Journal of Scientific & Industrial Research
Vol. 80, June 2021, pp. 499-507

A Comparative Performance Evaluation of a Set of Swarm Intelligence based Optimization Algorithms for Economic Operation with FACTS Devices in Power Systems

Vikash Kumar Gupta[1]* and Sudhansu Kumar Mishra[2]
[1]Department of Applied Sciences and Humanities, NIFFT, Hatia, Ranchi, India
[2]Department of EEE, BIT, Mesra, Ranchi, India

Received 09 November 2020; revised 05 February 2021; accepted 07 April 2021

In this article an effective Reactive Power Management (RPM) method using a Flexible AC Transmission System (FACTS) has been proposed, which minimizes the loss of energy, improves the power transfer capacity and reduces the overall cost of transmission network lines. The position of FACTS was optimized by two recently proposed heuristic optimization techniques, i.e., Gravitational Search Algorithm (GSA) and Teaching Learning Based Optimization (TLBO). It is observed that installing the FACTS in this optimal position improves the voltage profile at minimum installation cost. The overall effectiveness of the proposed approaches were examined by implementing it on a IEEE 30-bus network.

Keywords: Energy Loss, FACTS, GSA, Operating Cost, Reactive Power Management, TLBO

Introduction

The demand for power supply has increased manifold as a result of population growth and urbanization in the last few decades. Installation of a new power plant for enhancing the generation or extension of transmission lines in not easily possible due to different practical issues, such as, political, economical, environmental, technical aspects etc. It is necessary to exploit the maximum benefit from the existing power plants and transmission lines. To achieve this objective, one of the major steps includes the reduction of line loss during the flow of power. The line loss can be reduced by injecting or retrieving the reactive power with the assistance of FACTS.

FACTS were introduced by Hingorani *et al.*[1] in 1999. FACTS are very useful in maintaining voltage stability and compensation of reactive power. Mahdad *et al*.[2] have proposed the FACTS location and control scheme for the enhancement of power quality. The authors have described the power flow control in a network consisting of FACTS. [3] The role of SVCs and TCSCs during voltage collapse is extensively discussed.[4] The authors have introduced a new heuristic random search algorithm based on a population, named as Gravitational Search Algorithm (GSA).[5] To enhance the performance of GSA by handling various constraints is discussed in detail.[6] Rao *et al.*[7] have introduced the Teaching Learning Based Optimization (TLBO) which is motivated by the teaching and learning activities in a classroom. This is an algorithmic parameter free optimization technique, and hence, highly effective in solving different optimization problems. The TLBO algorithm properly tuned for solving different constrained and unconstrained optimization problem having multiple variables has been discussed.[8] Operating cost minimization of the system with FACTS by the implementation of the Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) is discussed.[9] Proper placement, replacement and sizing of the capacitor bank are discussed using GA.[10] Optimization of reactive power flow in a HVDC test system using GA is the main aim of the authors.[11] The authors have proposed advanced models of SVC for optimal power flow studies using the N.R. method.[12] Noroozian *et al.*[13] have discussed the application of series capacitors and phase shifters in power systems to monitor power flow. The key recommendations are to increase the operating voltage, automate, re-configure the network, improve operational efficiency, control demand, and modernize the system.

Siddhartha *et al.*[14] have improved the transmission and distribution efficiency by proposing some approaches such as proper operating voltage; network re-configuration, operational optimization, demand management, and system consolidation are the next steps after automation. A two-stage method of placing

*Author for Correspondence
Email: vikash1146@gmail.com

capacitors in a reconfigured system for reducing power loss and optimising voltage profile is discussed.[15] Various search optimization techniques were discussed in the literature to get the best solution for optimal power flow (OPF) issue using GSA, Jaya Optimizer, Glow Worm Swarm Optimization, Modified TLBO and teaching-learning-optimization technique.[16–19] A few multi-objective structures for the OPF issue are talked about using various optimization techniques.[20–23]

The following are the main contributions of this research work:

(i) The locations of weak nodes for the placement of FACTS are identified through the power flow method.

(ii) A multi-functional objective function is obtained for the RPM.

(iii) Restricting the overall system operating cost and the number of FACTS is taken into consideration.

(iv) Four distinct optimization techniques, including GA, PSO, TLBO and GSA are implemented to optimize the position of the FACTS in the system.

(v) A comparative performance evaluation of all four algorithms has been made in terms of minimum energy loss and overall cost.

