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# Optimal placement and sizing of FACTS devices for optimal power flow using metaheuristic optimizers

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ABSTRACT

This paper proposes the implementation of various metaheuristic algorithms in solving the optimal power flow (OPF) with the presence of Flexible AC Transmission System (FACTS) devices in the power system. OPF is one of the well-known problems in power system operations and with the inclusion of the FACTS devices allocation problems into OPF will make the solution more complex. Thus, seven metaheuristic algorithms: Barnacles Mating Optimizer (BMO), Marine Predators Algorithm (MPA), Moth–Flame Optimization (MFO), Particle Swarm Optimization (PSO), Gravitational Search Algorithm (GSA), Teaching–Learning-Based Optimization (TLBO) and Heap-Based Optimizer (HBO) are used to solve two objective functions: power loss and cost minimizations. These algorithms are selected from the different metaheuristics classification groups, where the implementation of these algorithms into the said problems will be tested on the modified IEEE 14-bus system. From the simulation results, it is suggested that TLBO and HBO perform better compared to the rest of algorithms.

## 1. Introduction

In modern power system planning and operations, the Optimal Power Flow (OPF) emerged as one of the complex problems to be solved. It is expected that the power system needs to be operated at optimal condition so that the maximum security and reliability can be achieved. OPF problem solution involving the non-convex, large scale and non-linear constrained optimization problems. It is aimed to find the optimal control variables of power systems' components such as real power generations, generator's voltages, transformers setting, reactive compensation elements etc. so that the minimization of objective functions can be obtained. In addition, electronically controlled Flexible AC Transmission System (FACTS) devices can mitigate most of the problems associated with power quality and overload in the power network. Proper allocation of these devices may increase the efficient utilization of the existing facilities [1]. Thus, the optimal solution that integrating the FACTS devices' allocation into OPF problems becoming one of interesting research topics to be addressed since the implementation of FACTS devices has been proved to improve the power quality of the power system network [2,3].

To date, there are various approached to solve OPF with the presence of FACTS devices that have been proposed in literature mainly using metaheuristic such as Particle Swarm Optimization (PSO) [4], Opposition Krill Herd Algorithm (OKHA) [5], Symbiotic Organisms Search (SOS) [6], Efficient Parallel Genetic Algorithm (EPGA) [7], Success History-based Adaptive Differential Evolution (SHADE) [1], Integrated Ant Lion Optimizer (IALO) and Grasshopper Optimization Algorithm (GOA) called as IALGOA [8] and many more apart from using the conventional techniques such as sequential quadratic programming that has been proposed in [9] and Newton method which has been proposed in [10].

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In related works for metaheuristic algorithms' performance in solving engineering problems, several comparative studies have been discussed and performed such as in [11–18]. From the literature reviews, it can be noticed that the application of metaheuristic algorithms into engineering problems is ever-increasing interest, year by year especially in OPF solution. Thus, this paper proposes an application of seven recent metaheuristic algorithms namely Barnacles Mating Optimizer (BMO), Marine Predator Algorithm (MPA), Moth–Flame Optimization (MFO), Particle Swarm Optimization (PSO), Gravitational Search Algorithm (GSA), Teaching–Learning-Based Optimization (TLBO) and Heap Based Optimizer (HBO) to solve OPF problem which considering the presence of FACTS devices in the power system network. The contributions of this paper can be listed as follow:

- The implementation of seven selected metaheuristic algorithms into OPF solution on the well-known IEEE 14-bus system with considering the integration of FACTS devices allocation problem.
- Conducting comparative studies among seven recent metaheuristic algorithms in the OPF solution field.
- Four cases of single objective of OPF solution by metaheuristic algorithms: loss and cost minimizations problems.

The rest of the paper is organized as follows: Section 2 discusses the OPF formulation followed by the brief description of seven metaheuristic algorithms in Section 3. The implementation of selected metaheuristic algorithms in solving OPF is presented in Section 4 and followed by the simulation studies in Section 5. Finally, Section 6 states the conclusion of this paper.

## 2. Optimal power flow problem formulation

The main purpose of OPF is to find the optimal setting of control variables in power system components to minimize the selected objective functions while satisfying all the equality and inequality constraints. In this paper, two objectives are identified to solve OPF for the system that considering the allocation problem of FACTS devices: (1) loss minimization and (2) cost of generation minimization.

### 2.1. Minimization of power loss

The first objective function is the total power loss minimization, $F_{Loss}$, as follows:

$$F_{Loss} = \sum_{i=j}^{nl} \sum_{j\neq i}^{nl} G_{ij} \left[V_i^2 + V_j^2 - 2V_iV_j \cos\left(\delta_i - \delta_j\right)\right] \tag{1}$$

where *nl* is the number of transmission line of the power system, $G_{ij}$ is the conductance at the transmission line *i-j*, $V_i$, $\delta_i$, $V_j$ and $\delta_j$ are the sending end voltage, phase angle of sending end, receiving end voltage, and phase angle of receiving ends respectively.

### 2.2. Minimization of generation cost

Second objective function that consider in this paper is the total cost that include the valve loading effects, $F_{Cost}$ $(P_{Gi})$, which is expressed as follows:

$$F_{Cost}\left(PT_G\right) = \sum_{i=1}^{N_G} a_i + b_iP_{Gi} + c_iP_{Gi}^2 + \left|d_i \cdot sin\left[e_i \cdot \left(P_{Gi}^{min} - P_{Gi}\right)\right]\right| \tag{2}$$

where $PT_G$ is the total power output of generators, $a_i$, $b_i$, $c_i$, $d_i$ and $e_i$ denote the cost coefficients of respected generator $P_{Gi}$ with valve loading effect consideration and $P_{Gi}^{min}$ is the minimum setting of power of $i$-th generator.

### 2.3. Model of FACTS devices

In this paper, three FACTS devices will be considered which are Static VAR compensator (SVC), Thyristor-Controlled Series Compensation (TCSC) and Thyristor Controlled Phase Shifter (TCPS). Shunt compensation device SVC supplements the reactive power of the system while TCSC and TCPS are the series compensation devices which are used to enhance the loading capability and power flow of the line. Basically, the modeling of these devices are based on [1].

For SVC, it consists of a fixed capacitor with a thyristor-controlled reactor. The reactance is varied by controlling the thyristor firing angle. SVC can be utilized for both inductive and capacitive compensation. In power flow study, reactive power provided by SVC, $Q_{SVC}$ can be expressed as follows:

$$Q_{SVC} = -V_i^2.B_{SVC} \tag{3}$$

where $B_{SCV}$ is the equivalent susceptance.

For TCSC on the other hand, it consists of a fixed series capacitor ($X_C$) in parallel with a thyristor-controlled reactor ($X_L$). Similar with [1], the reactance is considered as $X_C < X_L$ so that the TCSC acts as a variable capacitive reactance. The inductive reactance is varied by controlling the firing angle of the thyristors ($\gamma$). The effective reactance of TCSC can be expressed as follows:

$$X_{TCSC}(\gamma) = \frac{X_C X_L(\gamma)}{X_L(\gamma) - X_C} \tag{4}$$

The modified equivalent reactance ($X_{eq}$) of the transmission line after incorporating TCSC can be expressed as follows:

$$X_{eq} = (1 - \tau)X_{ij} \tag{5}$$

where $\tau = \frac{X_{TCSC}}{X_{ij}}$, which is termed as the degree of series compensation with $X_{ij}$ being the line inductive reactance. The power flow equations of the line incorporating

TCSC as well as the model of TCPS integration into the existing system can be obtained in details in [1].

