curve for placement of TCSC and SVC in 14 bus system

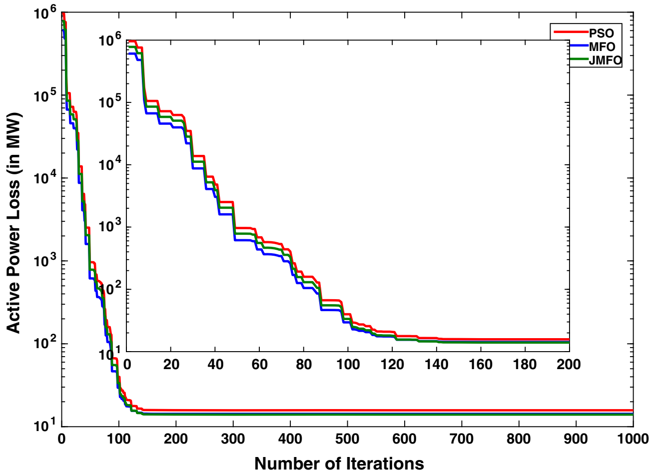

Fig. 3 Convergence curve for placement of TCSC and SVC in 30 bus system

4.3 IEEE 30 bus system with multiple FACTS device

Optimal location for placement of single and multiple types FACTS devices has been tested on IEEE 30 bus system using MFO in its virgin form as well as newly proposed JMFO. The experiments were carried out by varying the number of FACTS devices implemented in the network in order to determine the optimal number of devices which would give the minimum loss. The results obtained have been compared with a standard swarm based technique, PSO. The comparison based on loss minimization for multiple devices in three different cases has been reported in Table 2. It is observed that with 4 TCSCs of ratings −0.0027 p.u, 0.000518 p.u, −0.00711 p.u and 0.000842 p.u placed optimally at line numbers 5, 14, 18 and 36 could reduce the loss to 13.51 MW. Similarly SVCs of ratings $-45\,MVAR$, $18\,MVAR$ and $36\,MVAR$ placed at bus 9, bus 14 and bus 18 could bring down the transmission loss to 13.86 when JMFO is applied. The optimal combination of FACTS when TCSC and SVC are used together for the objective of power loss minimization. It is found that a configuration of 3 TSCSs and 2 SVCs can give the minimum power loss of 13.32 MW in comparison to 16.21 MW of an uncompensated device.The convergence curves for optimal number of devices in IEEE 30 bus system is shown in Fig. 4 which proves JMFO as the better performing algorithm.

5 Conclusion

A novel form of JAYA blended MFO for the minimization of active power loss during transmission has been presented in this paper. Two types of FACTS devices namely TCSC and SVC have been used for reducing the power loss in IEEE 14 bus and IEEE 30 bus systems. The objective of power loss reduction is achieved through various optimization techniques like PSO, MFO and JMFO where the installation cost of FACTS devices is considered for evaluating the fitness of the agents. it is worth mentioning that the concept of elimination of worst agents improves the performance of the algorithm greatly there by making JMFO significantly superior to the other techniques. The convergence curves also support the above statement in favor of JMFO.

Table 2 Minimization of active power loss through various optimization techniques using multiple FACTS device

Type of devices	No. of devices	PSO		MFO		JMFO	
		P_{loss} (MW)	IC (US$)	P_{loss} (MW)	IC (US$)	P_{loss} (MW)	IC (US$)
TCSC	4	14.01	3.6×10^4	13.69	3.2×10^4	13.51	2.7×10^4
SVC	3	14.59	7.2×10^5	14.22	6.4×10^5	13.86	6.1×10^5
BOTH	3 TCSC + 2 SVC	14.21	8.1×10^5	13.74	7.6×10^5	**13.32**	$\mathbf{7.2 \times 10^5}$

The bold numericals signifies the minimum installation cost and minimum power loss values obtained using the proposed technique