Related Works

The active and reactive loading of any system is increased with the help of FACTS and the system performance is observed by utilizing the GSA.[24] Even though at higher loading energy loss and operating cost reduces with FACTS. Steady-state power flow control in the network with embedded FACTS by considering active and reactive power as an independent control variable has been discussed in Xiao *et al*.[25] Li *et al*.[26] optimized the flow of reactive power in various IEEE's test networks by adopting the Hybrid Artificial Bee Colony (HABC) and Differential Evolution (DE) techniques. The solution of multi-objective like minimization of fuel cost, energy loss and voltage deviation are minimized for optimal power flow is considered using GSA in two test systems.[27] Optimal power flow using Hybrid TLBO algorithm to improve system stability by increasing the system's power transfer capacity with UPFC has been discussed by the authors.[28] Optimal adjustments of control variables such as continuous and discrete variables for the solution of multi-objective OPF problems is optimized using ABC algorithm.[29]

As per our search results, we have not found any paper on mechanism of utilization of current indices for determining the best position and size for different types of FACTS.

Prerequisite

FACTS are generally power electronics devices, which are able to regulate one or a significant number of the network variables, such as series or shunt impedance, current and voltage alone or in coordination with others. Two widely used variants of FACTS are TCSC and SVC.

A. SVC

SVC is a collection of electrical equipment. SVC provides a rapid flow of reactive power in the system of high voltage transmission lines. The main reason for SVC placement is the fast control and enhancement of voltages in the network. The SVC consists of a fixed value shunt reactor or capacitors. It may also contain one or many capacitor or reactor banks. These reactor or capacitor banks are controlled by thyristor valves placed in parallel. These SVC components are associated with the transmission network line with the shunt transformer. SVC's simple diagram is given in Fig. 1.

B. TCSC

TCSC gives a proficient method to control and increment the level of powertransferred in a system by modifying the evident impedance of an ideal transmission network line. TCSC's simple diagram were shown in Fig. 2. It consists of an arrangement of a controlled capacitor corresponding with a Thyristor Controlled Reactor (TCR).

Selection of Weak Node

The proper placement of FACTS in the transmission network is a critical and difficult task.

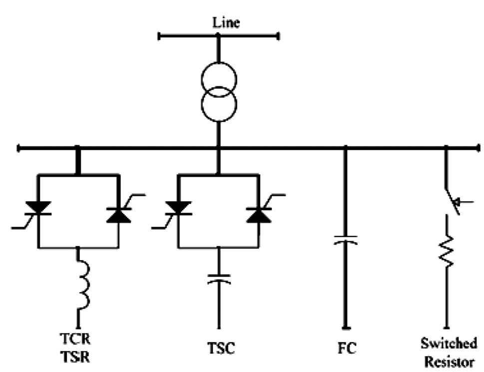

Fig. 1 — Simple diagram of SVC

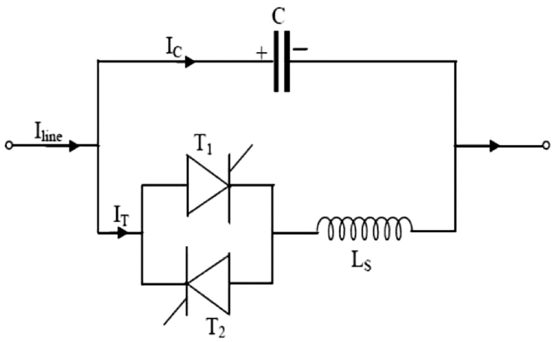

Fig. 2 — Simple diagram of TCSC

The locations of weak nodes for the placement of FACTS are identified through the power flow method. FACTS like TCSC and SVC are being used in various networks to bring down the flows in congested lines, reduce energy losses, improve the voltage distribution across all buses, and at the same time minimize the overall operating cost even at higher loading conditions. So, eight locations are selected for the installation of FACTS in a IEEE 30 bus network. SVCs locations are chosen by picking the lines with high reactive power. So the 21st, 7th, 17th & 15th buses are selected where satisfactory reactive injections by SVCs can enhance the network efficiency. TCSCs are places on the 25th, 41st, 28th & 5th lines to minimize the overall reactance of the line. FACTS controls the flow of reactive power which decreases the energy loss along with the system operating cost.