### 2.4. Constraints

In solving the OPF problem, all the feasible solutions need to fulfill all the equality and inequality constraints. For equality constraint, the power balance equation for real and reactive power must be satisfied and expressed as follow:

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{nB} V_j Y_{ij} \cos\left(\theta_{ij} + \delta_i - \delta_j\right) = 0 \ \forall i \in nB \tag{6}$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{nB} V_j Y_{ij} \sin\left(\theta_{ij} + \delta_i - \delta_j\right) = 0 \ \forall i \in nB \tag{7}$$

where $P_{Gi}$ and $Q_{Gi}$ are the real and reactive power generation at bus $i$, $P_{Di}$ and $Q_{Di}$ are the real and reactive load at bus $i$ and $nB$ is the total number of buses in the system.

When the FACTS devices are considered, the following equality constraints are used:

$$P_{Gi} + P_{is} - P_{Di} - V_i \sum_{j=1}^{nB} V_j Y_{ij} \cos\left(\theta_{ij} + \delta_i - \delta_j\right) = 0 \ \forall i \in nB \tag{8}$$

$$Q_{Gi} + Q_{is} + Q_{SVCi} - Q_{Di} - V_i \sum_{j=1}^{nB} V_j Y_{ij} \sin\left(\theta_{ij} + \delta_i - \delta_j\right) = 0 \ \forall i \in nB \tag{9}$$

where $P_{is}$ and $Q_{is}$ are the active and reactive power respectively, injected by the TCPS at bus $i$ [1] and $Q_{SVCi}$ is the injected reactive power at bus $i$ by the SVC.

The inequality constraint on the other hand, are the operating limits of the power system components which can represented as follow:

$$P_{Gi}^{min} \le P_{Gi} \le P_{Gi}^{max} i = 1, \ldots, N_G \tag{10}$$

$$Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max} i = 1, \ldots, N_G \tag{11}$$

$$V_{Gi}^{min} \le V_{Gi} \le V_{Gi}^{max} i = 1, \ldots, N_G \tag{12}$$

$$V_{Li}^{min} \le V_{Li} \le V_{Li}^{max} i = 1, \ldots, N_{Load} \tag{13}$$

$$Q_{Ck}^{min} \le Q_{Ck} \le Q_{Ck}^{max} k = 1, \ldots, N_{QC} \tag{14}$$

$$T_l^{min} \le T_l \le T_l^{max} l = 1, \ldots, N_T \tag{15}$$

$$\text{SVC: } Q_{SVC}^{min} \le Q_{SVC} \le Q_{SVC}^{max} \tag{16}$$

$$\text{TCSC: } \Phi_{TCSC}^{min} \le \Phi_{TCSC} \le \Phi_{TCSC}^{max} \tag{17}$$

$$\text{TCPS: } \tau_{TCPS}^{min} \le \tau_{TCPS} \le \tau_{TCPS}^{max} \tag{18}$$

where (10) and (11) represent the real and reactive power generations limits for thermal generation, respectively. Constraints on voltage of generator buses is expressed in (12), while (13) defined as the voltage limits at load buses with $N_G$ is the number of generator and $N_{Load}$ is the number of load buses. The limitation of injected MVAR and transformer tap setting are shown in (14) and (15), respectively while $N_{Qc}$ is the total number of injected MVAR and $N_T$ is the number of transformers in the system network.

It is worth to mention that all these constraints are satisfied by using the power flow program (MATPOWER) [19] to ensure the accurate results can be obtained.

## 3. Metaheuristic algorithms

### 3.1. Barnacles mating optimizer

Barnacles Mating Optimizer (BMO) has been proposed by [20–22] where it mimics the mating concept of barnacles. Barnacles are hermaphroditic organisms where they have both male and female reproduction organs. They are mating in two ways which are by copulate with the near neighbors by knocking their penis to allow the mating process and there is rare probability of sperm cast mating, where this is happened for isolate barnacles. These behaviors are inspired for exploitation and exploration process to be included in the BMO for solving optimization problems. In BMO, the exploitation process is adopted the concept of Punnet square by Hardy–Weinberg principle and the exploration process is adopted from sperm-cast mating. Only one parameter needs to be tuned namely *pl,* apart of number of population and maximum iteration in BMO. The concept of exploitation and exploration proposed in BMO can be obtained in details in [20].

### 3.2. Marine Predators Algorithm (MPA)

Next bio-inspired algorithm that will be used for solving OPF problem with FACTS devices is called Marine Predators Algorithm (MPA) that has been proposed in [23]. This algorithm is based on the marine behavioral of ocean predators by imposing the Brownian and Levy motions concepts in the algorithm. It follows the rules that naturally govern in optimal foraging strategy and encounters rate policy between predator and prey in marine ecosystem. The three phases of optimization are schematically proposed which are (1) prey movement using Brownian motion for exploration phase followed by (2) predator starts searching for its prey in Brownian motion while prey switches to Levy to efficiently search its close neighborhood and (3) finally the predator starts switching its behavior from Brownian to Levy strategy to more efficiently search a certain neighborhood. Another point which causes a behavioral change in marine predators is environmental issues such as the eddy formation or Fish Aggregating Devices (FADs) effects. The FADs are considered as local optima and their effect as trapping in these points in search space. Consideration of these longer jumps during simulation avoids stagnation in local optima.

### 3.3. Moth–Flame optimization (MFO)

Moth–Flame Optimization (MFO) algorithm is inspired from the moths' navigation method at night by maintaining a fixed angle with respect to the moon called transverse orientation proposed by Mirjalili [24]. However, they are trapped in a useless or deadly spiral path around artificial lights. In MFO, a logarithmic spiral equation is used for evaluating the moths' movement because it dictates how the moths update their positions around flames. The spiral equation allows a moth to fly "around" a flame and not necessarily in the space between them, where from this condition the exploration and exploitation of the search space can be guaranteed. It is assumed that the candidate solutions are moths and the problem's variables are the position of moths in the space. Therefore, the moths can fly in 1-D, 2-D, 3-D, or hyper dimensional space with changing their position vectors due to the MFO algorithm is also known as one of the population-based algorithms.

### 3.4. Particle Swam Optimization (PSO)

The comparison performance of the OPF analysis is not complete if not comparing the performance using the Particle Swam Optimization (PSO) algorithm. PSO is the most well-known algorithm that forming the Swarm Intelligence (SI) group of metaheuristic algorithms in solving optimization problems. It has been invented by Eberhart and Kennedy in 1995 where the algorithm is based on the social behavior of animals like a flock of birds or school of fishes [25]. PSO introduces the position and velocity of particles swarm in finding the optimal solution where it become the major influence in enhancing the exploitation and exploration abilities in searching for the optimality. All these particles will move within the searching space towards the location of food (optimal location) in a specific speed and continuously change their respective positions to arrive at the destination. Their movement is guided by their own experience namely $P_{best}$, and the experience of the other particles in a group known as $G_{best}$. Each particle will update its velocity as well as its position in order to obtain the next best search solution. In PSO, there are five parameters need to set viz. inertia weight, $w$, acceleration coefficients for cognitive and social components, $c_1$ and $c_2$, and independently random vectors, $r_1$ and $r_2$ which are uniform distributed random numbers between [0, 1].

