ARCHIVES OF ELECTRICAL ENGINEERING VOL. 70(1), pp. 161 –172 (2021)

DOI 10.24425/aee.2021.136059

Optimal placement and sizing of FACTS devices based on Autonomous Groups Particle Swarm Optimization technique

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(Received: 06.04.2020, revised: 28.08.2020)

Abstract: This paper presents the application of Flexible Alternating Current Transmission System (FACTS) devices based on heuristic algorithms in power systems. The work proposes the Autonomous Groups Particle Swarm Optimization (AGPSO) approach for the optimal placement and sizing of the Static Var Compensator (SVC) to minimize the total active power losses in transmission lines. A comparative study is conducted with other heuristic optimization algorithms such as Particle Swarm Optimization (PSO), Time-varying Acceleration Coefficients PSO (TACPSO), Improved PSO (IPSO), Modified PSO (MPSO), and Moth-Flam Optimization (MFO) algorithms to confirm the efficacy of the proposed algorithm. Computer simulations have been carried out on MATLAB with the MATPOWER additional package to evaluate the performance of the AGPSO algorithm on the IEEE 14 and 30 bus systems. The simulation results show that the proposed algorithm offers the best performance among all algorithms with the lowest active power losses and the highest convergence rate.

Key words: active power losses minimization, AGPSO, FACTS, MFO, PSO, SVC

1. Introduction

In recent years, the demand for electricity has increased dramatically as a result of economic and population growth. Nevertheless, the expansion of transmission and power generation is limited due to finite resources and environmental restrictions. This leads to the overloading of certain transmission lines and inappropriate performance of the electrical network, which in turn affects the power system stability and security [1]. Flexible Alternating Current Transmission System (FACTS) devices provide a felicitous solution for a robust performance of the power system networks by controlling the power flow and regulating the bus voltages of the electrical power systems. This reduces the power system losses and improves the voltage profile. In addition, the optimal implementation of FACTS controllers in the power system networks increases the capacity of networks without the expensive construction of new transmission systems [2–4]. FACTS devices are based on high-speed power electronics components that are connected to the electrical networks to increase controllability and maximize the capacity of the transferred power with a fast time response taking into consideration the power system constraints [5, 6]. According to the connection mode of FACTS controllers in the power system networks, there are three main categories: a) series controllers such as thyristor switched series capacitor (TSSC) and thyristor-controlled series capacitor (TCSC), that are utilized to control the active power flow and enhance the transient stability, b) shunt controllers as static synchronous compensator (STATCOM) and static var compensator (SVC), which are used to adjust the buses voltage and control the reactive power flow, c) extensive controllers such as unified power flow controller (UPFC), which is a hybrid of the other two categories [7]. In order to attain the maximum advantages through the implementation of FACTS devices, appropriate rating devices must be situated at optimal locations. Several optimization techniques have been applied for the allocation of FACTS controllers, which can be classified as linear, analytical programming, and heuristic search methods. The optimal placement and proper parameter sizing of FACTS devices is a complex optimization problem. Heuristic search methods are the fastest, reliable and efficient techniques for these problems [8, 9]. Many heuristic techniques have been exercised to obtain the favorable setting of FACTS devices [10–13]. In [10], a hybrid algorithm combining JAYA blended with moth flame is proposed to reduce the transmission losses of the power system networks through installation of a SVC and TCSC. Although the proposed technique has outperformed the comparative algorithms, the heavy loading condition has not been investigated. Reference [12] suggested a harmony search technique for optimal setting of the SVC controller to enhance the voltage stability. The location of the SVC is predefined by using the L-index. However, the convergence rate of the proposed method is quite slow. In [13], a modified PSO algorithm has been introduced to determine the optimum location and parameters of a STATCOM in order to minimize voltage deviations under normal operating conditions. Nevertheless, the proposed algorithm depends on constant acceleration coefficients, which reduce the ability of particles to explore and exploit the entire search space.