Objective Function

The primary objective is to maintain the total system operating cost as low as possible. The numerical equation of the energy loss can be defined as in Eq. (1) exposed to the requirements given underneath:

$$Energy_{Loss} = \sum_{k=1}^{L} g_k(V_i^2 + V_j^2 - 2V_iV_j\cos(\theta_i - \theta_j)) \quad (1)$$

where, V_i, V_j: Voltages at ith and jth bus;

g_k: real part of admittance matrix;

L: Total number of bus;

θ_i, θ_j: Phase angle of ith and jth bus

$Q_i^{min_i^{max}}$; (Reactive power constraints): $V_i^{min_i^{max}}$; (Voltage magnitude constraints): $Qg_i^{min_i^{max}}$; (Reactive generation constraints)

The total working expense can be given as:

$$Cost_{TOTAL} = C_{SVC} + C_{TCSC} + C_{Loss} \quad \ldots (2)$$

where $Cost_{SVC}$, $Cost_{TCSC}$ and $Cost_{Loss}$ are the SVC's, TCSC's and Loss cost respectively and given as:

$$Cost_{SVC} = 0.0003(F1)^2 - 0.305(F1) + 127.38 \text{ (\$/kVar)} \quad \ldots (3)$$

$$Cost_{TCSC} = 0.0015(F2)^2 - 0.7130(F2) + 153.75 \text{ (\$/kVar)} \quad \ldots (4)$$

$$Cost_{Loss} = 0.06 \times 8760 \times 10^5 \times Energy_{Loss} \text{(\$/kVar)} \quad \ldots (5)$$

The equations resulting from the flow of real and reactive power between buses i and j in the wake of joining FACTS would show up as:

$$P_{ij} = V_i^2 g_{ij}' - V_iV_j(g_{ij}'\cos\theta_{ij} + b_{ij}'\sin\theta_{ij}) \quad \ldots (6)$$

$$Q_{ij} = -V_i^2 b_{ij}' - V_iV_j(g_{ij}'\sin\theta_{ij} - b_{ij}'\cos\theta_{ij}) \quad \ldots (7)$$

$$P_{ji} = V_j^2 g_{ij}' - V_iV_j(g_{ij}'\cos\theta_{ij} - b_{ij}'\sin\theta_{ij}) \quad \ldots (8)$$

$$Q_{ji} = -V_j^2 b_{ij}' + V_iV_j(g_{ij}'\sin\theta_{ij} + b_{ij}'\cos\theta_{ij}) \quad \ldots (9)$$

where, g' and b': real and imaginary parts of Ybus with the incorporation of FACTS,

$$Y_{bus}' = g' - jb' \, (10) \quad \ldots (10)$$

By then, load flow is simulated with this changed Ybus in calculating the objective function for each iteration's population in the instances of GA, PSO, GSA and TLBO methods.

Proposed Approach

Two different recently proposed heuristic optimization techniques i.e. GSA and TLBO have been implemented for optimal position and size of FACTS. These techniques have shown achievement in solving the optimization problem. A brief explanation of these techniques is given below.

GSA

GSA is an analytical technique that depends on the gravitational law of physics. It provides an efficient optimized solution for a non-linear problem.

Let there will be N number of variable string/masses having K dimension.

$$X_i = (x_i^j \ldots, x_i^d \ldots, x_i^k) \quad \ldots (11)$$

where i=1, 2, 3…..N

G(t), the gravitational constant is calculated by:

$$G(t) = G_o e^{-\beta \frac{t}{T}} \quad \ldots (12)$$

where β: is a constant; T: maximum iteration/Time.

$F_{ij}(t)$, gravitational force following up on the two masses 'i' and 'j' at iteration/time 't' can be stated as:

$$F_{ij}^d(t) = G(t) \times \frac{mass_{pi}(t) \times mass_{aj}(t)}{R_{ij} + \varepsilon} \times (x_i^d(t) - x_j^d(t)) \quad \ldots (13)$$

where $mass_{pi}$ and $mass_{aj}$: passive and active gravitational mass of 'i' and 'j' respectively. $R_{ij}(t)$ is the euclidiean space between the mass 'i' and 'j',which may be defined as:

$$R_{ij}(t) = ||X_i(t). X_j(t)|| \quad \ldots (14)$$

The overall force following up on the mass of the dimension d can be calculated as:

$$F_i^d(t) = \sum_{j \in Kbest, j \neq i}^{N} rand_j \times F_{ij}^d(t) \quad \ldots (15)$$

The overall mass of the variable string is dependent on its fitness value in the function and can be evaluated as:

$$Mass_i(t) = \frac{mass_i(t)}{\sum_{j=1}^{N} mass_j(t)} \quad \ldots (16)$$

where, m_i (t) is given as:

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \quad \ldots (17)$$

where, *$fit_i(t)$* , *best (t)* and *worst (t)* are fitness, best and worst values at time 't' respectively.