### 3.5. Gravitational Search Algorithm (GSA)

Gravitational Search Algorithm (GSA) is inspired by the law of Newtonian gravity and mass interaction. It can be categorized as physics-based metaheuristic algorithm and the algorithm is proposed in 2009 by [26] where can be recognized as the first algorithm to solve optimization problem that fall under this category. In GSA, each mass (agent or candidate of solution) has four specifications: position, inertial mass, active gravitational and passive gravitational masses. The position of the mass corresponds to a solution of the problem and its gravitational and inertia masses are determined using a fitness or objective functions. Each mass is treated as a solution and the optimal solution is navigated by properly adjusting the gravitational and inertia masses. By lapse of time, it is expected that masses be attracted by the heavier mass and this mass can be considered as an optimum solution in the search space. The GSA could be considered as an isolated system of masses, which is like a small artificial world of masses obeying the Newtonian laws of gravitation and motion.

### 3.6. Teaching-Learning Based Optimization (TLBO)

A TLBO is inspired by the teaching and learning process in the classroom invented by [27,28] where later had numerous debate regarding the discrepancies arose such as the terms, flowchart, pseudo code and the program code as mentioned in [29,30]. Nevertheless, as far as NFL theorem is concerned, the different types of setting and problems also can give different results and interpretations. Thus, this work is using the program that has been developed by [31] which has catered all the issues raised by [29].

Similar with other metaheuristic algorithms, TLBO uses population-based solution where the population is treated as a group or a class of learners, the design variables are analogues to subjects offered to learners and the learners' result is analogues to the 'fitness'. The process of acquiring knowledge is divided into teacher and learner phases and the teacher is considered as the best solution so far [32]. This algorithm can be said classified as a non-parameter algorithm since apart of number of population and maximum iteration, there is no parameter need to be adjusted or tuned to obtain the optimal results. This algorithm is fall under human-based metaheuristic algorithm group.

### 3.7. Heap-Based Optimizer (HBO)

Heap-Based Optimizer (HBO) utilizes the heap data structure to map the concept of Corporate Rank Hierarchy (CRH) [33]. HBO can be classified as human-based metaheuristic algorithm group. The development of HBO is based on three pillars, which are the interaction between the subordinates and their immediate boss, the interaction between the colleagues, and self-contribution of the employees in the corporate company. The primary objective of this CRH is giving the formal activities an organized shape and achieving the end goals optimally. CRH manifests the population while the search agent represents a heap node. The search agent's fitness is the master of the heap node, and the population index of the search agent is the value of the heap node. In HBO, to obtain an appropriate balance between exploration and exploitation, the mathematical equations are carefully derived from three major CRH activities. In addition, a self-adaptive parameter called Gamma is designed to escape local optima and avoid premature convergence without compromising the exploitation capability of the HBO.

## 4. Metaheuristic optimizers for OPF solution with FACTS devices allocation problem

In general, OPF solution can be defined as follows:

$$\begin{aligned} &\text{Minimize } F(x,u) \\ &s.t \quad g(x,u) = 0 \\ &\qquad h(x,u) \leq 0 \end{aligned} \tag{19}$$

where $F(\boldsymbol{x}, \boldsymbol{u})$ is the objective function, $g(\boldsymbol{x}, \boldsymbol{u})$ is the equality constraints and $h(\boldsymbol{x}, \boldsymbol{u})$ is the inequality constraints. $\boldsymbol{x}$ and $\boldsymbol{u}$ are the control and state variables respectively since in power system, to obtain the optimality, not only the control variable; the state variables also play a vital role for the security of the power system operation. In this paper, four case studies will be implemented on IEEE 14-bus system where the OPF with FACTS devices will be solved by all six selected metaheuristic algorithms, as follows:

Case 1: OPF problems with SVC and TCSC for loss minimization
Case 2: OPF problems with SVC and TCPS for loss minimization
Case 3: OPF problems with SVC and TCSC for cost minimization
Case 4: OPF problems with SVC and TCPS for cost minimization

So, the set of control and state variables in OPF solution can be expressed as follow:

$$\boldsymbol{x}^T = \left[\boldsymbol{P}_{\boldsymbol{G}_2} \cdots \boldsymbol{P}_{\boldsymbol{G}_{NG}}, \boldsymbol{V}_{\boldsymbol{G}_1} \cdots \boldsymbol{V}_{\boldsymbol{G}_{NG}}, \boldsymbol{T}_1 \cdots \boldsymbol{T}_{NT}, \boldsymbol{Bus}_{SVC}, \boldsymbol{Q}_{SVC}, \boldsymbol{Branch}_{TCSC/TCPS}, \boldsymbol{\Phi}_{TCSC}/\boldsymbol{\tau}_{TCPS}\right] \tag{20}$$

$$u^T = \left[P_{G_1}, Q_{G_1} \cdots Q_{G_{NG}}, V_{L_1} \cdots V_{L_{NL}}\right] \tag{21}$$

where $P_{G1}$ is the slack bus generation, $P_{Gi}$ = the real power generation at voltage controlled buses at the slack bus, $V_{Gi}$ = the voltage magnitude at voltage controlled buses, $T_i$ = the tap settings of transformer, $Bus_{SVC}$ is the location of the SCV to be installed, $Q_{SVC}$ = the shunt injected VAR, $Branch_{TCSC/TCPS}$ is the location of TCSC or TCPS at which branch to be installed, $V_{Li}$ = the voltage magnitude at load buses and $Q_{Gi}$ is the reactive power generation for all generator units.

The application of the selected metaheuristic optimizers in solving OPF problem is to find the optimal values of control variables to minimize all the objective functions that have been discussed in previous section while fulfilling all the constraints. Initially, number of search agents or population and the maximum iteration are set. Then, all the function details such as boundary of searching areas and the function evaluation (minimization of objective functions) are determined. Each set of solution are mapped into the load flow data and load flow MATPOWER program is executed to obtain the selected objective (Cases 1 and 2). It is worth to highlight that the penalty function is enforced for the violation of inequality constraints of real power at slack bus, voltage magnitude at load buses and reactive power generations, which can be expressed as follows:

$$penalty = \lambda_P \left(P_{G1} - P_{G1}^{lim}\right)^2 + \lambda_V \sum_{i-1}^{NL} \left(V_{Li} - V_{Li}^{lim}\right)^2 + \lambda_Q \sum_{i-1}^{NG} \left(Q_{Gi} - Q_{Li}^{lim}\right)^2 \tag{22}$$

where $\lambda_P$, $\lambda_V$, and $\lambda_Q$ are the penalty factors. General flow of metaheuristic optimizers' application into OPF problem is depicted in Fig. 1.

## 5. Results and discussion

*Case 1: OPF problems with SVC and TCSC for loss minimization*

Simulations for solving OPF are executed using MATLAB and the modified IEEE 14-bus system is used for all cases. IEEE 14-bus system can be considered as small-scale problem that consists of 14 buses, 5 generators, 3 transformers and 11 loads. The modification is to change the synchronous compensator at buses 3, 6 and 8 to a thermal generator as shown in Fig. 2. As both the location and rating of FACTS devices are yet to be optimized, those are indicated with dotted lines in the diagram.