The main challenges of the conventional PSO algorithm are slow convergence rate and local minima trapping. Consequently, the application of the conventional PSO to FACTS allocation fails to achieve the global solution. In this work, the problems of the classical PSO algorithm are addressed through the implementation of a new improved particle swarm optimization algorithm known as the Autonomous Group Particle Swarm Optimization (AGPSO) technique. In contrast to the traditional PSO method, the AGPSO approach provides several autonomous strategies for particle behavior that result in better exploitation and exploration of the search space, as explained in Section 4. This paper aims to optimize the placement and size of SVC based on the

AGPSO technique in order to minimize the active power losses in the electrical power system. The proposed approach can find the best solution with significantly fewer iterations and a high convergence rate compared to other optimization algorithms.

The remainder of this article has the following structure: Section 2 describes the modeling of SVC devices. Section 3 presents the problem formulation. Section 4 describes the proposed AGPSO methodology. The results obtained are analyzed in Section 5. Finally, the conclusion is presented in Section 6.

2. Static VAR Compensator (SVC) modeling

The SVC is one of the shunt-connected FACTS controllers, which is widely utilized for the reactive power compensation in the transmission power systems. The output of the SVC can be regulated to exchange inductive or capacitive current to control a specific power system parameter [6, 14]. In this paper, the SVC is modeled as a reactive power injection device. The structure of the SVC is shown in Fig. 1. It consists of a capacitor bank connected in parallel to a thyristor-controlled reactor. The reactive power output of the SVC can be expressed as given below:

$$Q_i = -V_i^2 \times B_{svc}\,, \tag{1}$$

where V_i is the voltage magnitude of the i-th bus and B_{svc} represents the susceptance of the SVC. The value of B_{svc} can be controlled by adapting the firing angle of the thyristors as given in reference [15]:

$$B_{svc} = \frac{x_l - (2\pi - 2\alpha + \sin(2\alpha))\left(\dfrac{xl}{\pi}\right)}{x_l x_c}\,, \tag{2}$$

where x_l and x_c are the reactance of the reactor and capacitor, respectively, and α represents the firing angle of the thyristors.

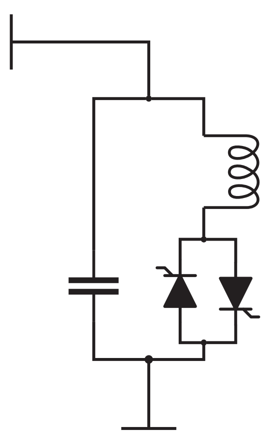

Fig. 1. Schematic diagram of SVC

3. Problem formulation

3.1. Objective function

This paper is intended to reduce the active power losses in the transmission lines, which can be expressed as follows:

$$p_L = \sum_{m=1}^{NT} G_l \left[V_i^2 + V_j^2 - 2V_i V_j \cos\delta_{ij}\right], \tag{3}$$

where NT is the total number of transmission lines, V_i and V_j are the voltage magnitudes of the buses i and j, respectively, at ends of the $m-$th line, δ_{ij} is the voltage angle difference between bus i and bus j, and G_l is the conductance of the $m-$th line.

3.2. Constrains

The optimization problem is subjected to the following constraints:

$$P_{G_i} - P_{D_i} - \sum_{j-1}^{N} V_i V_j \left[G_{ij}\cos(\delta_{ij}) + B_{ij}\sin(\delta_{ij})\right] = 0, \tag{4}$$

$$Q_{G_i} - Q_{D_i} - \sum_{j=1}^{N} V_i V_j \left[G_{ij}\sin(\delta_{ij}) - B_{ij}\cos(\delta_{ij})\right] = 0, \tag{5}$$

$$V_{i\_\min} \leq V_i \leq V_{i\_\max}, \tag{6}$$

$$S_{ij} \leq S_{i\_\max}, \tag{7}$$

$$Q_{svc}^{\min} \leq Q_{svc} \leq Q_{svc}^{\max}, \tag{8}$$

where P_{Gi}, P_{Di} are the active power generated and demanded at bus i, Q_{Gi}, Q_{Di} are the reactive power generated and demanded at bus i, N is the total number of buses, S_{ij} is the apparent power flow inline $i-j$, $S_{ij\_\max}$ is the thermal limit of line $i-j$, G_{ij} and B_{ij} are the transfer conductance and susceptance between bus i and bus j, respectively and $Q_{svc}^{\min}$, $Q_{svc}^{\max}$ are the maximum and minimum reactive power offered by the SVC device.

