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GIANT TREVALLY OPTIMIZED CONGESTION MANAGEMENT USING FACTS CONTROLLER ALLOCATION IN DEREGULATED ELECTRICITY MARKETS

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Keywords: Deregulated power system; Congestion; Flexible alternating current transmission system (FACTS) devices; Giant trevally optimizer; Power loss.

One of the technical issues arising from deregulation is transmission line congestion. The size and location of FACTS controllers like thyristor-controlled series compensators (TCSCs) and static VAR compensator (SVC) devices significantly affect their efficiency in congestion management problems. As a nonlinear problem, locating and sizing these devices in a power network is difficult. To solve this issue, this paper presents the technique for optimal FACTS placement using the giant trevally optimizer (GTO) algorithm for congestion management (CM). Three objective functions are considered to reduce the congestion, including voltage stability and eliminating real power loss overall cost. To determine the best location for FACTS devices in the MATLAB R2020b tool, the suggested GTO approach is implemented and discussed for the IEEE 14-bus and IEEE 30-bus systems. It is also compared with existing GSA, BBO, and ICSA approaches under three loading situations. From the simulation results, GTO minimized total costs and real power losses better than existing algorithm algorithms, and GTO provides high net saving costs.

1. INTRODUCTION

The deregulation of the electricity market has transformed the entire market drastically. A new player is entering the market nowadays, contributing to every aspect: generation, transmission, distribution, revenues, etc. [1]. All deregulated electricity networks will have an independent system operator to maintain coordination (ISO). Transmission congestion is the term used to describe this transmission line problem [2–4]. Congestion must be reduced or avoided to guarantee optimal power flow, improve power quality, stop equipment failure, and prevent additional blackouts [5,6].

Flexible alternating current transmission system (FACTS) device installation, generating rescheduling, and optimal power flow are some techniques employed for CM [7,8]. The power transfer capability of electrical networks is significantly increased when FACTS devices, such as shunt-series devices, like UPFCs, or static series compensators (SSSCs), TCSCs, SVCs, and static compensators (STATCOMs), are installed [9,10]. Many researchers have recently proposed solutions to alleviate transmission line congestion. A few studies are described below;

Using a metaheuristic approach to congestion management is more favorable than traditional methods. Several methods enable the most effective actual power rescheduling of power system power plants, such as the improved crow search algorithm (ICSA) [11], the hybrid lion algorithm with moth-based mutation algorithm [12], and the bat algorithm (BA) [13], which is recommended to lower generation/congestion costs and system loss. To reduce congestion, [14] suggested using a location-based marginal cost approach based on congestion management to develop a gravitational search algorithm (GSA) for assigning TCSC with OPF and available transfer capability (ATC) [15]. A biogeography-based optimization (BBO) technique was proposed for the optimal residence of UPFC for congestion reduction and voltage profile enhancements of an interconnected power system [16]. However, this method has low convergence, which is the major drawback. A strategy based on a genetic algorithm that generates scaling factors (GA-GSF) was proposed in [17] to lower the generators' overall cost, market the power price, and remove transmission line congestion. For CM, it was discovered that the TCSC, SVC, and UPFC are the three FACTS devices that can be best located.

In [18], atom search optimization metaheuristic approach (ASO) and machine learning (ML) with cubic spline models. In contrast, the hybridization of machine learning and metaheuristic exhibits promising potential in achieving real-time fault localization with improved accuracy. [19] presents a permissive dataset-required deep learning-based approach to defect identification and classification. Obtaining huge, labeled datasets is the most challenging aspect of any deep learning system. The model is put through a rigorous battery of performance tests. An efficient voltage control device based on the FACTS was presented in [20]. It consists of a static synchronous compensator (STATCOM) and SC to moderate the SSR. The results were verified using the IEEE First SSR benchmark system. The outcomes show that SSSCs with fuzzy logic controllers (FLC) as their foundation outperform STATCOM.