The acceleration of the variables/masses is needed to be calculated to determine the velocity of the variables/masses. The acceleration can be given as:

$$a_i^d = \frac{F_i^d(t)}{M_{ii}(t)} \quad \ldots (18)$$

Velocity of the variable string /masses will be modified by the given equation:

$$Velocity_i(t+1) = rand_i \times Velocity_i(t) + a_i(t) \ldots (19)$$

where, $Velocity_i$ (t) : velocity and $a_i(t)$: acceleration at time 't' for i^{th} iteration. $rand_i$: random number in [0,1].

Similarly, the position of variables will be updated as:

$$X_i(t+1) = X_i(t) + Velocity_i(t+1) \quad \ldots (20)$$

By updating the string variables we can minimize our objective function.

TLBO

The TLBO algorithm depends on the teacher-student learning process into a classroom. Algorithm is basically population dependent. The algorithm has two phases of learning: (i) teaching phase/mode and (ii) learning phase/mode. The advantage of this technique is that it doesn't require the tuning of the different controlling parameters as compared to other popular optimization techniques. It just relies upon the population size and the number of cycles.

Teaching Mode

The teaching mode is motivated by the teaching of the teacher in the classroom. The teacher being the most experienced person in the classroom conveys his wisdom to the students. He tries to strengthen the mean understanding of the students. The understanding gained by the students depends on the way the teacher teaches and the students learn. Consider, there are 'n' number of students (population size, S = 1,2,3,4...n). Also the number of subjects can be defined as 'm' (i.e. variables, g = 1, 2, 3, 4…m). At any teaching cycle 'i' the result mean of a student in any particular subject 'g' can be calculated as $M_{g,i}$. The difference between the teacher's performance and the average outcome of the students' learning can be expressed as:

$$Diff\_mean_{g,i} = r_i(X_{g,sbest,i} - T_F M_{g,i}) \quad \ldots (21)$$

where, r_i : arbitrary random number within [0,1]. The T_F value is taken as '1'. $X_{g,kbest,i}$: best result (the teacher's result in g^{th} subject). From the difference mean the initial population is updated under the teaching mode as:

$$Xnew_{g,s,i} = X_{g,s,i} + diff\_mean_{g,i} \quad \ldots (22)$$

where, the $X_{new,g,s,i}$: updated population form of $X_{g,s,i}$. it ought to likewise be noticed that if the updated population gives the improved results, the population will be taken to the learning mode only.

Learning Mode

This algorithm is based on the sharing of knowledge by the students among themselves. The knowledge of the students also increases by interaction and discussions. In this phase, two random students (i.e. population, say R and S) are selected and their learning is compared. The more knowledgeable student shares his knowledge with the other. If student 'R' is better than student ''S', then 'R' can be updated as:

$$X_{g,R,i_{new}} = X_{g,R,i} - rand \times (X_{g,R,i} - X_{g,S,i}) \quad \dots (23)$$

Else,

$$X_{g,S,i_{new}} = X_{g,S,i} - rand \times (X_{g,S,i} - X_{g,R,i}) \quad \dots (24)$$

By the exchange of knowledge among students the population is improved and better results can be obtained. As many times both the modes are executed, the knowledge gets improved and the required optimum solution can be obtained.

Results and Discussion

The simulation of the PSO, TLBO, GA and GSA algorithms is evaluated on an IEEE 30-bus network. The performance of the network is assessed using all the techniques for 100 iterations to reconfigure the reactive power flow, voltage magnitude enhancement, minimization of operating cost and transmission loss for various reactive loading cases. The programs are executed on MATLAB 2015a and simulated on 4GB RAM, 1.2 GHz core i5 processor.

The location of various variables including the existing and FACTS are presented in Table 1. In Table 2 the flow of reactive power in the branches for different loadings are presented. The voltage level of the nodes where SVCs were present is given in Table 3. The energy loss in the network before and after the installation of FACTS is presented in Table 4. The total network operating costs before and after the placement of SVC and TCSC are given in Table 5.

It is clear from Table 1 that the position for the installation of SVCs and TCSCs is obtained from the load flow analysis. It is clear from Table 2 that the flow of reactive power in the lines has decreased after placing FACTS. The optimal placement of the FACTS device has brought about a re-dispatch power flow in the lines. From Table 3, we can see that there

Table 1 — Location of variable in the system

TCSC's in lines	SVC's at bus	Transformer tap branch locations	Bus Generator locations
25, 41, 28, 5	21, 7, 17, 15	6–9, 6-10, 4–12, 28–27	2, 5, 8, 11, 13

Table 2 — Flow of reactive power in lines at different loadings using different optimization techniques