4. Autonomous Groups Particle Swarm Optimization (AGPSO) methodology

The PSO algorithm has been widely applied to the allocation of FACTS devices due to its less tuned user control parameters, uncomplicated implementation, and low computational costs [16]. However, the PSO algorithm is suffering from a slow convergence rate and sensitivity to fall into local optima [13, 17]. In this section, the Autonomous Groups Particle Swarm Optimization (AGPSO) is proposed to overcome these drawbacks. A brief overview of the conventional PSO is presented in the following subsection.

4.1. Standard Particle Swarm Optimization technique

PSO is an optimization algorithm that mimics the navigation and foraging of a bird flock or a fish school that uses swarm individuals (particles) motion around the search space to find the best solution. Particle motion is influenced by the achieved personal best position of the particle and the overall best position of the swarm. Each particle is defined by two vectors: the position vector and the velocity vector [18,19]. Position of each particle changes at every iteration according to the updated velocity as given below:

$$v_i^{l+1} = \omega v_i^l + c_1 r_1 \left(p\text{best}_i - x_i^l\right) + c_2 r_2 \left(g\text{best} - x_i^l\right), \tag{9}$$

$$x_i^{l+1} = x_i^l + v_i^l L, \tag{10}$$

$$\omega_l = \omega_{\max} - \left(\frac{\omega_{\max} - \omega_{\min}}{L}\right) l, \tag{11}$$

where l is the current iteration, and L is the maximum iteration, v_i^{l+1} is the velocity vector of the particle i in the iteration $l + 1$, ω is the inertia weight constant c_1 and c_2 are acceleration coefficients, r_1 and r_2 are random parameters, $p$best and $g$best are the best particle position and best global position respectively, x_i^{l+1} is the position vector of particle i in iteration $l + 1$, $\omega_{\max}$, $\omega_{\min}$ are the maximum and minimum values of the inertia weight constant.

4.2. AGPSO algorithm

According to the PSO algorithm, two parameters play a major role in controlling the behavior of the particles in the search space, namely cognitive and social coefficients (c_1 and c_2). When the social coefficient c_2 is relatively higher than the cognitive coefficient c_1, then the particles search the problem space more globally. In contrast, when c_1 is relatively greater than c_2, then the particles have a high local exploration capability [20]. In the traditional PSO algorithm, these parameters are considered as fixed values. Consequently, personal and social behavior for all particles reacts in the same manner, leading to the aforementioned disadvantages of the classical PSO technique. According to reference [21], the AGPSO approach provides variable values for c_1 and c_2 at each iteration. This leads to the generation of a variety of particle behaviors to overcome falls in local optima and increase the convergence speed of the optimization process. The individuals (particles) are divided into four autonomous groups inspired by the termite colony, each of which has a mathematical model for updating the values of the constants c_1 and c_2 as given in Table 1.

In this work, the third root and cubic functions are allocated to the acceleration coefficient models of the AGPSO groups as shown in Table 1. For the first and second groups, the values of c_1 and c_2 are updated according to the third root and cubic functions, respectively. Whereas, those values for the third group are updated according to the third root function for c_1 and the cubic function for c_2 and vice versa for the fourth group [21]. Fig. 2 shows the values of the time-varying accelerator coefficients c_1 and c_2 which have been adapted using various functions with different curvatures, intersection points, and slopes that allow a high diversity of the action of the particles during the optimization procedure. This leads to a better balance between exploitation and exploration of the search space.

Table 1. Update scheme of c_1 and c_2

Groups of particles	**Update model of c_1**	**Update model of c_2**
Group 1	$1.95 - \dfrac{2l^{1/3}}{L^{1/3}}$	$\dfrac{2l^{1/3}}{L^{1/3}} + 0.05$
Group 2	$\dfrac{-2l^3}{L^3} + 2.5$	$\dfrac{2l^3}{L^3} + 0.5$
Group 3	$1.95 - \dfrac{2l^{1/3}}{L^{1/3}}$	$\dfrac{2l^3}{L^3} + 0.5$
Group 4	$\dfrac{-2l^3}{L^3} + 2.5$	$\dfrac{2l^{1/3}}{L^{1/3}} + 0.05$