According to the literature above review, power system operation should also ensure minimum congestion costs. Implementing efficient optimization techniques plays a significant role in achieving better cost-minimization solutions [21–23]. Most optimization algorithms used to manage transmission congestion suffer from convergence issues with large systems, with local optima tricking occurring after a few iterations. This research offers the efficient Giant Trevally optimization (GTO) technique to enhance convergence and achieve values close to global optimal values to address this issue. By strategically deploying the TCSC and SVC FACTS devices, the GTO algorithm minimizes actual loss and lowers the network's overall cost. The IEEE 14-bus and 30-bus systems have examined the GTO algorithm to reduce congestion. The significant contribution of the presented work is described below:

- Proposed a giant trevally optimization (GTO) algorithm for preventing premature local convergence while ensuring better search capabilities;
- GTO was developed to decrease overall power losses, maintain voltage stability, and limit real power losses during congestion while retaining the system's parameters within acceptable ranges;

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- We are analyzing the performance of GTO and other optimization techniques such as ICSA, GSA, and BBO with three reactive loading conditions.

The work is structured as follows: section 3 explains the issue formulation and goal function, whereas Section 2 deals with modeling FACTS devices. Section 4 gives the suggested GTO-based problem-solving procedure and associated steps for implementation. Section 5 covers the performance of the proposed and current works. Section 6 presents the work's conclusion in its final state.

2. ALLOCATION FACTS DEVICES

By strategically installing FACTS devices in the most opportune network segments to optimize network efficiency, the endeavor seeks to reduce costs and power losses. Figure 1 displays the modeling for the SVC and TCSC.

2.1 MODELLING OF TCSC

Utilizing a series capacitor bank switched by a thyristor, TCSC modifies series capacitance reactions. The circuit only allows for the simultaneous switching of either of the two. Resonance is avoided by doing this. This may be stated mathematically as Equation (1),

$$X_{ij} = X_{line} + X_{TCSC}, \quad (1)$$

$$X_{TCSC} = \frac{x_c * x_l}{\frac{x_c}{\pi}[2(\pi-\alpha)+\sin(2\alpha)]-x_l}, \quad (2)$$

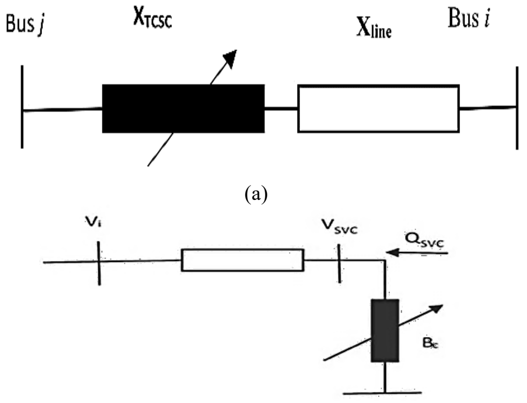
where, X_{TCSC} - reactance of TCSC, x_l and x_c Denotes the capacitor and reactor offer reactance, respectively, while the thyristors' firing angle is indicated by α.

2.1. MODELLING OF SVC

A parallel filter circuit, a reactor and capacitor controlled by a thyristor, and an SVC are the components of this static compensation device. This may be stated mathematically as eq. (2),

$$\Delta Q_i = Q_{SVC} = -V_i^2 B_{SVC} \quad (3)$$

$$B_{SVC} = \frac{x_l - \frac{x_c}{\pi}[2(\pi-\alpha)+\sin(2\alpha)]}{x_c * x_l} \quad (4)$$



(b)

Fig. 1 – Modeling of (a) TCSC (b) SVC.

3. CONGESTION MANAGEMENT (CM) PROBLEM

3.1 OBJECTIVE FUNCTION

The CM challenge has been formulated to reduce generation costs and total power loss under various equality and inequality constraints.