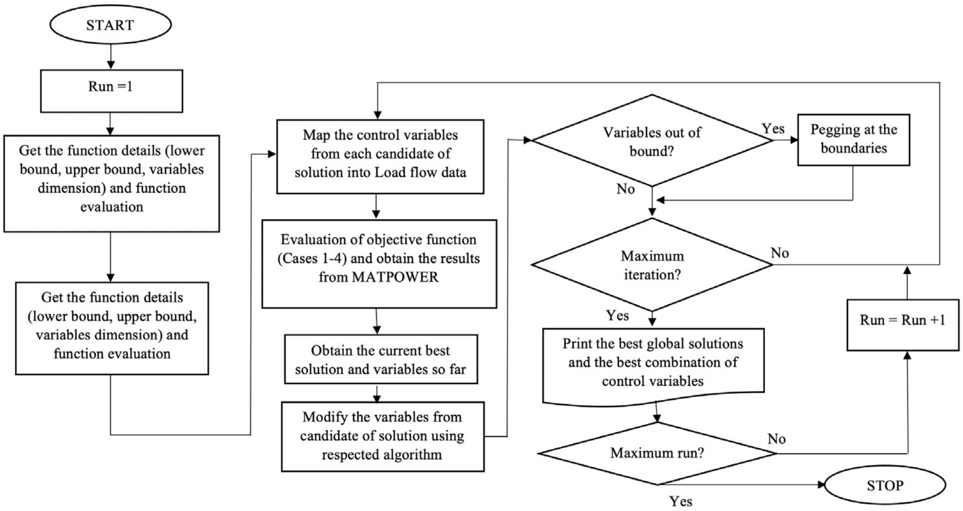


**Fig. 1.** Flow of metaheuristic algorithms for solving OPF problem with FACTS devices' allocation.

**Table 1**
Coefficients for thermal generators for modified IEEE 14-bus system.

| Generator | Bus | $a$ | $b$ | $c$ | $d$ | $e$ |
|---|---|---|---|---|---|---|
| $T_{G1}$ | 1 | 0 | 20 | 0.0430292599 | 18 | 0.037 |
| $T_{G2}$ | 2 | 0 | 20 | 0.25 | 16 | 0.038 |
| $T_{G3}$ | 3 | 0 | 40 | 0.01 | 12 | 0.045 |
| $T_{G4}$ | 6 | 0 | 40 | 0.01 | 13.5 | 0.041 |
| $T_{G5}$ | 8 | 0 | 40 | 0.01 | 13.5 | 0.041 |

All simulations for solving OPF problem with FACTS devices using all metaheuristic optimizers are implemented using MATLAB on a MacBook Pro Processor 2.40 GHz Quad-Core Intel Core i5, 8 GB RAM. For all four cases, the control variables to be optimized is 16 variables that consist of the components that have been discussed previously. Table 1 shows the coefficients of thermal generators with valve-loading effects. The population of all algorithms is set to 30 and the maximum iteration is set to 100. For all simulations, 16 control variables need to be optimized that consist of real power generation, voltage at generator buses, transformers tap setting and FACTS devices' allocation while the number of state variables are 15 viz. real power generation at slack bus, reactive power generation and voltage at load buses. All these setting have been used for all cases to obtain fair results for all simulations. It is worth to mention that the following assumptions have been made while adding the FACT devices [1]:

• SVC is not installed on generator buses as the generator itself can exchange reactive power.
• TCSC/ TCPS are not installed on branches having tap changing transformers.

Table 2 shows the detail results of the control variables with slack generator at bus 1 as well as reactive power generations obtained by all algorithms viz. BMO, MPA, MFO, PSO, GSA, TLNO and HBO. These results are the best result obtained from 30 free running of simulations. From this table, it can be seen that TLBO outperformed other compared algorithms which is highlighted in boldface. TLBO achieved the minimum total power loss, 0.918 MW and the second-best result is obtained by MFO which produced 0.949 MW. The difference results obtained between TLBO with the MFO is 0.031 MW. The worst result is obtained by GSA where the significant loss minimization from TLBO compared to GSA is about 49% reduction of power loss. This shows the effectiveness of TLBO compared to other algorithms. It is worth to mention that the total power loss for original condition without optimization of OPF and FACTS devices' allocation is 10.218 MW. Thus, from the simulations that have been conducted, it can be concluded that this is tremendous improvement of power loss reduction.

It also can be noted from the table that all algorithms gave the optimal results within the specified limits that have been set for the simulation. Most algorithms determined the SVC are located at bus 14 which are resulted from BMO, PSO, TLBO and HBO while MPA and MFO suggested the SVC should located at bus 13. Only GSA proposed to install the SVC at bus 7. These locations are not installed at generator buses. For TCSC, the location for install it varies for all algorithms which contributed significantly different for minimizing the power loss for this system. The convergence curve for all algorithms in solving this case is depicted in Fig. 3. It can be concluded that all algorithms are converged within 100 iterations.

*Case 2: OPF problems with SVC and TCPS for loss minimization*

In this case, the TCPS is considered that replacing the TCSC as in Case 1, where the optimal location and angle of TCPS be optimized by all algorithms. Table 3 shows the best of detail results obtained for all algorithms in 30 runs of simulation. Again, it can be noted that TLBO outperformed other compared algorithms in terms of obtaining the minimum loss production, which is highlighted in boldface. For this case, it can be noted that all algorithms able to obtain the optimal results within the boundaries,