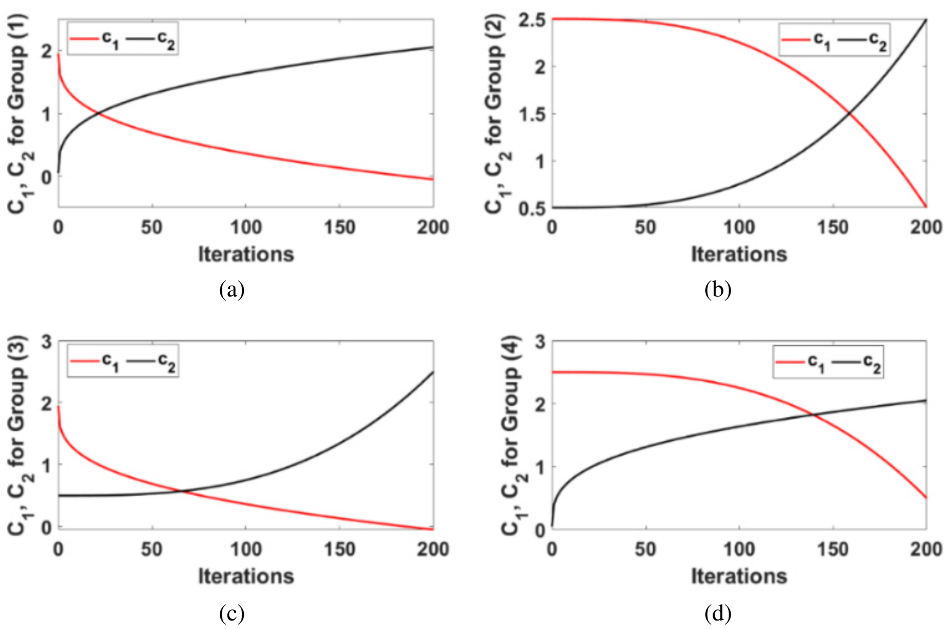

Fig. 2. Update strategies of c_1 and c_2: (a) first group; (b) second group; (c) third group; (d) fourth group

The flowchart of the AGPSO algorithm is as shown in Fig. 3. Firstly, all individuals are randomly initialized in the search space. Then, the particles are randomly divided into four predefined autonomous groups. For each iteration, the fitness, *p*best of each particle, and *g*best of the swarm are calculated. For all particles, the coefficients c_1 and c_2 are updated using the mathematical model for each group. After that, the new values accelerator coefficients are substituted in (9) and (10) to determine the velocities and positions of particles. Then, the inertia weight is calculated from (11). If the termination criteria are satisfied, then the optimal solution is obtained. Otherwise, go to the next iteration.

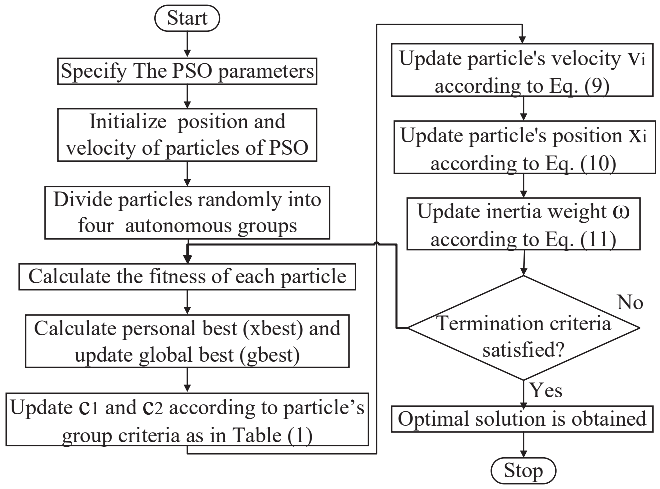

Fig. 3. Flowchart of the AGPSO algorithm

5. Simulation results and discussion

In order to recognize the effectiveness and applicability of the AGPSO technique, the IEEE 14 and 30 bus systems have been tested to find the optimal placement and size of the SVC controller. The bus and line data of the standard IEEE 14 and 30 bus systems can be found in [22]. The findings obtained are compared to Time-varying Acceleration Coefficients PSO (TACPSO) [21], Improved PSO (IPSO) [23], Modified PSO (MPSO) [24] and Moth-Flam Optimization (MFO) algorithms [25]. The parameters of the PSO algorithms are listed in Table 2.