(i) Real power loss

A transmission system's inherent resistance makes real power losses inevitable. Eqn. (5) and (6) represent the real power loss (MW) that must be minimized:

$$P_{loss} = \sum_{r=1}^{nl} G_{r(mn)}[V_m^2 + V_n^2 - 2V_m V_n \cos(\delta_{mn})]. \quad (5)$$

(ii) Total cost

It is the sum of the generation cost function and FACTS device cost function, which is expressed below:

$$C_{TG} = \min_{P_{Gi}} \sum_{i=1}^{N_G} C_{Gi}(P_{Gi}) + C_{FACTS}, \quad (6)$$

where, $C_{Gi}(P_{Gi})$ - production cost, C_{FACTS} - the cost of the FACTS device and N_G - number of generators.

The production cost function is expressed in Eqn. (7),

$$C_{Gi}(P_{Gi}) = a_i + b_i P_{Gi} + c_i P_{Gi}^2. \quad (7)$$

Because FACTS devices are expensive, cost-profit studies should be used to evaluate the cost-effectiveness of novel FACTS devices in different settings.

$$C_{FACTS} = c.x_{FACTS}(k).P_{LK}^2.base\ power. \quad (8)$$

(iii) Voltage Stability

A major issue in the design and operation of electric power systems is voltage stability (VS). The capacity of the power system to keep voltage levels within permitted bounds during regular operation and also following a disruption is known as voltage stability.

$$V_s = VSM_0 + \Delta VSM \quad (9)$$

The voltage stability margin (VSM) denotes the voltage stability margin in the base case, whereas ΔVSM indicates the change in the voltage stable margin after CM.

$$\Delta VSM = -\frac{\partial VSM}{\partial Q_{dx}^{TCSC}} \cdot Q_x^{TCSC} - \frac{\partial VSM}{\partial Q_{dy}^{TCSC}} \cdot Q_y^{TCSC} + \sum_{k \in SD} \frac{\partial VSM}{\partial Q_{dk}^{TCSC}} \cdot \Delta Q_{Dk}. \quad (10)$$

The optimization algorithm minimizes the above-mentioned multi-objective functions. During the optimization process, the inequality and equality constraints must be satisfied.

3.1. CONSTRAINTS

3.2.1 EQUAL CONSTRAINTS

The equality constraint is a power balance equation, and it is expressed as follows for the base setup (without any FACTS devices):

$$P_{Gm} - P_{Lm} - V_m \sum_{n=1}^{N_B} V_n Y_{mn} \cos(\theta_{mn} + \delta_m - \delta_n) = 0.\ \forall\ m \in N_B. (11)$$

$$Q_{Gm} - Q_{Lm} - V_m \sum_{n=1}^{N_B} V_n Y_{mn} \sin(\theta_{mn} + \delta_m - \delta_n) = 0\ \forall\ m \in N_B. (12)$$

The following changes are made to the power balance calculations in the event of FACTS devices:

$$P_{Gm} + P_{sm} - P_{Lm} - V_m \sum_{n=1}^{N_B} V_n Y_{mn} \cos(\theta_{mn} + \delta_m - \delta_n) = 0\ \forall\ m \in N_B, (13)$$

$$Q_{Gm} + Q_{sm} + Q_{SVCm} - Q_{Lm} - V_m \sum_{n=1}^{N_B} V_n Y_{mn} \sin(\theta_{mn} + \delta_m - \delta_n) = 0\ \forall\ m \in N_B, \quad (14)$$

where Q_{sm} and P_{sm} - reactive and active power, respectively, inserted by the TCSC at bus m, Q_{SVCm} - SVC injects reactive power at bus m. The SVC does not have a power injection system.