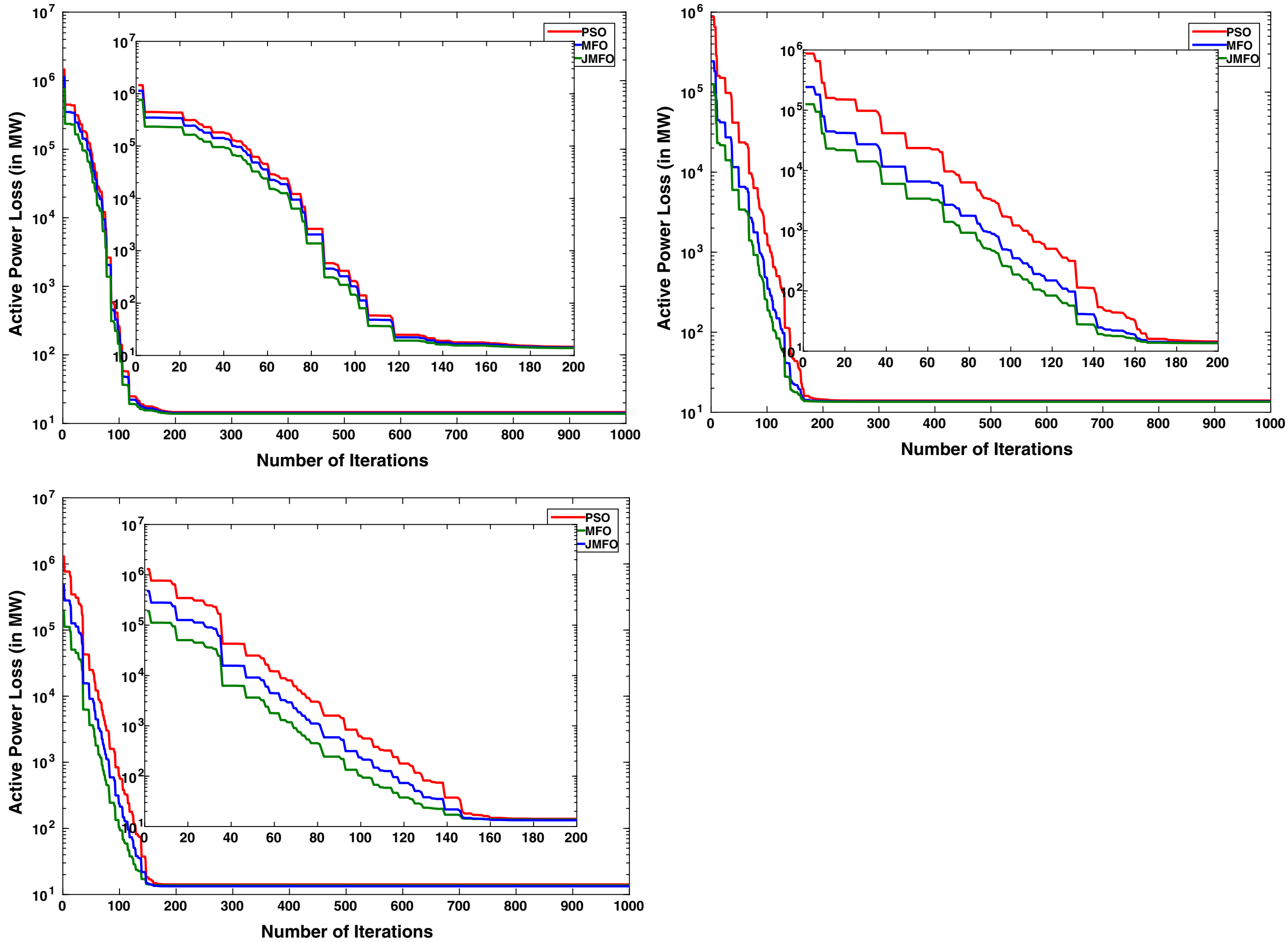

Fig. 4 Convergence curve for placement of TCSC and SVC in 30 bus system

References

Akumalla SS, Peddakotla S, Kuppa SRA (2016) A modified cuckoo search algorithm for improving voltage profile and to diminish power losses by locating multi-type facts devices. J Control Autom Electr Syst 27(1):93–104

Ara AL, Kazemi A, Niaki SN (2012) Multiobjective optimal location of facts shunt-series controllers for power system operation planning. IEEE Trans Power Deliv 27(2):481–490

Benabid R, Boudour M, Abido M (2009) Optimal location and setting of svc and tcsc devices using non-dominated sorting particle swarm optimization. Electr Power Syst Res 79(12):1668–1677

Bhattacharyya B, Goswami S (2012) Optimal planning for the placement of facts devices by differential evolution technique for the increased loadabilty of a power system. In: 2012 Asia-pacific power and energy engineering conference. IEEE, pp 1–4

Bhattacharyya B, Gupta VK (2014) Fuzzy based evolutionary algorithm for reactive power optimization with facts devices. Int J Electr Power Energy Syst 61:39–47

Cai L, Erlich I, Stamtsis G (2004) Optimal choice and allocation of facts devices in deregulated electricity market using genetic algorithms. In: IEEE PES power systems conference and exposition. IEEE, pp 201–207

Duan C, Fang W, Jiang L, Niu S (2015) Facts devices allocation via sparse optimization. IEEE Trans Power Syst 31(2):1308–1319

Fughar A, Nwohu M (2014) Optimal location of statcom in Nigerian 330 kv network using ant colony optimization meta-heuristic. Glob J Res Eng

Gerbex S, Cherkaoui R, Germond AJ (2001) Optimal location of multi-type facts devices in a power system by means of genetic algorithms. IEEE Trans Power Syst 16(3):537–544

Gitizadeh M, Kalantar M (2009) Genetic algorithm-based fuzzy multi-objective approach to congestion management using facts devices. Electr Eng 90(8):539–549

Hingorani NG, Gyugyi L, El-Hawary M (2000) Understanding FACTS: concepts and technology of flexible AC transmission systems, vol 1. IEEE Press, New York

Idris RM, Khairuddin A, Mustafa M (2010) Optimal allocation of facts devices in deregulated electricity market using bees algorithm. WSEAS Trans Power Syst 5(2):108–119