Line No.	100% loading			110% loading			120% loading		
	Initial Q-flow	Q-flow using GSA and TLBO		Initial Q-flow	Q-flow using GSA and TLBO		Initial Q-flow	Q-flow using GSA and TLBO	
27	0.0939	GA	0.1939	0.1037	GA	0.2945	0.1135	GA	0.0987
		PSO	0.0060		PSO	0.0065		PSO	0.0584
		TLBO	0.2018		TLBO	0.0065		TLBO	0.0924
		GSA	0.1610		GSA	0.3481		GSA	0.2645
9	0.0731	GA	0.0168	0.0762	GA	0.0713	0.0793	GA	0.0631
		PSO	0.1431		PSO	0.1442		PSO	0.1104
		TLBO	0.1599		TLBO	0.1442		TLBO	0.1775
		GSA	0.0284		GSA	−0.1899		GSA	0.0384
26	0.0608	GA	0.0648	0.0633	GA	0.0508	0.0659	GA	0.0425
		PSO	−0.0289		PSO	−0.0508		PSO	0.0280
		TLBO	0.0758		TLBO	0.0508		TLBO	0.0518
		GSA	−0.0056		GSA	0.0443		GSA	0.0429
18	0.0507	GA	0.0427	0.0591	GA	0.0549	0.0675	GA	0.0507
		PSO	−0.0085		PSO	0.0409		PSO	−0.0448
		TLBO	0.0192		TLBO	0.0409		TLBO	0.1028
		GSA	−0.0854		GSA	0.0054		GSA	−0.0250

Table 3 — Bus Voltage using TLBO and GSA techniques for various reactive loadings

SVC in Bus	100% loading			110% loading			120% loading		
	Initial Voltage	Bus Voltage using GSA and TLBO		Initial Voltage	Bus Voltage using GSA and TLBO		Initial Voltage	Bus Voltage using GSA and TLBO	
21	1.0311	GA	1.0658	1.0265	GA	1.0659	1.0219	GA	1.0873
		PSO	1.0860		PSO	1.0641		PSO	1.1089
		TLBO	1.0303		TLBO	1.0241		TLBO	1.1089
		GSA	1.0245		GSA	1.0134		GSA	1.0060
7	1.0085	GA	1.0102	1.0076	GA	1.0095	1.0066	GA	1.0093
		PSO	1.0149		PSO	1.0139		PSO	1.0089
		TLBO	1.0065		TLBO	1.0039		TLBO	1.0089
		GSA	1.0034		GSA	1.0013		GSA	1.0034
17	1.0364	GA	1.0677	1.0324	GA	1.0682	1.0283	GA	1.0869
		PSO	1.0926		PSO	1.0724		PSO	1.1047
		TLBO	1.0454		TLBO	1.0424		TLBO	1.1047
		GSA	1.0190		GSA	1.0280		GSA	1.0190
15	1.0306	GA	1.0640	1.0271	GA	1.0653	1.0235	GA	1.0796
		PSO	1.0920		PSO	1.0721		PSO	1.1006
		TLBO	0.0569		TLBO	1.0321		TLBO	1.1006
		GSA	1.0145		GSA	1.0110		GSA	1.0745

Table 4 — Comparative statement of energy loss for various reactive loading with TLBO and GSA

Loading	Energy Loss (p.u.)				
	Initial loss	With GA	With PSO	With TLBO	With GSA
100%	0.0711	0.0441	0.0436	0.0461	0.0363
110%	0.0716	0.0473	0.0447	0.0470	0.0369
120%	0.0721	0.0499	0.0450	0.0476	0.0383

Table 5 — Operating Cost at various loadings using optimization techniques

Loading (%)	Initial operating cost ($)	Optimization techniques	Operating Cost using optimization techniques ($)	Net saving ($)
100		GA	23,81,395	13,55,621
	37,37,016	PSO	23,21,663	14,15,353
		TLBO	24,54,400	12,82,616
		GSA	19,36,961	18,00,055
110	37,63,296	GA	25,35,488	12,27,808
		PSO	23,79,500	13,83,796
		TLBO	25,00,900	12,62,396
		GSA	19,68,553	17,94,743
120	37,89,576	GA	26,69,664	11,19,912
		PSO	23,95,240	13,94,336
		TLBO	25,29,500	12,60,076
		GSA	20,41,065	17,75,511

is an improvement in the bus voltages where SVCs are placed even for the higher loading. There is a significant loss reduction in the system using different optimization techniques after placing FACTS, as is clear from Table 4. It is shown in Table 5 that there are net savings in the total system's operating cost after the placement of SVC and TCSC.

The variation in energy loss with PSO, TLBO, GA and GSA based techniques at 120 percent reactive loading are presented in Fig. 3. The variation in the operating cost with PSO, TLBO, GA and GSA based techniques at 120 percent reactive loading is shown in Fig. 4.