Table 2. Parameters of PSO algorithms

Parameters	**TACPSO**	**MPSO**	**IPSO**	**AGPSO**	**PSO**
Inertial weight	0.4–0.9	0.4–0.9	0.4–0.9	0.4–0.9	0.4–0.9
Updating of c_1	$0.5 + 2e^{-(4l/L)^2}$	$2.55 + \left(\frac{-2.05}{L}\right) l$	$2.5 + 2\left(\frac{l}{L}\right)^2 - 2\left(\frac{2l}{L}\right)^2$	Table 1	2
Updating of c_2	$2.2 + 2e^{-(4l/L)^2}$	$1.25 + \left(\frac{l}{L}\right)$	$0.5 - 2\left(\frac{l}{L}\right)^2 + 2\left(\frac{2l}{L}\right)^2$		2
r_1	0–1	0–1	0–1	0–1	0–1
r_2	0–1	0–1	0–1	0–1	0–1

For all algorithms, the population size is selected as 50 search agents (particles for PSO algorithms and moth for MFO) and the maximum number of iterations is 200. In order to demonstrate the effect of the SVC on the active power losses and voltage profile under heavy loading conditions, the total reactive load is modified to 30 MVAR at buses 14 and 26 for the IEEE 14 and 30 bus systems, respectively. For both systems, all PV bus voltages are maintained within the range of 0.95–1.1 p.u., whilst all PQ bus voltages are kept within the range of 0.95–1.05 p.u. The limits of the reactive power of the selected SVC are ±100 MVAR. The MVA base is taken as 100 for both tested systems. The software that implements algorithms is developed in the MATLAB 2018b environment with an additional Matpower package and simulated on an 8 GB RAM, 2.8 GHz core i7 processor. Power flow calculations are carried out using the Newton–Raphson method to obtain the bus voltages and power losses of all tested systems. It is worth mentioning that the total real power losses of the IEEE 14 bus system before and after modification are 13.3933 MW and 14.4373 MW, respectively. Fig. 4 illustrates the active power loss curves of all algorithms for IEEE 14 bus system. As can be seen, without installing the SVC in the IEEE 14 bus power network, the total active power losses are 14.4373 MW. On the other hand, using the SVC based on the AGPSO algorithm reduces the active power losses of the tested system to 13.3323 MW. The optimal setting of the SVC is 29.1658 MVAR connected to bus 14.

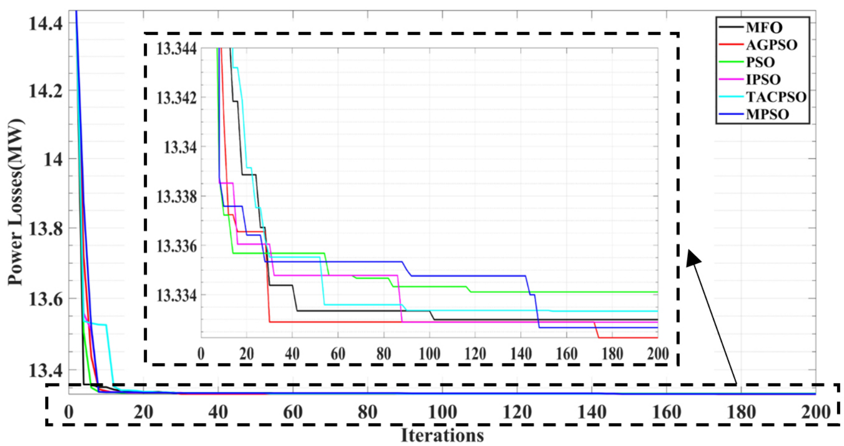

Fig. 4. Convergence curves of all algorithms for the tested IEEE 14 bus system

As evident from Fig. 4, the AGPSO algorithm exhibits the best performance during the optimization process. The AGPSO algorithm finds a solution close to the global optima in a few numbers of iterations. For example, the solution offered by the AGPSO at the 28^{th} iteration reduces the total active power losses to 13.3329 MW (i.e. the resulting power losses are higher than the final solution by 0.01%). On the other hand, only IPSO and MPSO algorithms reach this solution at iterations 86 and 148, respectively. Also, the standard PSO algorithm converged to a non-global solution compared to the AGPSO algorithm, resulting in higher values of the active power system losses. At the end of the iterations, the highest real power losses are acquired by the traditional PSO followed by the TACPSO and MFO algorithms.