Jumaat SA, Musirin I, Othman MM, Mokhlis H (2011) Transmission loss minimization using svc based on particle swarm optimization. In: 2011 IEEE symposium on industrial electronics and applications. IEEE, pp 419–424

Jumaat SA, Musirin I, Othman MM, Mokhlis H (2012) Optimal placement and sizing of multiple facts devices installation. In: 2012 IEEE international conference on power and energy (PECon). IEEE, pp 145–150

Mirjalili S (2015) Moth-flame optimization algorithm: a novel nature-inspired heuristic paradigm. Knowl Based Syst 89:228–249

Nguyen KP, Vo DN, Fujita G (2016) Hybrid cuckoo search algorithm for optimal placement and sizing of static var compensator. In: Handbook of research on modern optimization algorithms and applications in engineering and economics, IGI Global, pp 288–326

Nireekshana T, Rao GK, Raju SS (2016) Available transfer capability enhancement with facts using cat swarm optimization. Ain Shams Eng J 7(1):159–167

Parastar A, Pirayesh A, Nikoukar J (2007) Optimal location of facts devices in a power system using modified particle swarm optimization. In: 2007 42nd international universities power engineering conference. IEEE, pp 1122–1128

Phadke A, Fozdar M, Niazi K (2012) A new multi-objective fuzzy-ga formulation for optimal placement and sizing of shunt facts controller. Int J Electr Power Energy Syst 40(1):46–53

Prasad D, Mukherjee V (2016) A novel symbiotic organisms search algorithm for optimal power flow of power system with facts devices. Eng Sci Technol Int J 19(1):79–89

Ranganathan S, Kalavathi MS et al (2016) Self-adaptive firefly algorithm based multi-objectives for multi-type facts placement. IET Gener Transm Distrib 10(11):2576–2584

Rao R (2016) Jaya: a simple and new optimization algorithm for solving constrained and unconstrained optimization problems. Int J Ind Eng Comput 7(1):19–34

Rashed GI, Shaheen H, Cheng S (2007) Optimal location and parameter setting of TCSC by both genetic algorithm and particle swarm optimization. In: 2007 2nd IEEE conference on industrial electronics and applications. IEEE, pp 1141–1147

Rashedi E, Nezamabadi-Pour H, Saryazdi S, Farsangi MM (2007) Allocation of static var compensator using gravitational search algorithm. World 1:10

Ravi K, Rajaram M (2013) Optimal location of facts devices using improved particle swarm optimization. Int J Electr Power Energy Syst 49:333–338

Saravanan M, Slochanal SMR, Venkatesh P, Abraham JPS (2007) Application of particle swarm optimization technique for optimal location of facts devices considering cost of installation and system loadability. Electr Power Syst Res 77(3–4):276–283

Shaheen HI, Rashed GI, Cheng S (2011) Optimal location and parameter setting of UPFC for enhancing power system security based on differential evolution algorithm. Int J Electr Power Energy Syst 33(1):94–105

Sharma AK (2006) Optimal number and location of tcsc and loadability enhancement in deregulated electricity markets using MINLP. Int J Emerg Electr Power Syst. https://doi.org/10.2202/1553-779X.1117

Singh S, David A (2001) Optimal location of facts devices for congestion management. Electr Power Syst Res 58(2):71–79

Subhashini K, Chinta P (2019) An augmented animal migration optimization algorithm using worst solution elimination approach in the backdrop of differential evolution. Evolut Intell 12(2):273–303

Sumpavakup C, Srikun I, Chusanapiputt S (2010) A solution to the optimal power flow using artificial bee colony algorithm. In: 2010 international conference on power system technology. IEEE, pp 1–5

Sundareswaran K, Bharathram P, Siddharth M, Vaishnavi G, Shrivastava NA, Sarma H (2009) Voltage profile enhancement through optimal placement of facts devices using queen-bee-assisted GA, In: Power Systems, 2009. ICPS'09. International Conference on IEEE, pp 1–5

Sute S, Rajderkar V (2012) Sensitivity based analysis for the optimal placement of upfc for congestion management. In: IRNet transactions on electrical and electronics engineering

Tabatabaei N, Aghajani G, Boushehri N, Shoarinejad S (2011) Optimal location of facts devices using adaptive particle swarm optimization mixed with simulated annealing. Int J Tech Phys Probl Eng (IJTPE) 7:60–70

Taleb M, Salem A, Ayman A, Azma M (2016) Optimal allocation of TCSC using adaptive cuckoo search algorithm. In: 2016 eighteenth international Middle East power systems conference (MEPCON). IEEE, pp 387–391

Ushasurendra S, Parathasarthy S (2012) Congestion management in deregulated power sector using fuzzy based optimal location technique for series flexible alternative current transmission system (facts) device. J Electr Electron Eng Res 4(1):12–20

Vaidya P, Rajderkar V (2011) Optimal location of series facts devices for enhancing power system security. In: 2011 4th international conference on emerging trends in engineering & technology. IEEE, pp 185–190