3.2.2 INEQUALITY CONSTRAINTS

The generator bus voltage restrictions are in (17), while the control limits for the generation of active and reactive power are in Equations (15) and (16), respectively.

$$P_{Gi}^{min} \le P_{Gi} \le P_{Gi}^{max}\ \forall\ i\ \in\ N_G, \quad (15)$$

$$Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max}\ \forall\ i\ \in\ N_G, \quad (16)$$

$$V_{Gi}^{min} \le V_{Gi} \le V_{Gi}^{max}\ \forall\ i\ \in\ N_G. \quad (17)$$

The security and Transformer tap changing setting range limits [24] are expressed in eqn. (16) and (17), respectively,

$$V_{LP}^{min} \le V_{LP} \le V_{LP}^{max} \;\; \forall\, p \in N_L, \tag{18}$$
$$S_{ql} \le S_{ql}^{max} \;\; \forall\, q \in nl, \tag{19}$$
$$T_t^{min} \le T_t \le T_t^{max} \;\; \forall\, t \in N_T. \tag{20}$$

FACTS device limits [25]:

TCSC: $\tau_{TCSCm}^{min} \le \tau_{TCSCm} \le \tau_{TCSCm}^{max} \; \forall\, m \in N_{TCSC}$ (21)

SVC: $Q_{SVCj}^{min} \le Q_{SVCj} \le Q_{SVCj}^{max} \; \forall\, i \in N_{SVC}$ (22)

where, N_{SVC} and N_{TCSC} are represents the numbers of SVC and TCSC devices, respectively, in the network

4. PROPOSED GTO-BASED OPTIMAL LOCATION OF FACTS DEVICE FOR CM

To increase load capacity, minimize installation costs, and meet several other objectives, the optimal location for FACTS devices (TCSC and SVC) is determined in this study using the giant trevally optimized (GTO) approach. The GTO algorithm achieves the best and optimum answer by removing the poorest outcomes.

4.1 GIANT TREVALLY OPTIMIZER (GTO)

Giant trevallies (GT) mimic the behavior of seabirds when hunting with the proposed GTO algorithm. The GTO algorithm can handle many optimization problems by employing a generalized structure that adapts to different problem characteristics. Unlike algorithms tailored to specific problem types, GTO is flexible in application across combinatorial and continuous optimization problems. GTO algorithm provides distinct advantages over BBO, GSA, and ICSA optimization techniques, such as faster convergence, reduced computational overhead, better scalability, and robustness across diverse problem types. Its unique ability to dynamically adapt parameters and its flexible structure makes it a strong candidate for solving complex optimization problems in various domains.

In the algorithm, the population matrix is made up of vectors for each member of the population, as shown in equation (23).

$$\mathbf{A}=\begin{bmatrix} A_1 \\ \vdots \\ A_i \\ \vdots \\ A_N \end{bmatrix}_{N\times dim} = \begin{bmatrix} a_{1,1} & \cdots & a_{1,j} & \cdots & a_{1,dim} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{i,1} & \cdots & a_{i,j} & \cdots & a_{i,dim} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{N,1} & \cdots & a_{N,j} & \cdots & a_{N,dim} \end{bmatrix}_{N\times dim}, \tag{23}$$

where **A** - candidate solution of GTO, A_i – i^{th} candidate solution of GTO, Dim - decision variables for a given problem, N - GTO member's number, $a_{i,j}$ - a value of the j^{th} variable stated by the i^{th} candidate result. For them to function, each trevally must be assigned a random position in the problem space

$$A_{i,j} = min_j + \left(max_j - min_j\right) \times K, \tag{24}$$

where, $max_j$and min_j - minimum and maximum value that a population member.

Step 1: Extensive Search

At this stage, big trevally hunting movement patterns are reproduced utilizing (25):

$$A\,(t+1) = Best_p \times K + \left((max - min) \times K + min\right) \times Levy(dim), \tag{25}$$

where, $Best_p$ is the huge trevally's current search space, which is defined by their last search position; $Levy(dim)$ is the Levy flight; and $A\,(t+1)$ is the location vector of the enormous trevally in the following iteration.

$$Levy(dim) = S_z \times \frac{r\times\sigma}{|v|^{1/\beta}}, \tag{26}$$

$$\sigma = \left(\frac{\Gamma(1+\beta)\times\sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right)\times\beta\times2^{\left(\frac{\beta-1}{2}\right)}}\right), \tag{27}$$

where, S_z – step size (set to 0.01), β - index of the Levy flight ranges from 0 to 2, r and v - random numbers.