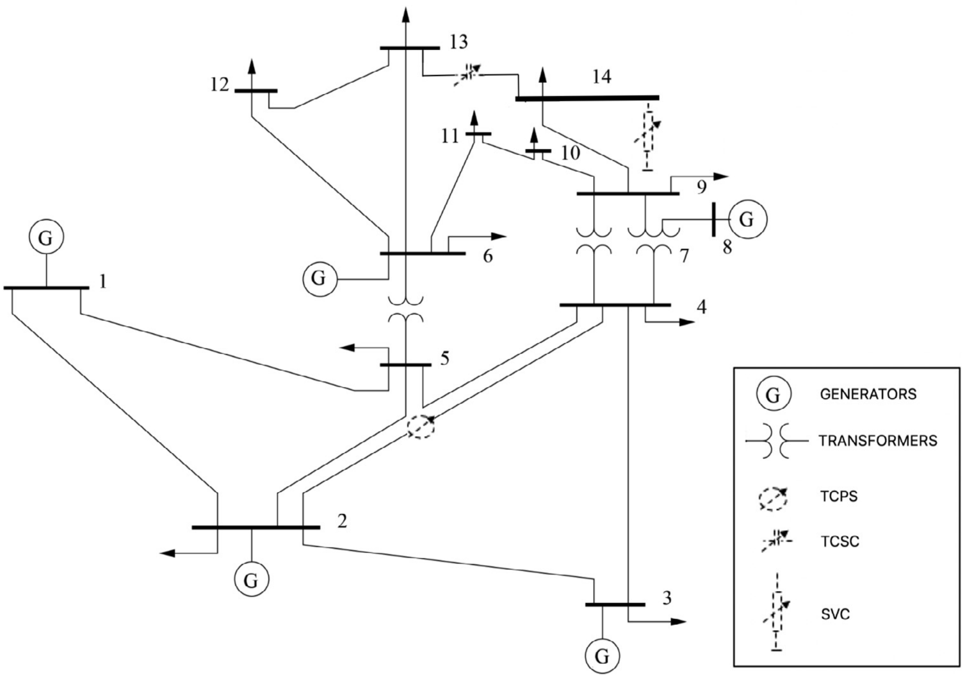


**Fig. 2.** Modified IEEE 14-bus system.

**Table 2**
Detail results for different algorithms on Case 1.

| Control variables | Min | Max | BMO | MPA | MFO | PSO | GSA | TLBO | HBO |
|---|---|---|---|---|---|---|---|---|---|
| $P_{G2}$ | 10 | 140 | 10.0000 | 12.9168 | 10.0000 | 11.6665 | 32.3766 | 10.0000 | 10.0000 |
| $P_{G3}$ | 10 | 100 | 88.7592 | 92.3804 | 100.0000 | 78.8669 | 59.3109 | 82.4516 | 82.1314 |
| $P_{G6}$ | 10 | 100 | 32.5512 | 35.4701 | 28.4597 | 39.7532 | 46.8738 | 34.1794 | 38.4139 |
| $P_{G8}$ | 10 | 100 | 78.4944 | 69.1903 | 71.4546 | 79.1750 | 61.3109 | 83.2532 | 79.1186 |
| $V_1$ | 0.95 | 1.1 | 1.0613 | 1.0624 | 1.0516 | 1.0709 | 1.0445 | 1.0649 | 1.0293 |
| $V_2$ | 0.95 | 1.1 | 1.0521 | 1.0545 | 1.0430 | 1.0630 | 1.0338 | 1.0561 | 1.0234 |
| $V_3$ | 0.95 | 1.1 | 1.0433 | 1.0522 | 1.0449 | 1.0550 | 1.0224 | 1.0503 | 1.0146 |
| $V_6$ | 0.95 | 1.1 | 0.9824 | 1.0260 | 1.0486 | 1.0351 | 1.0304 | 1.0371 | 1.0262 |
| $V_8$ | 0.95 | 1.1 | 0.9583 | 1.0392 | 1.0579 | 1.0297 | 1.0245 | 1.0590 | 1.0174 |
| $T_{4-7}$ | 0.9 | 1.1 | 1.1 | 1.06 | 1.04 | 1.1 | 1.04 | 1 | 1 |
| $T_{4-9}$ | 0.9 | 1.1 | 0.9 | 0.96 | 0.9 | 0.9 | 1 | 1 | 0.98 |
| $T_{5-6}$ | 0.9 | 1.1 | 1.1 | 1 | 0.98 | 1 | 0.98 | 1 | 0.98 |
| SVC bus no. | | | 14 | 13 | 13 | 14 | 7 | 14 | 14 |
| $Q_{SVC}$(MVAR) | −10 | 10 | 10.0000 | 9.9587 | 7.6357 | 4.0764 | −0.9047 | 2.0756 | 10.0000 |
| TCSC branch | | | 13 (6–13) | 20 (13–14) | 2 (1–5) | 3 (2–3) | 12 (6–12) | 11 (6–11) | 20 (13–14) |
| $\tau$TCSC$_1$(%) | 0 | 50% | 0.12 | 0.19 | 0.17 | 0.02 | 0.23 | 0.50 | 0.10 |
| Loss (MW) | | | 1.013 | 0.958 | 0.949 | 0.95 | 1.784 | **0.918** | 0.969 |
| State variables | | | | | | | | | |
| $P_{G1}$ | 50 | 332.4 | 50.21 | 50 | 50.03 | 50.49 | 60.91 | 50.03 | 50.31 |
| $Q_{G1}$ | −40 | 50 | 2.08 | 0.10 | 0.98 | 0.28 | 2.72 | 1.41 | −4.85 |
| $Q_{G2}$ | −40 | 40 | 5.05 | 0.51 | −3.81 | 6.19 | −3.84 | 1.32 | 10.23 |
| $Q_{G3}$ | −6 | 40 | 13.59 | 16.10 | 17.80 | 15.44 | 16.65 | 15.53 | 13.46 |
| $Q_{G6}$ | −6 | 24 | 23.47 | 0.14 | 5.70 | 8.14 | 15.37 | 11.27 | 11.47 |
| $Q_{G8}$ | −6 | 24 | 1.14 | 16.90 | 16.22 | 16.72 | 15.02 | 14.39 | 7.47 |

whether for control variables as well as for state variables. The convergence curve for all algorithms in solving this case is depicted in Fig. 4. It can be seen that GSA converged too soon which is less than 10 iterations which resulted the worst results compared to others.

*Case 3: OPF problems with SVC and TCSC for cost minimization*

For this case, the minimization of generator cost is considered as stated in Eq. (2) which including the valve-loading effects of the power generation. The control variables to be optimized is similar with Case 1, only the objective now is to find minimum cost generation. Detail optimal results obtained by all algorithms are tabulated in Table 4, where the best cost minimization is achieved by TLBO which is 5943.47 $/hour and the worst result is obtained by GSA, 5978.56 $/hour. The difference results obtained between