Table 3 provides a summary of the simulation results, reporting the optimal size and location of the SVC for all algorithms. For each technique, Table 3 also reports the corresponding active power losses for the tested IEEE 14 bus system. The voltage profile of the tested system is improved using the optimal size and location of the SVC based on AGPSO, as shown in Fig. 5.

Table 3. The optimal solution for all algorithms of the tested IEEE 14 bus system

Algorithms	SVC location (bus)	SVC rating (Mvar)	Active power losses (MW)
MFO	14	29.4832	13.3330
AGPSO	14	**29.1658**	**13.3323**
PSO	14	29.4072	13.3341
IPSO	14	28.8439	13.3329
TACPSO	14	29.5180	13.3333
MPSO	14	29.4945	13.3327

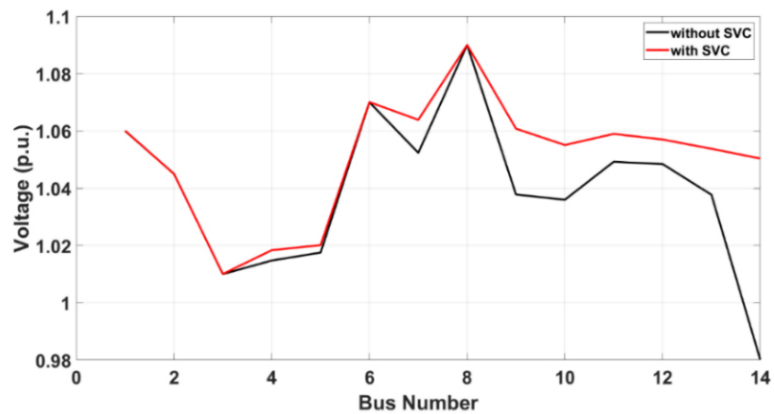

Fig. 5. The voltage profile of the tested IEEE 14 bus system

In the case of the IEEE 30 bus system, the modification of the load at bus 26 increases the total real power losses from 17.5569 MW to 25.8210 MW. Fig. 6 shows the active power loss curves of all algorithms for the IEEE 30 bus system. Among the tested algorithms, the best solution for minimizing the active power losses is offered by the AGPSO algorithm, which reduces the power losses from 25.8210 to 17.4755 MW by installing the SVC at bus 26 with a size of 31.4222 MVAR. The AGPSO approach has significant convergence profiles relative to all other algorithms and rapidly reaches a point close to the optimal solution at the 31^{st} iteration followed by the TACPSO algorithm at the 49^{th} iteration. Despite the MFO algorithm providing a close solution to the AGPSO algorithm, the conversion rate was slower and higher iterations were required to find the solution. The highest active power losses are achieved by the IPSO algorithm followed by MPSO and conventional PSO techniques. Table 4 provides a summary of the optimal solution of all algorithms for the IEEE 30 bus.

Fig. 7 shows the change in the voltage profile of the IEEE 30 bus system with and without installing the SVC device based on the AGPSO algorithm. It is evident that without using the SVC controller, the voltages at buses 25, 26, 27, 29, and 30 are dropped to 0.88, 0.69, 0.93, 0.91, and 0.89 p.u., respectively, and became out of the allowable limits. In contrast, the AGPSO algorithm