Step 2: Choosing the Area

Giant trevally select an area with abundant food inside the search area, and it can seek prey by identifying and choosing the best location.

$$A\,(t+1) = Best_p \times X \times K + Mean_{info} - Ai(t) \times K \tag{28}$$

$$Mean_{info} = \frac{1}{N}\sum_{i=1}^{N} Ai(t). \tag{29}$$

Using the Sphere function, eq. (28) 's effectiveness in selecting the area has been evaluated. All solutions are of higher quality.

Step 3. Attacking

During the GTO's exploitation period, the trevally seeks the bird or prey. Snell's law is followed to do this. In this case, the visual distortion V can be calculated with (30).

$$V = \sin(\theta_1^{\circ}) \times D, \tag{30}$$
$$D = \left|Best_p - Ai(t)\right|, \tag{31}$$

where, D – the distance between the attacker and prey. A mathematical simulation of GT behavior while chasing and flying is conducted using (32).

$$A\,(t+1) = L + V + H, \tag{32}$$

where L - to mimic pursuing the bird and increase the launch speed, the H - jump slope function allows the algorithm to switch from exploration to exploitation in an adaptable manner.

$$L = Ai(t) \times \sin(\theta_2^{\circ}) \times F_{obj}\left(Ai(t)\right), \tag{33}$$
$$H = K\times\left(2 - t \times \frac{2}{T}\right). \tag{34}$$

In this case, T and t are the maximum and current number of iterationskuky

In the exploitation stage, the method looks for opportunities to exploit the solutions' proximity since, as iterations proceed, H drops from 2 to 0.

5. RESULTS AND DISCUSSIONS

The recommended work implements a GTO-based congestion management strategy using an Intel Pentium Gold processor with a clock speed of 4.01 GHz and 4 GB RAM. The IEEE 14-bus and 30-bus test systems explained below, are used to test it for this purpose. It is done using MATLAB R2020b (64-bit) software. The efficiency of the proposed GTO algorithm in addressing the congestion problem is in contrast to other techniques such as ICSA [11], GSA [14], and BBO [16]. Following an increase in demand, the specifics of the congested lines are noted, and a power flow assessment is conducted. The three case studies are as follows:

Case 1: Adding 100% Reactive Loading
Case 2: Adding 150% Reactive Loading
Case 3: Adding 200% Reactive Loading

5.1. PERFORMANCE ANALYSIS OF IEEE 14-BUS TEST SYSTEM

Nine load buses, twenty transmission lines, four TCSCs, four SVCs, and five power-generating units make up the IEEE-14 bus system. Considering load flows, the total real and reactive power losses before FACTS devices are 54.54 MVAr and 13.393 MW, respectively. There is an actual power demand of 259 MW and a real power generation capacity of 772.4 MW.

Although there is a 73.5 MVAr demand for reactive power, there is an 82.4 MVAr output. Various FACTS are displayed beside the IEEE 14 bus line architecture in Fig. 2.

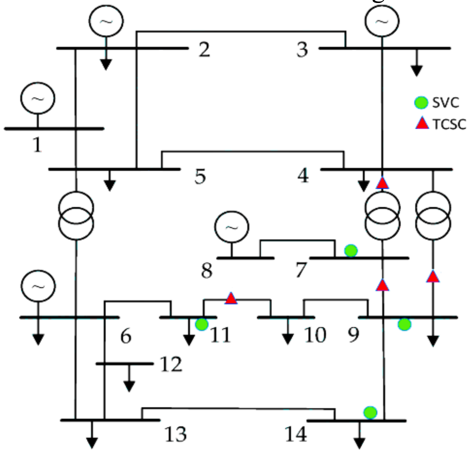


Fig. 2 – Single line schematic of IEEE 14-bus system with the installation of FACTS devices.