The Wilcoxon Signed rank test and the pairwise Sign test are both employed to confirm the GSA's supremacy. Indeed, the Sign test and the Wilcoxon Signed rank test are two well-known non-parametric statistical tests, have been proposed for comparing the two heuristic approaches pairwise. To ensure a fair comparison, we ran the test for 20 times with each algorithm. In Table 6 the required minimum number of victories significance levels of α=0.05 and α =0.01 for one algorithm over another are presented. The outcomes when the energy loss were used as the victorious parameter is presented in Table 7. It is revealed from Table 8 that the GSA-based model has a significant advantage over the other models, with a magnitude of α =0.05.

Sign test p-value and h-value with loss of energy as the triumphant parameter in given in Table 9. Similarly, the Friedman test is often used, which is

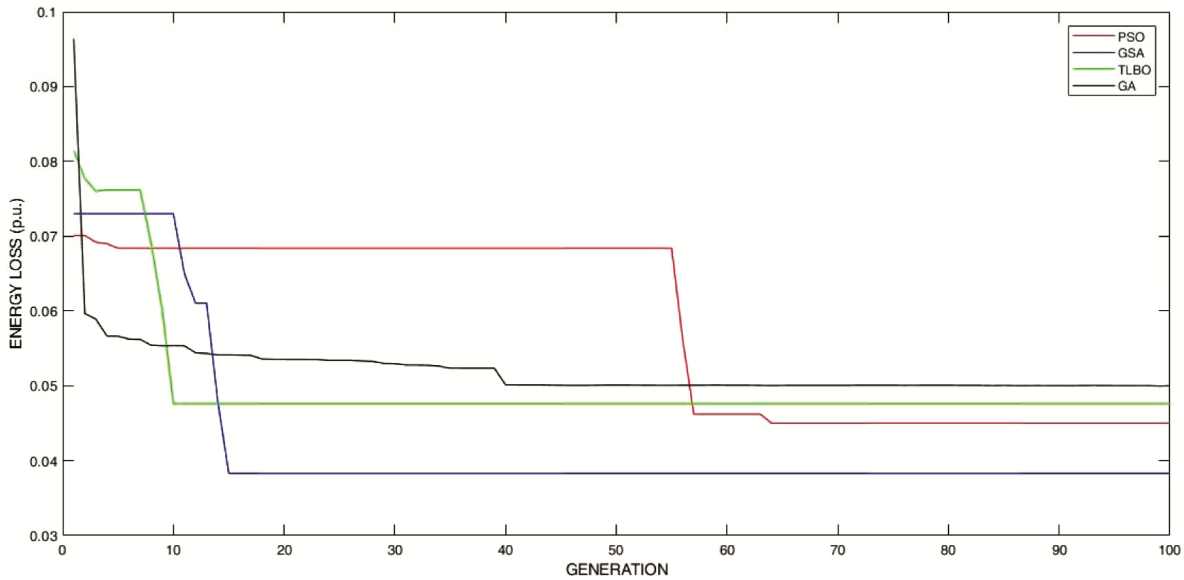

Fig. 3 — Variation in energy loss with PSO, TLBO, GA, and GSA at 120 percent reactive loading

