Performance Analysis of Different Search Algorithms in Optimization of Power System Operation

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Abstract—**A Flexible AC Transmission System (FACTS) device such as Static Var Compensator (SVC) in a power system improves the voltage profile, reduces power loss and overall cost of the system. To find optimal location and size of the FACTS device, different search algorithms are used. This study focuses on the comparative performance analysis of Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) algorithm to find optimal location and rated value of SVC for the purpose of optimizing total power loss, total cost and improving voltage profile of the power system. Algorithms' computational efficiency is also investigated. To show validity of the proposed techniques, simulations are carried out on IEEE 14 bus and IEEE 57 bus.**

Keywords-Power System Optimization; Static Var Compensator (SVC); Genetic Algorithm (GA); Particle Swarm Optimization (PSO); Ant Colony Optimization (ACO).

I. INTRODUCTION

The operation of power system is becoming more and more challenging because of continuously increasing load demand which is causing extreme stress on the transmission lines, voltage instability, increase in loss and cost. To meet the ever increasing demand, it is essential to maximize the utilization of the existing transmission system.

In recent years, due to advancement in high power solid-state switches, transmission controllers have been developed which provide more flexibility and controllability. A new solution for controlling power flow known as Flexible AC Transmission System (FACTS) was introduced in 1988 by Hingorani [1]. FACTS devices have made the power system operation more flexible and secure. They have the ability to control, in a fast and effective manner. FACTS controllers minimize loss, enhance the voltage profile and increase the load ability margin of power systems [2].

FACTS devices include Thyristor Controlled Series Compensator (TCSC), Static Var Compensator (SVC), Thyristor Controlled Phase Angle Regulator (TCPAR), Static Compensator (STATCOM), Unified Power Flow Controller (UPFC), etc. The most widely used shunt FACTS devices within power networks is the SVC because of its low cost and good performance in system enhancement. It is a shunt-connected static var generator or absorber. Its output is adjusted to exchange capacitive or inductive current to provide voltage support. Again, if it is installed in a proper location, it can also reduce power losses [3].

Various FACTS controllers, their modelling and their impact on power systems have been reported in the literature [4]-[10]. But, most effective use of the FACTS devices largely depends on how these devices are placed in the power systems, i.e. on type, location and size [11]. An optimal location of FACTS devices allows controlling its power flows. As a result, the reliability of the power systems is enhanced [12]. Optimal location and rated value can be found by applying popular search algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Improved Harmony Search (IHS), Ant Colony Optimization (ACO) etc.

Genetic Algorithm was initially developed by John Holland, during 1970's. The genetic algorithm is a search algorithm that iteratively transforms a set (called a population) of mathematical objects (typically fixed-length binary character strings) , each with an associated fitness value, into a new population of offspring objects using the Darwinian principle of natural selection and using operations such as crossover (sexual recombination) and mutation.

Particle Swarm Optimization (PSO) is a population based stochastic optimization technique developed by Kennedy and Eberhart (1995), inspired by social behaviour of bird flocking or fish schooling. The main idea is based on the food-searching behaviour of birds. It is observed that they take into consideration of the global level of information to determine their direction. The global and local best positions are computed at each iteration and the output is the new direction of search. Once this direction is detected, it is followed by the cluster of birds.

ACO is a probabilistic technique for optimization initially proposed by Marco Dorigo(1991). Ant Colony Optimization (ACO) method is quite similar to Particle Swarm Optimization (PSO). It also falls in swarm intelligence method, and it constitutes some meta-heuristic optimizations. The algorithm is based on the behaviour of ants seeking a path between their colony and a source of food.

Various research using different FACTS devices and different algorithms have been reported [13]-[20]. Different algorithms show different performances for different aspects. This article therefore analyses the performance of GA, PSO and ACO technique to determine optimal location and rated value of SVC in transmission network. The optimized loss, cost and improved voltage profile of the algorithms are compared and discussed. The required iterations per bus to meet the convergence criterion are also shown. The methods are verified for IEEE 14 bus and IEEE 57 bus.

II. PROBLEM FORMULATION

A. Mathematical Formulation

In this present research, optimal location and size of SVC have been found by formulating multi-objective optimal power flow (OPF). Certain objectives subject to satisfying some network constraints have been minimized. Mathematically, the OPF problem can be written as follows:

Minimize,

$$F(x,u)=\begin{bmatrix} f_1(x,u) \\ . \\ . \\ f_k(x,u) \end{bmatrix} \quad (1)$$

Where, $k = 1, 2,\ldots\ldots\ldots$ number of objectives

Subject to

$$g(x,y)=0$$
$$h(x,u)\le 0$$

Here, x and u represent vector of dependent and control variables respectively. For example, the dependent variables include slack bus power, bus voltage angles, load bus voltage magnitudes etc. Whereas, control variables include PV bus voltage magnitude, generated power etc. The real and reactive power balance equations are denoted by $g(x,u)$ and components operational limits are denoted by $h(x,u)$.