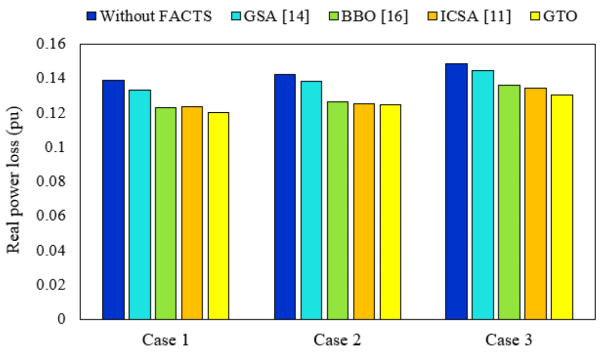


Fig. 3 – Comparison analysis of FACTS devices for IEEE 14-bus system.

Allocating FACTS devices maximizes the network loading capacity while minimizing actual power loss in Fig. 3. In case 1, the allocation of FACTS devices reduces the loss from 0.139 pu without FACTS devices to 0.133 pu, 0.123 pu, 0.1237 pu, and 0.1201 pu using GSA, BBO, ICSA, and GTO techniques, respectively. Table 1 shows the difference in cost between the IEEE-14 system with and without FACTS using various methods. Without FACTS devices, the entire cost comprises the cost arising from active power loss alone.

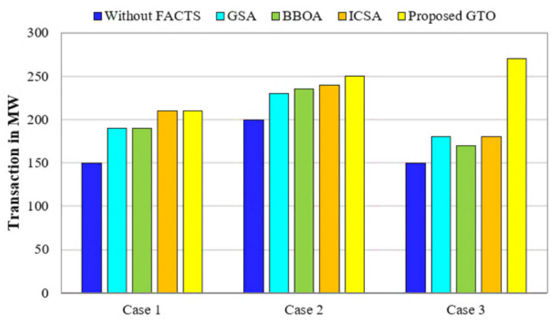


Fig. 4 – Comparison analysis of optimal power dispatch.

Figure 4 illustrates the best power dispatch using several methods, both with and without FACTS. The graph compares the optimal power dispatch (in MW) for three different cases using various methods: without FACTS, GSA (gravitational search algorithm), BBOA (biogeography-based optimization algorithm), ICSA (improved cuckoo search algorithm), and the proposed GTO (giant trevally optimizer). In Case 1, the proposed GTO method achieves the highest power dispatch, surpassing the other techniques. Case 2 shows a similar pattern, with GTO yielding slightly higher values than other methods.

In Case 3, the difference is more pronounced, with GTO showing significantly better performance, dispatching close to 300 MW, indicating its superior efficiency in optimizing power transmission compared to the others. Table 1, Cases 1, 2, and 3 show that the generation cost is less using the proposed GTO algorithm.

Table 1

Comparative analysis of objective function in IEEE-14 bus system.

Case studies	Total power loss cost system ($)	Algo-rithms	Cost of FACTS devices ($)	Generation cost with FACTS devices ($)
Case 1	1.1195×10^7	GSA	3.651×10^5	1.0714×10^7
		BBO	3.159×10^5	1.012×10^7
		ICSA	2.314×10^5	0.6995×10^7
		GTO	2.015×10^5	0.2647×10^7
Case 2	1.1361×10^7	GSA	3.021×10^5	1.1289×10^7
		BBO	2.580×10^5	1.0118×10^7
		ICSA	2.412×10^5	1.021×10^7
		GTO	2.179×10^5	0.854×10^7
Case 3	1.1805×10^7	GSA	3.388×10^5	1.162×10^7
		BBO	2.751×10^5	1.069×10^7
		ICSA	2.569×10^5	1.089×10^7
		GTO	2.369×10^5	0.895×10^7

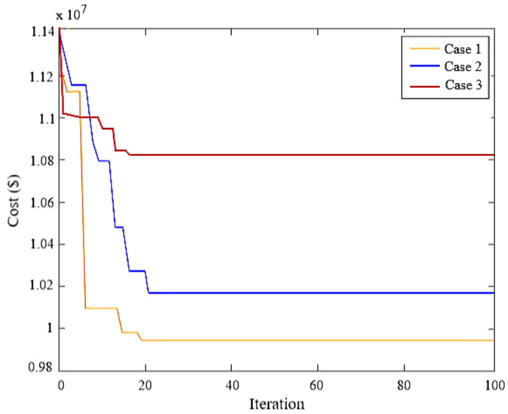


Fig. 5 – Total cost with GTO-based FACTS in different cases for IEEE 14-bus system.