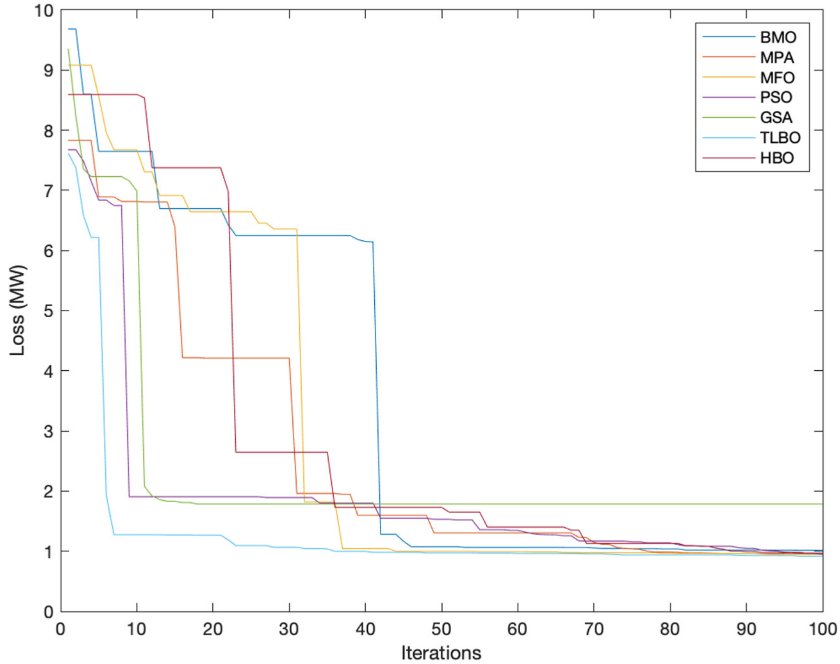


**Fig. 3.** Convergence curve for all algorithms of Case 1.

**Table 3**
Detail results for different algorithms on Case 2.

| Control variables | Min | Max | BMO | MPA | MFO | PSO | GSA | TLBO | HBO |
|---|---|---|---|---|---|---|---|---|---|
| $P_{G2}$ | 10 | 140 | 10.0000 | 14.8119 | 10.0000 | 10.0000 | 38.4064 | 10.2753 | 10.0000 |
| $P_{G3}$ | 10 | 100 | 84.2983 | 96.6241 | 80.3790 | 85.0134 | 59.2636 | 87.6470 | 91.0320 |
| $P_{G6}$ | 10 | 100 | 35.2974 | 23.2973 | 19.5523 | 47.4428 | 42.3520 | 33.3663 | 34.1893 |
| $P_{G8}$ | 10 | 100 | 80.0688 | 75.2264 | 99.7471 | 67.4491 | 62.1601 | 78.6063 | 74.6654 |
| $V_1$ | 0.95 | 1.1 | 0.9819 | 1.0484 | 1.0380 | 1.0506 | 1.0299 | 1.0575 | 1.0462 |
| $V_2$ | 0.95 | 1.1 | 0.9734 | 1.0406 | 1.0277 | 1.0414 | 1.0204 | 1.0489 | 1.0380 |
| $V_3$ | 0.95 | 1.1 | 0.9620 | 1.0396 | 1.0192 | 1.0448 | 1.0113 | 1.0437 | 1.0340 |
| $V_6$ | 0.95 | 1.1 | 1.0447 | 1.0593 | 1.0342 | 1.0107 | 1.0275 | 1.0462 | 0.9794 |
| $V_8$ | 0.95 | 1.1 | 1.0547 | 1.0685 | 1.0408 | 1.0239 | 1.0252 | 1.0617 | 1.0093 |
| $T_{4-7}$ | 0.9 | 1.1 | 0.9 | 1 | 0.94 | 1 | 0.98 | 0.98 | 1.02 |
| $T_{4-9}$ | 0.9 | 1.1 | 0.9 | 0.94 | 1.02 | 1.1 | 1 | 0.98 | 1.04 |
| $T_{5-6}$ | 0.9 | 1.1 | 0.92 | 0.96 | 1 | 1.02 | 0.96 | 1 | 1.06 |
| SVC bus no. | | | 4 | 14 | 7 | 10 | 9 | 7 | 13 |
| $Q_{SVC}$(MVAR) | | | 5.4418 | 5.9269 | 10.0000 | 6.1182 | 1.3519 | −8.0615 | 7.7771 |
| TCPS branch | | | 20 (13–14) | 15 (7–9) | 15 (7–9) | 15 (7–9) | 11 (6–11) | 15 (7–9) | 4 (2–4) |
| ΦTCSPS(deg.) | −5 | 5 | 1.1121 | 1.0517 | 4.4096 | −2.3108 | 0.3972 | 0.4510 | 0.3412 |
| Loss (MW) | | | 1.0397 | 0.9605 | 0.9815 | 1.0367 | 1.9184 | **0.9384** | 0.9835 |
| State variables | | | | | | | | | |
| $P_{G1}$ | 50 | 332.4 | 50.38 | 50.00 | 50.30 | 50.13 | 58.74 | 50.04 | 50.10 |
| $Q_{G1}$ | −40 | 50 | 0.80 | 0.01 | 3.97 | 0.39 | 3.67 | 1.01 | −0.44 |
| $Q_{G2}$ | −40 | 40 | 9.84 | −0.66 | 1.22 | −8.76 | 4.80 | 2.19 | 1.08 |
| $Q_{G3}$ | −6 | 40 | 11.97 | 16.00 | 14.35 | 22.66 | 24.45 | 15.81 | 15.14 |
| $Q_{G6}$ | −6 | 24 | 14.64 | 8.61 | 23.34 | 15.16 | 18.29 | 19.90 | 11.33 |
| $Q_{G8}$ | −6 | 24 | 6.38 | 13.51 | 3.26 | 9.29 | 13.32 | 14.60 | 13.12 |

TLBO with the GSA is 35.09 \$/hour which is significant about \$35.09/hour × 8760 h (24 hour/day × 365 days) = \$ 307,388.40 cost saving per year. From this table also, it can be seen that the results obtained by PSO violating the minimum state variable's limit for reactive power generation at bus 6 viz. $Q_{G6}$ which is highlighted in red boldface.

The location for SVC installation is varied obtained by all algorithms where TLBO and HBO locate at bus 14, while MFO and PSO decided to install the SVC at bus 4. For TCSC location, MPA, MFO, TLBO and HBO gave the similar results where the TCSC need to be installed at branch 3 (line 2–3), while others gave varies results. The convergence curve for this case is plotted in Fig. 5 where all algorithms converged within less than 70 iterations.