B. Objective Functions

1) Cost

The total cost is calculated from fuel cost and SVC cost. The fuel cost can be determined from the following quadratic equation.

$$\min(\ F(P_i)) = \sum_{i=1}^{NG} (a_i P_i^2 + b_i P_i + c_i) \quad (2)$$

Where, a_i, b_i, c_i are cost coefficients, P_i is real power generation and NG is the number of generation buses.

The SVC cost can be determined from the following equation.

$$\min(\ C_{SVC}) = \min(\ 0.0003\ S^2 - 0.305\ S + 127.38) \quad (3)$$

Where, C_{SVC} denotes Cost of SVC, S denotes Operating range of SVC in MVAR.

The objective function is then formulated using total cost.

2) Power Loss

The objective function is formulated using total real power loss. The value of current depends on the bus voltages and transmission line parameters. After getting all branch data the loss is accumulated and finally the total loss is found.

3) Voltage Deviation

To have a good voltage performance, the voltage deviation at each load bus must be made as small as possible. The minimum voltage deviation (VD) is determined by the following equation:

$$\min(\ VD\ ) = \min(\ \sum_{i=1}^{n} (|V_i - 1|)^2\ ) \quad (4)$$

Where, V_i denotes voltage magnitude at load bus i.

C. Constraints

1) Facts Device Constraints

The FACTS device i.e. SVC injects extra reactive power to the PQ bus. So, the search domain for FACTS device constraint is location and value. The location domain is only PQ buses. Due to capacity limit, the FACTS device rated value limit is represented by following equation.

$$Q^{\min} \le Q \le Q^{\max} \quad (5)$$

Where, Q is the FACTS device rated value in MVAR.

2) Power Loss Constraints

The system should have minimum loss. But, the FACTS devices have a limit up to which the loss can be minimized. So, the loss constraint is

$$P_{Loss}^{\min} \le P_{Loss} \le P_{Loss}^{\max} \quad (6)$$

Where, P_{Loss} denotes Real power loss in MW.

3) Cost Constraints

Due to decrease in fuel cost the total cost per unit decreases. But, the per unit cost increases due to FACTS device cost. It is also not possible to make the loss zero. So, the power system should be optimized in such a way that the ultimate per unit cost must be less than per unit cost without using FACTS device. Hence, the cost constraint is as follow:

$$F^{\min} \le F \le F^{\max} \quad (7)$$

Where, F denotes Total cost.

4) Voltage Profile Constraints

The desired value of voltage for each bus is unity in per unit scale. But, the reality is the voltage of buses never to be equal to unity. So, a range of voltage is considered as bus voltage profile constraints in the time of optimization.

$$\left|V_i^{\min}\right| \le \left|V_i\right| \le \left|V_i^{\max}\right| \quad (8)$$

Where, V_i denotes Voltage of i^{th} bus in per unit.

5) Power Balance Constraints

Total generated power of the power system must be equal to the sum of total power demand and total power loss. These criteria can be expressed by the following equations.

$$\sum P_G = \sum P_D + \sum P_L \quad (9)$$

$$\sum Q_G = \sum Q_D + \sum Q_L \quad (10)$$

Where, P_G= Generated real power in MW
P_D= Real power demand in MW
P_L= Real power loss in MW
Q_G= Generated reactive power in MVAR
Q_D= Reactive power demand in MVAR
Q_L= Reactive power loss in MVAR

Power demand and power loss are variables. But, power generation is limited from minimum to maximum output due to economy and capacity. Hence, power generation constraints can be represented as

$$\left|P_{Gi}^{\min}\right| \leq \left|P_{Gi}\right| \leq \left|P_{Gi}^{\max}\right| \quad (11)$$

$$\left|Q_{Gi}^{\min}\right| \leq \left|Q_{Gi}\right| \leq \left|Q_{Gi}^{\max}\right| \quad (12)$$

Where, P_{Gi}=Real power generation at i^{th} bus
Q_{Gi}= Reactive power generation at i^{th} bus.

III. Implementation of GA, PSO, ACO

A. *Genetic Algorithm*

Genetic Algorithm begins with a set of solutions (represented by chromosomes) called population. Solutions from one population are taken and used to form a new population. This is motivated by a hope, that the new population will be better than the old one. Solutions which are then selected to form new solutions (offspring) are selected according to their fitness - the more suitable they are the more chances they have to reproduce. This is repeated until some conditions are satisfied. The space of all feasible solutions (the set of solutions among which the desired solution resides) is called search space (also state space). Each point in the search space represents one possible solution. Each possible solution can be marked by its fitness for the problem. With GA the best solution among a number of possible solutions is determined.

The better fitness values among the population are selected as the parents to produce a better generation. This fittest test is accomplished by adopting a selection scheme in which higher fitness individuals are being selected for contributing offspring in the next generation. Many selection schemes such as Roulette Wheel, Random, Rank, Tournament and Boltzmann selection schemes are available.

A simple genetic algorithm that yields good results in many practical problems is composed of three operators:

1) *Reproduction*

This operator is an artificial version of natural selection based on Darwinian survival of the fittest among string creatures. Reproduction operator can be implemented in algorithmic form in a number of ways.