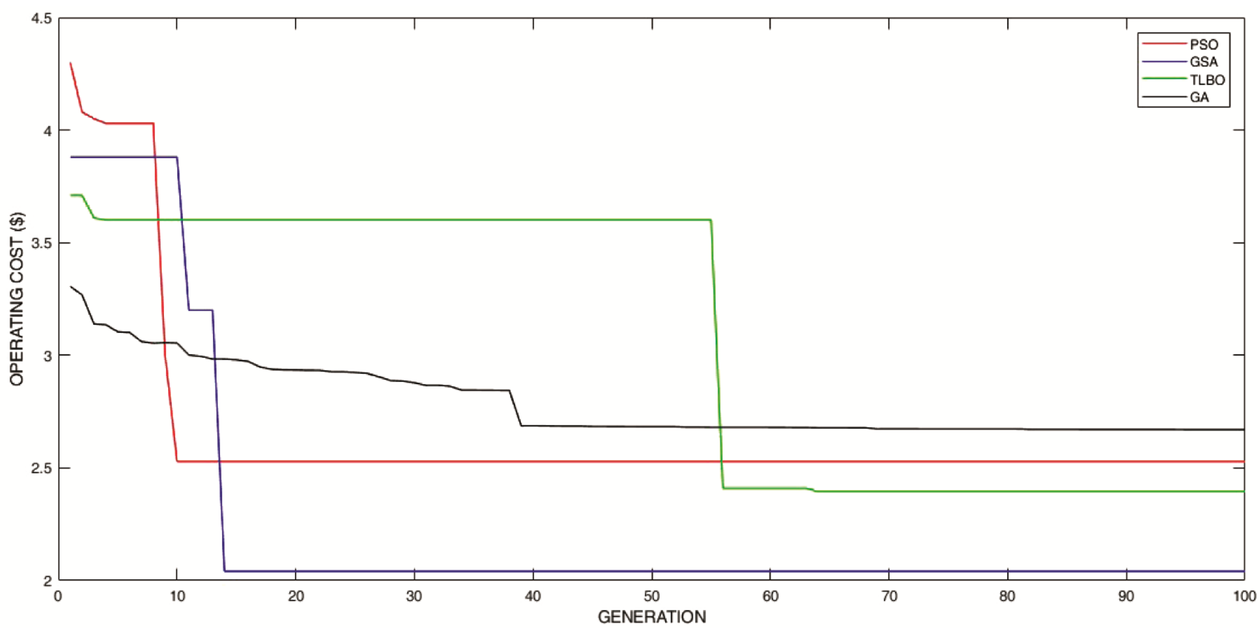

Fig. 4 — Variation in operationg cost with PSO, TLBO, GA, and GSA at 120 percent reactive loading

Table 6 — Minimum number of wins required to achieve significance levels of α=0.05 and α =0.01

No. of cases	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
$\alpha = 0.05$	5	6	7	7	8	9	9	10	10	11	12	12	13	13	14	15	15	16	17	18	18
$\alpha = 0.01$	5	6	6	7	7	8	9	9	10	10	11	12	12	13	13	14	14	15	16	16	17

Table 7 — Critical value for the two tailed sign tests achieved α = 0.05 and α = 0.01using loss of energy as victorious parameter

GSA	GA	PSO	TLBO
Wins (+)	20	18	17
Loss (−)	0	2	3
Detected difference	$\alpha = 0.05$	$\alpha = 0.05$	$\alpha = 0.05$

Table 8 — Sign test using loss of energyas a victorious parameter

Comparison	p-value	h-value
GSA with GA	0.0008	1
GSA with PSO	0.0004	1
GSA with TLBO	0.0009	1

Table 9 — Wilcoxon signed test with MSE as winning parameter

Comparison	p-value	h-value
GSA with GA	0.0001	1
GSA with PSO	0.0025	1
GSA with TLBO	0.0001	1

Table 10 — Ranking table for the Friedman test

Methods	GSA	GA	PSO	TLBO
Mean Ranks	17	5.2	8.2	17.2

Table 11 — Parameter for the Friedman test

Source	Sum of Squares	Degree of Freedom	Mean Square	Chi-Square	Critical value(p)
Column	141.1	4	35.275	56.44	1.6214E-11
Error	58.9	76	0.775		
Total	200	99			

similar to the paired t-test in statistical procedure and is commonly used to detect dominance activity between the two algorithms. In Tables 10 and 11 comparision of the performance of all algorithms is given.

Conclusions

In this paper, GSA and TLBO have been successfully tested and implemented for reactive power management by minimizing the energy loss along with the reduction in the overall cost of the system. Two other optimization techniques, like GA and PSO have also been used to solve the aforementioned problem. According to the simulation results the proposed GSA approach gives superior performance in terms of flexibility, operating cost, minimizing loss of energy as compared to the other three approaches. Furthermore, statistical testing, such as the Sign test and Friedman test have also been conducted to assess the dominance of the proposed GSA over the others.

References

1 Hingorani N G & Gyugyi L, Understanding FACTS: Concepts and Technology of Flexible ac Transmission Systems, IEEE Press, New York, 1999.

2 Mahdad B, Bouktir T & Srairi K, Strategy of location and control of FACTS for enhancing power quality, In *Proc IEEE Mediterranean Electrotechnical Conference, MELECON, Malaga*, (2016) 1068–1072.

3 Xiao Y, Song Y H &Sun Y Z, Power flow control approach to power systems with embedded FACTS, *IEEE Trans Power Syst*, **17** (2002) 943–950.

4 Cañizares C A & Faur Z T, Analysis of SVC and TCSC controllers in voltage collapse, *IEEE Trans on Power Syst*, **14** (1999) 158–165.

5 Rashedi E, Nezamabadi-Pour H & Saryazdi S, GSA: a gravitational search algorithm, *Inf sci*, **179** (2009) 2232–2248.

6 Poole D J, Allen C B & Rendall T C, Analysis of constraint handling methods for the gravitational search algorithm, In *Proc IEEE Congress on Evolutionary Computation (CEC), Beijing, China*, (2014) 2005–2012.