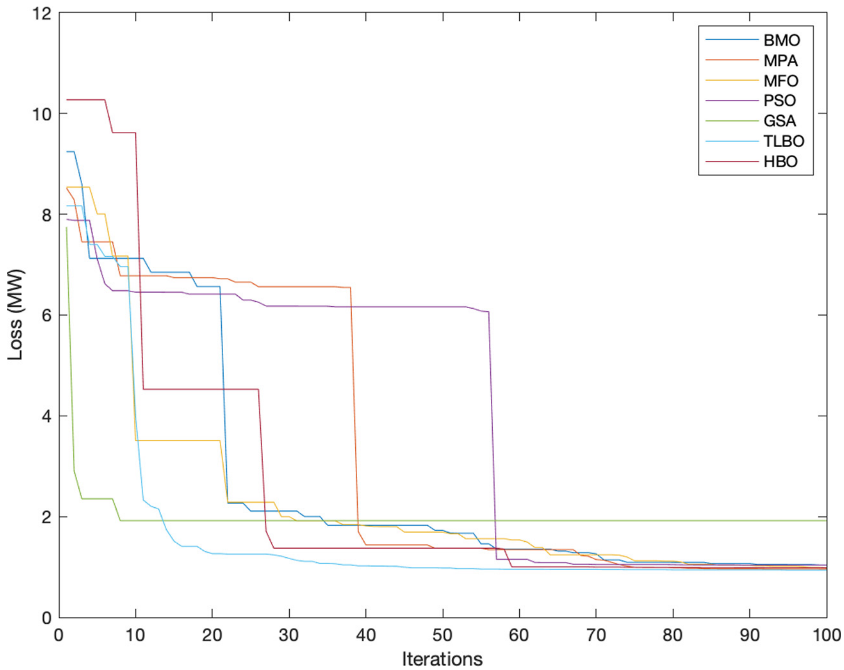


**Fig. 4.** Convergence curve for all algorithms of Case 2.

**Table 4**
Detail results for different algorithms on Case 3.

| Control variables | Min | Max | BMO | MPA | MFO | PSO | GSA | TLBO | HBO |
|---|---|---|---|---|---|---|---|---|---|
| $P_{G2}$ | 10 | 140 | 101.5744 | 101.4882 | 101.4663 | 101.5536 | 81.1452 | 101.4167 | 101.3172 |
| $P_{G3}$ | 10 | 100 | 10.0000 | 10.0000 | 10.0000 | 10.0000 | 10.0000 | 10.0000 | 10.0000 |
| $P_{G6}$ | 10 | 100 | 10.0000 | 10.0000 | 10.0000 | 10.0000 | 10.0000 | 10.0000 | 10.0000 |
| $P_{G8}$ | 10 | 100 | 10.0000 | 10.0000 | 10.0000 | 10.0000 | 10.0000 | 10.0000 | 10.0000 |
| $V_1$ | 0.95 | 1.1 | 1.0903 | 1.1000 | 1.1000 | 1.1000 | 1.0873 | 1.0997 | 1.0953 |
| $V_2$ | 0.95 | 1.1 | 1.0802 | 1.0855 | 1.0839 | 1.0913 | 1.0712 | 1.0868 | 1.0838 |
| $V_3$ | 0.95 | 1.1 | 1.0459 | 1.0520 | 1.0486 | 1.0613 | 1.0335 | 1.0554 | 1.0512 |
| $V_6$ | 0.95 | 1.1 | 1.0399 | 1.0182 | 1.0611 | 1.1000 | 1.0027 | 1.0605 | 1.0643 |
| $V_8$ | 0.95 | 1.1 | 1.0668 | 1.0012 | 1.0622 | 1.1000 | 1.0225 | 1.0635 | 1.0681 |
| $T_{4-7}$ | 0.9 | 1.1 | 0.98 | 1.1 | 1.1 | 1.04 | 1.04 | 1 | 1.06 |
| $T_{4-9}$ | 0.9 | 1.1 | 1.04 | 0.92 | 0.9 | 0.9 | 0.96 | 1.02 | 0.94 |
| $T_{5-6}$ | 0.9 | 1.1 | 1.02 | 1.02 | 0.98 | 0.9 | 1.02 | 0.96 | 0.96 |
| SVC bus no. | | | 7 | 10 | 4 | 4 | 9 | 14 | 14 |
| $Q_{SVC}$(MVAR) | −10 | 10 | −10.0000 | 4.4615 | −10.0000 | 10.0000 | −1.3232 | 10.0000 | 7.1425 |
| TCSC branch | | | 1 (1–2) | 3 (2–3) | 3 (2–3) | 20 (13–14) | 7 (4–5) | 3 (2–3) | 3 (2–3) |
| $\tau$TCSC$_1$(%) | 0 | 50% | 0.00 | 0.28 | 0.27 | 0.00 | 0.23 | 0.29 | 0.25 |
| Cost ($/hr) | | | 5947.30 | 5944.87 | 5944.33 | 5946.23 | 5978.56 | **5943.47** | 5943.61 |
| State variables | | | | | | | | | |
| $P_{G1}$ | 50 | 332.4 | 134.94 | 134.91 | 134.90 | 134.91 | 156.22 | 134.91 | 135.02 |
| $Q_{G1}$ | −40 | 50 | −6.90 | 4.68 | 7.79 | −5.58 | 4.70 | 1.89 | −2.73 |
| $Q_{G2}$ | −40 | 40 | 23.22 | 18.70 | 14.48 | 28.47 | 29.57 | 18.80 | 19.26 |
| $Q_{G3}$ | −6 | 40 | 21.63 | 21.70 | 18.16 | 25.11 | 22.56 | 22.88 | 19.69 |
| $Q_{G6}$ | −6 | 24 | 20.35 | 8.81 | 12.66 | **−13.69** | 14.99 | −3.20 | −0.11 |
| $Q_{G8}$ | −6 | 24 | 11.94 | 2.36 | 19.20 | 15.02 | 13.68 | 3.80 | 13.73 |

*Case 4: OPF problems with SVC and TCPS for cost minimization*

In this case, the setting for control and state variables are similar with the Case 2 and the objective function is similar with Case 3. The detail results of simulation for this case are depicted in Table 5. From this table, it can be noted that HBO outperformed others by obtaining the minimum cost of generation which is 5944.09 $/hour. The next best result is obtained by MFO followed by TLBO, MPA, PSO and finally GSA. From this table also can be noted that the state variable for $Q_{G6}$ by PSO and GSA is violated the minimum boundary setting. The convergence curve for this case is shown in Fig. 6 where all algorithms converged within less than 90 iterations.

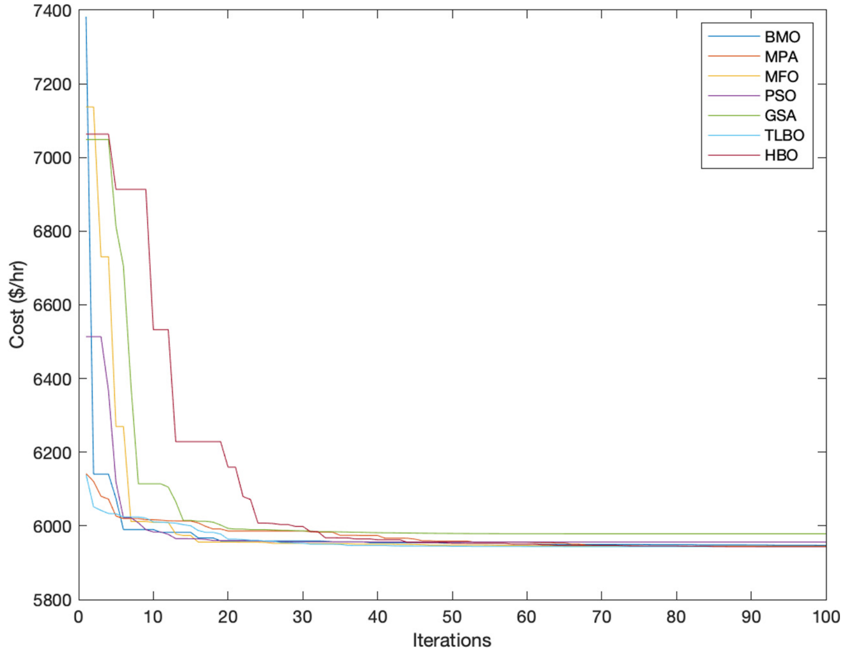


**Fig. 5.** Convergence curve for all algorithms of Case 3.

**Table 5**
Detail results for different algorithms on Case 4.

| Control variables | Min | Max | BMO | MPA | MFO | PSO | GSA | TLBO | HBO |
|---|---|---|---|---|---|---|---|---|---|
| $P_{G2}$ | 10 | 140 | 101.4401 | 101.5148 | 101.4998 | 101.9774 | 85.8511 | 101.4947 | 101.4576 |
| $P_{G3}$ | 10 | 100 | 10.0060 | 10.0000 | 10.0000 | 10.0000 | 10.0000 | 10.0000 | 10.0000 |
| $P_{G6}$ | 10 | 100 | 10.0000 | 10.0000 | 10.0000 | 10.0000 | 10.0000 | 10.0002 | 10.0000 |
| $P_{G8}$ | 10 | 100 | 10.0000 | 10.0000 | 10.0000 | 10.0000 | 10.0000 | 10.0003 | 10.0003 |
| $V_1$ | 0.95 | 1.1 | 1.1000 | 1.0983 | 1.1000 | 1.1000 | 1.0636 | 1.0967 | 1.0934 |
| $V_2$ | 0.95 | 1.1 | 1.0838 | 1.0846 | 1.0838 | 1.0894 | 1.0495 | 1.0839 | 1.0797 |
| $V_3$ | 0.95 | 1.1 | 1.0449 | 1.0487 | 1.0488 | 1.0581 | 1.0193 | 1.0510 | 1.0442 |
| $V_6$ | 0.95 | 1.1 | 1.0301 | 1.0528 | 1.0244 | 1.0732 | 1.0228 | 1.0548 | 1.0561 |
| $V_8$ | 0.95 | 1.1 | 1.0376 | 1.0539 | 1.0359 | 1.0739 | 1.0328 | 1.0682 | 1.0478 |
| $T_{4-7}$ | 0.9 | 1.1 | 1.1 | 1.08 | 1.08 | 1.1 | 1.02 | 1 | 1.06 |
| $T_{4-9}$ | 0.9 | 1.1 | 0.94 | 0.9 | 0.98 | 0.9 | 1 | 1.02 | 0.92 |
| $T_{5-6}$ | 0.9 | 1.1 | 1 | 0.98 | 1 | 0.9 | 1.06 | 0.98 | 1 |
| SVC bus no. | | | 14 | 4 | 14 | 4 | 7 | 4 | 13 |
| QSVC (MVAR) | | | 5.5973 | 2.5071 | 6.2399 | 9.9900 | −2.4268 | 0.5953 | 9.6657 |
| TCPS branch | | | 1 (1–2) | 1 (1–2) | 3 (2–3) | 20 (13–14) | 11 (6–11) | 1 (1–2) | 6 (3–4) |
| $\Phi$TCSPS(deg.) | −5 | 5 | 0.38 | 0.75 | −2.00 | 5.00 | 1.81 | 1.40 | −2.01 |
| Cost ($/hr) | | | 5945.79 | 5945.27 | 5944.34 | 5954.96 | 5974.59 | 5945.05 | **5944.09** |
| State variables | | | | | | | | | |
| $P_{G1}$ | 50 | 332.4 | 134.99 | 134.9 | 134.87 | 134.91 | 151.57 | 134.91 | 134.9 |
| $Q_{G1}$ | −40 | 50 | 8.50 | 3.35 | 8.02 | 0.51 | −8.13 | 1.38 | 0.15 |
| $Q_{G2}$ | −40 | 40 | 14.21 | 17.92 | 13.19 | 29.01 | 6.26 | 16.67 | 14.99 |
| $Q_{G3}$ | −6 | 40 | 15.35 | 19.07 | 18.76 | 24.88 | 20.84 | 22.03 | 17.78 |
| $Q_{G6}$ | −6 | 24 | 4.06 | 6.40 | 1.83 | **−18.61** | **38.70** | 8.96 | 9.15 |
| $Q_{G8}$ | −6 | 24 | 14.54 | 12.84 | 12.87 | 20.77 | 9.72 | 8.39 | 7.89 |