Figure 5 graph represents the convergence of cost ($) over iterations for three cases in an optimization process. Initially, all three cases start with a cost of around $\$1.14 \times 10^7$. As the iterations progress, the costs decrease, with Case 1 (orange) showing the steepest reduction, reaching a final cost below $\$1 \times 10^7$ after about 20 iterations. Case 2 (blue) also reduces significantly but levels off around $\$1.02 \times 10^7$ after 30 iterations. Case 3 (red), however, shows the slowest improvement, stabilizing around $\$1.1\times10^7$ without a significant drop. This indicates that Case 1 provides the most cost-efficient solution, while Case 3 has the slightest reduction in price.

5.2. PERFORMANCE ANALYSIS OF IEEE 30-BUS TEST SYSTEM

Fourteen transmission lines, three TCSCs, three SVCs, and six generators comprise the IEEE-30 bus system. A total of 900.2 MW of real power is generated, 283.4 MW of connected load is consumed, and 126.2 MW of reactive load is consumed. Suggested locations for the TCSCs in the IEEE

30 bus system are branches 7, 15, and 20, based on the Lmn sensitivity index. Buses 26, 29, and 30 serve SVC stations. Figure 6 displays the positions of the IEEE-30 bus system's one-line schematic and the FACTS device placements.

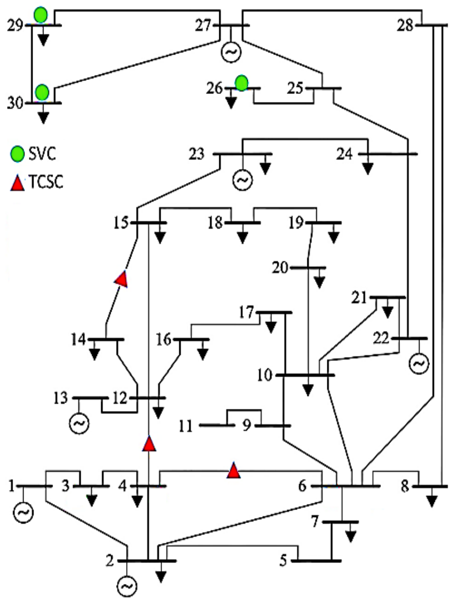


Fig. 6 – Line diagram of IEEE 30-bus system with the installation of FACTS devices.

Figure 7 shows the total real power losses in each scenario before and after installing FACTS devices. It shows that installing TCSC devices with the suggested GTO algorithm also reduces the real power loss, which is 0.1752 pm to 0.1402 for case 1, 0.1789 pu to 0.1454 pu for case 2, and 0.1841 to 0.1589 for case 3.

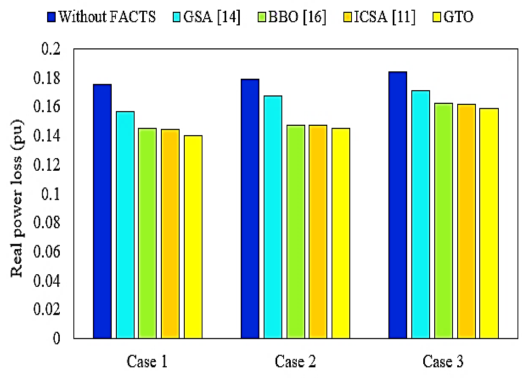


Fig. 7 – Comparison analysis of FACTS devices for IEEE 30-bus system.