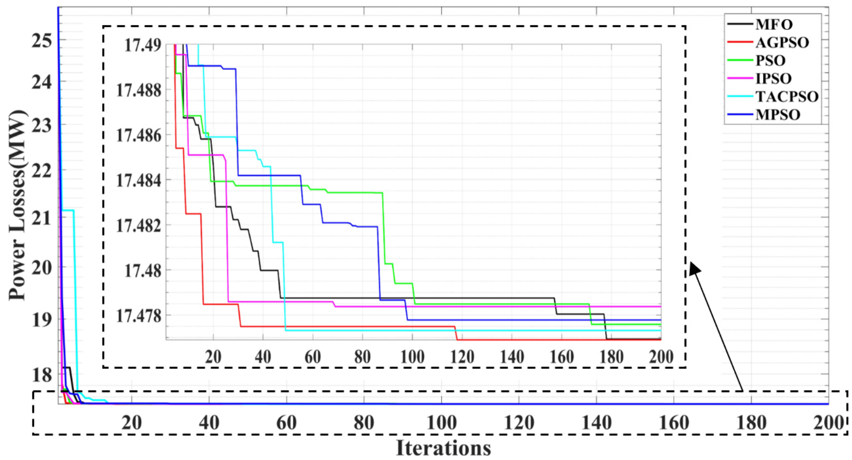

Fig. 6. Convergence curves of all algorithms for the tested IEEE 30 bus system

Table 4. The optimal solution for all algorithms of the tested IEEE 30 bus system

Algorithms	SVC location (bus)	SVC rating (Mvar)	Active power losses (MW)
MFO	26	30.0069	17.4769
AGPSO	26	**29.9248**	**17.4755**
PSO	26	30.3122	17.4776
IPSO	26	30.2082	17.4784
TACPSO	26	29.8664	17.4773
MPSO	26	30.1313	17.4778

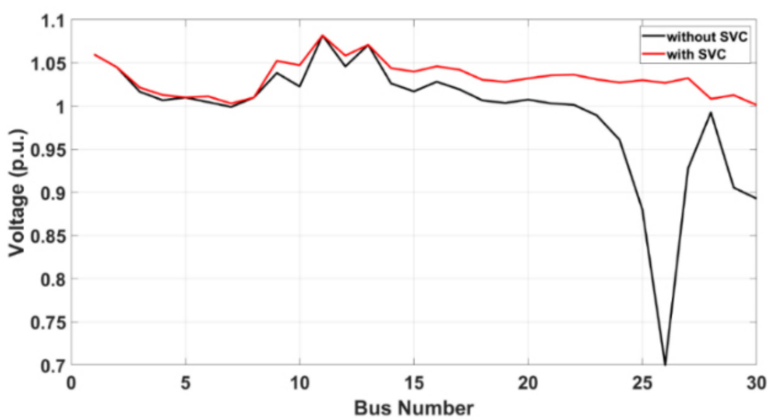

Fig. 7. The voltage profile of the tested IEEE 30 bus system

offers an appropriate size of the SVC which is capable of providing adequate reactive power during heavy loading conditions. This improves the voltage profile and keeps the bus voltage within the secured limits. As can be seen, the voltage at busses 25, 26, 27, 29, and 30 maintained within the permissible limits at 1.03, 1.027, 1.032, 1.008, 1.013, and 1.001 p.u., respectively.

6. Conclusions

The PSO algorithm has been widely applied to the allocation of FACTS devices, however, the main challenges of this algorithm are trapped in local optima and a slow convergence rate. The Autonomous Groups Particle Swarm Optimization (AGPSO) approach uses the principle of autonomous groups inspired by the diversity of individuals in natural colonies to address the drawbacks of the traditional PSO. The AGPSO technique has been proposed to obtain the optimal location and size of the SVC in the IEEE 14 and 30 bus systems. By installing the SVC based on AGPSO, the total active power losses of the IEEE 14 and 30 bus systems are reduced by 7.22% and 32.32%, respectively. In addition, the voltage profile of the power systems is improved within the allowable limits. In order to demonstrate the effectiveness of the proposed algorithm, a comparative study has been performed with other algorithms, such as PSO, TACPSO, MPSO, IPSO, and MFO. algorithms. According to the simulation results, the AGPSO algorithm obtains the near-global optimum solution with the lowest number of iterations that resulted in finding the best solution with the rapid convergence rate compared to other tested heuristics algorithms. In future work, the authors aim to apply the proposed algorithm to a real network.

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