For further analyzing the performance of all algorithms in solving the OPF with FATCS devices' allocation problems, the statistical results for all cases are recoded and presented in Table 6. From this table, it can be concluded that TLBO performed better in most of the cases especially in cases 1 and 2 while HBO able to perform better in case 4. Even though HBO performed better in case 3 for maximum and mean results, TLBO is the best in finding the minimum cost of generation in case 3. Overall, the TLBO and HBO produce very competitive performance and outperformed most of the algorithms for all cases.

## 6. Conclusion

In this paper, seven metaheuristic algorithms namely BMO, MPA, MFO, PSO, GSA TLBO and HBO have been proposed to solve OPF with the FACTS allocation problems. To analyze and assess the performance of all algorithms in solving the problems, they have

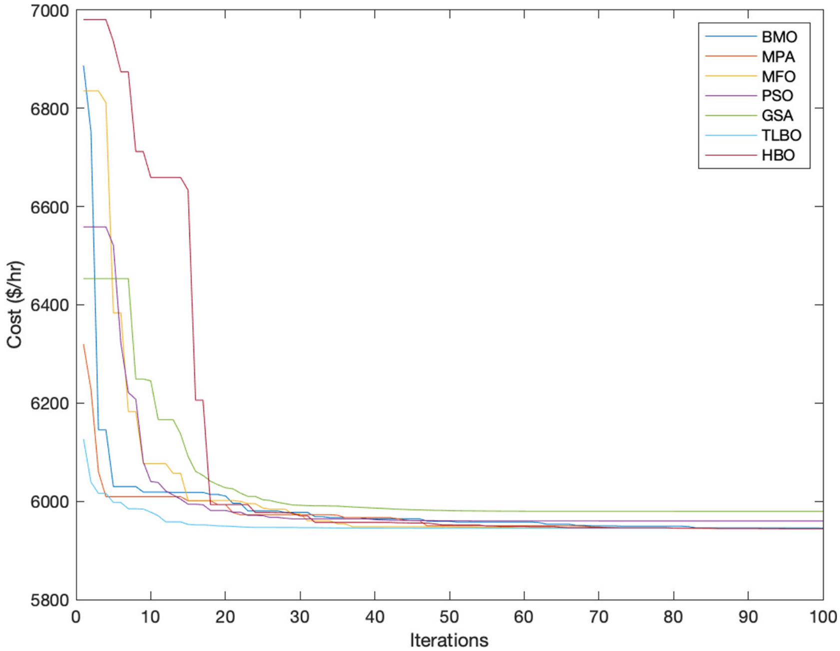


**Fig. 6.** Convergence curve for all algorithms of Case 4.

**Table 6**
Statistical results for different algorithms on all cases.

| Case | Statistical | BMO | MPA | MFO | PSO | GSA | TLBO | HBO |
|---|---|---|---|---|---|---|---|---|
| Case 1 | Min | 1.0128 | 0.9580 | 0.9485 | 0.9496 | 1.7843 | **0.9178** | 0.9693 |
| | Max | 3.1459 | 1.1476 | 3.1784 | 1.8373 | 4.6530 | **1.0989** | 1.5959 |
| | Mean | 1.3678 | 1.0266 | 1.3529 | 1.3160 | 2.6493 | **0.9954** | 1.1579 |
| | Std Dev. | 0.5094 | **0.0460** | 0.4178 | 0.2424 | 0.5270 | 0.0498 | 0.1405 |
| Case 2 | Min | 1.0397 | 0.9605 | 0.9815 | 1.0367 | 1.9184 | **0.9384** | 0.9835 |
| | Max | 1.9611 | 1.2155 | 2.1340 | 2.1959 | 2.9145 | **1.1074** | 1.4250 |
| | Mean | 1.2613 | 1.0455 | 1.2469 | 1.3484 | 2.2952 | **1.0010** | 1.1316 |
| | Std Dev. | 0.2025 | 0.0631 | 0.2676 | 0.2375 | 0.2408 | **0.0456** | 0.1118 |
| Case 3 | Min | 5947.3039 | 5944.8731 | 5944.3298 | 5956.2265 | 5978.5605 | **5943.4727** | 5943.6109 |
| | Max | 6005.0696 | 5950.7428 | 5958.9405 | 6396.1937 | 6845.4320 | 6025.7163 | **5949.3704** |
| | Mean | 5972.1610 | 5946.8668 | 5948.8930 | 6031.1177 | 6436.6284 | 5982.8453 | **5945.8152** |
| | Std Dev. | 17.9978 | **1.0714** | 3.8833 | 92.0980 | 226.4421 | 30.9961 | 1.1595 |
| Case 4 | Min | 5945.7940 | 5945.2709 | 5944.3410 | 5959.9625 | 5979.5883 | 5945.0462 | **5944.0926** |
| | Max | 6015.2284 | **5954.0831** | 5959.3588 | 6056.7575 | 6976.2456 | 6029.1131 | 5955.0994 |
| | Mean | 5969.1528 | 5947.5460 | 5950.0005 | 6006.6263 | 6493.3314 | 5993.2388 | **5946.8637** |
| | Std Dev. | 17.0312 | **2.3427** | 3.7261 | 32.3930 | 255.3215 | 24.1129 | 2.4264 |

been applied on two OPF objective functions viz. transmission loss as well as generation cost on modified IEEE 14-bus system through four cases. Statistical and comparative analysis show that TLBO and HBO produce very competitive performance and outperformed the rest of algorithms for most of the cases. Therefore, they can be an effective alternative for solving OPF problem with the presence of FACTS devices.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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