7 Rao R V, Savsani V J & Vakharia D P, Teaching-Learning-Based Optimization: A Novel Method for Constrained Mechanical Design Optimization Problems, *Comput Aided Des*, **43** (2011) 303–315.

8 Rao R V, Savsani V J & Balic J, Teaching learning based optimization algorithm for constrained and unconstrained real parameter optimization problems, *Eng Optim*, **44** (2012) 1447–1462.

9 Gupta V K, Bhattacharyya B & Kumar S, Enhancement of power system loadability with FACTS, *J Inst Eng (India): Series B*, **95** (2014) 113–120.

10 Mohammad A S M, Ladjevardi M, Jafarian A & Fuchs A F, Optimal placement, replacement and sizing of capacitor banks in distribution networks by genetic algorithm, *IEEE Trans Power Delivery*, **19** (2004) 1794–1801.

11 Kilic U, Ayan K & Arifoglu U, Optimizing reactive power flow of HVDC systems using genetic algorithm, *Int J Electr Power Energy Syst*, **55** (2014) 1–12.

12 Acha E, Ambriz-Perez H & Fuerte-Esquivel C, Advanced SVC models for newton-raphson load flow and newton optimal power flow studies, *IEEE Trans on Power Syst*, **15** (2000) 129–136.

13 Noroozian M & Andersson G, Power flow control by use of controllable series components, *IEEE Trans Power Delivery*, **8** (1993) 1420–1429.

14 Bhatt M S, Energy efficiency improvement of electrical transmission distribution networks, *J Sci Ind Res*, **62** (2003) 473–490.

15 Reddy M D & Reddy V C V, A two-stage methodology of optimal capacitor placement for the reconfigured network, *Indian J Eng Mater Sci*, **17** (2010) 105–112.

16 Duman S, Güvenç U, Sönmez Y & Yörükeren N, Optimal power flow using gravitational search algorithm, *Energy Convers Manag*, **59** (2012) 86–95.

17 Warid W, Hizam H, Mariun N & Abdul-Wahab N I, Optimal power flow using the Jaya algorithm, *Energies*, **9** (2016) 1–18.

18 Reddy S S & Rathnam C S, Optimal power flow using glowworm swarm optimization, *Int J Electr Power Energy Syst*, **80** (2016) 128–139.

19 Bouchekara H R E H, Abido M A & Boucherma M, Optimal power flow using teaching-learning-based optimization technique, *Int J Electr Power Syst Res*, **114** (2014) 49–59.

20 Reddy S S, Solution of multi-objective optimal power flow using efficient meta-heuristic algorithm, *Electr Eng*, **100** (2018) 401–413.

21 El-Fergany A A & Hasanien H M, Single and multi-objective optimal power flow using Grey Wolf optimizer and differential evolution algorithms, *Electr Power Compon Syst*, **43** (2015) 1548–1559.

22 Jamal R, Men B & Khan N H, A novel nature inspired meta-heuristic optimization approach of GWO optimizer for optimal reactive power dispatch problems, *IEEE Access*, **8** (2020) 202596–202610.

23 Ismail B, Wahab N I A, Othman M L, Radzi M A M, Vijyakumar K N & Naain M N M, A comprehensive review on optimal location and sizing of reactive power compensation using hybrid-based approaches for power loss reduction, voltage stability improvement, voltage profile enhancement and loadability enhancement, *IEEE Access*, **8** (2020) 222733–222765.

24 Bhattacharyya B & Kumar S, Loadability enhancement with FACTS using gravitational search algorithm, *Int J Electr Power Energy Syst*, **78** (2016) 470–479.

25 Xiao Y, Song Y H & Sun Y Z, Power flow control approach to power systems with embedded FACTS, *IEEE Trans on Power Syst*, **17** (2002) 943–950.

26 Li Y, Wang Y & Li B, A hybrid artificial bee colony assisted differential evolution algorithm for optimal reactive power flow, *Int J Electr Power Energy Syst*, **52** (2013) 25–33.

27 Bhattacharya A & Roy P K, Solution of multi-objective optimal power flow using gravitational search algorithm, *IET Gener Transm Distrib*, **6** (2012) 751–763.

28 Madhubalan S, Padma S & Abdul Shabeer H, Stability enhancement of power system with UPFC using hybrid TLBO algorithm, *J Sci Ind Res*,**79** (2020) 112–115.

29 Adaryani M R & Karami A, Artificial bee colony algorithm for solving multi-objective optimal power flow problem, *Int J Electr Power Energy Syst*, **53** (2013) 219–230.