Table 2 compares the prices of different approaches and indicates that the total cost of active power loss equals the entire cost of the IEEE-30 bus system without FACTS. When FACTS is implemented, the whole cost consists of real power loss fines and FACTS installation fees. Table 2 illustrates how applying the suggested GTO method reduces the generation cost in Cases 1, 2, and 3. With FACTS controllers, the congestion cost is lower than in their absence.

Figure 8 shows the GTO convergence curve for a total cost with FACTS added in various case situations. Compared to the other current algorithm, the total cost achieved for cases 1, 2, and 3 is significantly reduced at 1.175×10^7, 1.201×10^7, and 1.319×10^7. In the base case for IEEE 30-bus systems, GTO saved more than GSA, BBO, and ICSA by \$805,000, \$65,000, and \$59,000, respectively.

Table 2

Comparative analysis of objective function in IEEE-30 bus system

Case studies	Total power loss cost system (\$)	Algo-rithms	Costof FACTS devices (\$)	Generation cost with FACTS devices (\$)
Case 1	1.4089×10^7	GSA	3.021×10^5	1.266×10^7
		BBO	2.864×10^5	1.177×10^7
		ICSA	2.702×10^5	1.166×10^7
		GTO	2.514×10^5	1.066×10^7
Case 2	1.4361×10^7	GSA	3.476×10^5	1.351×10^7
		BBO	3.075×10^5	1.215×10^7
		ICSA	3.028×10^5	1.205×10^7
		GTO	3.011×10^5	1.151×10^7
Case 3	1.4899×10^7	GSA	3.774×10^5	1.392×10^7
		BBO	3.517×10^5	1.327×10^7
		ICSA	3.527×10^5	1.318×10^7
		GTO	3.368×10^5	1.303×10^7

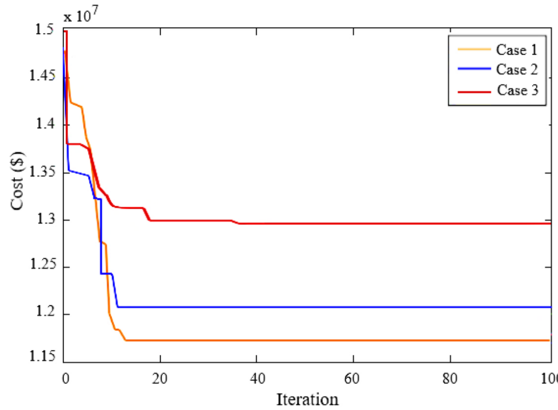


Fig. 8 – Total cost with GTO-based FACTS at different cases for IEEE 30-bus system.

6. CONCLUSION

This research presents an optimal allocation strategy for FACTS devices (TCSC, SVC) using the GTO algorithm to reduce power loss and total costs in a deregulated power system. To find the optimal location for FACTS devices, the proposed GTO method was evaluated in IEEE 14-bus and IEEE 30-bus systems, utilizing three instances and the MATLAB R2020b tool. FACTS devices are placed optimally in the network, and fitness function variables are set using the GTO algorithm. Simulated results show that GTO produces minimum objectives for FACTS location. Therefore, GTO minimized total costs and real power losses better than ICSA, GSA, and BBO algorithms. For all loading conditions, net savings were higher with GTO than with ICSA, GSA, and BBO approaches. GTO saved \$172,000, \$129,620, and \$126,300 more at 100% reactive loading in the IEEE 14-bus system than the GSA, BBO, and ICSA algorithms did in that order. GTO made similar savings in the primary case for IEEE 30 bus systems over GSA, BBO, and ICSA, which were \$805,000, \$65,000, and \$59,000, respectively. The limitation of the proposed work is that it involves more complex dynamics in larger systems. This computational demand could increase, potentially slowing down the optimization process. Future limitations can be addressed by hybridizing the GTO algorithm with deep learning techniques to improve real-time fault detection and system optimization. Machine learning models could assist in identifying optimal locations for FACTS devices in dynamic grid environments.

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