2) *Crossover*

It occurs after reproduction or selection. It creates two new population or strings from two existing ones by genetically recombining randomly chosen parts formed by randomly chosen crossover point.

3) *Mutation*

It is the occasional random alteration of the value of a string position. Mutation creates a new string by altering value of existing string.

B. *Particle Swarm Optimization*

There are two main ideas behind the optimization properties of PSO:

- A single particle (which can be seen as a potential solution to the problem) can determine “how good” its current position is. It benefits not only from its problem space exploration knowledge but also from the knowledge obtained and shared by the other particles.
- A stochastic factor in each particle's velocity makes them move through unknown problem space regions. This property combined with a good initial distribution of the swarm enable an extensive exploration of the problem space and gives a very high chance of finding the best solutions efficiently.

The mathematical model of PSO is given below:

$$v_i^{k+1} = w_i v_i^k + c_1 * rand_1 * (P_{best,i} - s_i^k) + c_2 * rand_2 * (G_{best,i} - s_i^k) \quad (13)$$

$$s_i^{k+1} = s_i^k + v_i^{k+1} \quad (14)$$

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iterw_{\max}} * iter \quad (15)$$

Where,

v_i^k =Velocity of i^{th} particle at k^{th} iteration
v_i^{k+1} =Velocity of i^{th} particle at $(k+1)^{th}$ iteration
s_i^k = Current position of particle i at k^{th} iteration
s_i^{k+1} =Current position of particle i at $(k+1)^{th}$ iteration

$P_{best,i}$ =Best position of i^{th} particle

$G_{best,i}$ = Best position among the particles (group best)

c_1 = Coefficient of the self-recognition component

c_2 = Coefficient of the social component

$c_1 + c_2 = 4$ $rand_1$ and $rand_2$ are usually chosen between [0, 1]

$w =$ Inertia weight

$w_{\max}$ = Initial value of inertia weight

$w_{\min}$ = Final value of inertia weight

$iter$ = Current iteration number

$iterw_{maz}$ = Maximum iteration

C. Ant Colony Optimization

In the natural world, ants (initially) wander randomly, and upon finding food return to their colony while laying down pheromone trails. If other ants find such a path, they are likely not to keep travelling at random, but to instead follow the trail; returning and reinforcing it if they eventually find food.

Over time, however, the pheromone trail starts to evaporate, thus reducing its attractive strength. The more time it takes for an ant to travel down the path and back again, the more time the pheromones have to evaporate. A short path, by comparison, gets marched over more frequently, and thus the pheromone density becomes higher on shorter paths than longer ones. Pheromone evaporation also has the advantage of avoiding the convergence to a locally optimal solution. If there were no evaporation at all, the paths chosen by the first ants would tend to be excessively attractive to the following ones. In that case, the exploration of the solution space would be constrained.

Thus, when one ant finds a good (i.e., short) path from the colony to a food source, other ants are more likely to follow that path, and positive feedback eventually leads to all the ants' following a single path. The idea of the ant colony algorithm is to mimic this behaviour with "simulated ants" walking around the graph representing the problem to solve.

Mathematically,

For the node ($x_1, x_2, x_3, \ldots\ldots, x_n$), the fitness function is

$$f(x) = 1 - \frac{1}{1 + F(x)} \tag{16}$$

Here, *F(x)* is the objective function.

The quantity of pheromone deposited by an ant at a visited node is

$$Phero\ (x) = \frac{1}{f(x)} \tag{17}$$

When each of the nodes in the topological neighbourhood of a node has been allocated the pheromone, the ant chooses a node using the probability

$$prob\ (x) = \frac{Phero\ (x)}{\sum Phero\ (x)} \tag{18}$$

Here the summation applies to all nodes, which are in the topological neighbourhood of the given node.

The pheromone update used in the work is given by

$$PheroUpdate(x) = 0.01 * Phero(x) \tag{19}$$

The procedure adopts the following formula for the pheromone evaporation.

$$PheroEvapo\,(x) = \frac{No.ofEncounteredVisits\ *\ Phero(x)}{100} \tag{20}$$

IV. Simulation Results and Discussions

The search algorithms GA, PSO and ACO are simulated to compare their performances. The simulation has been completed by developing and incorporating codes in MATLAB version 7.14). MATPOWER 4.1 (a package of code) has been used as associates of main code to get and format system data. The simulations have been performed on IEEE 14 bus system and IEEE 57 bus system. The convergence criterion is also determined from the simulation to observe algorithm performance.

Parameters of GA, PSO and ACO are given below:

TABLE I. Parameters of Different Algorithms

GA		PSO		ACO	
Population	20	Particles	20	Nodes	10
Cross over probability	0.8	C1	2.5	Pheromone update rate	0.01
Mutation probability	0.01	C2	1.5	Pheromone evaporation rate	0.99
		W_{max}	0.9	attractiveness	1.00
		W_{min}	0.4		

A. IEEE 14 Bus System

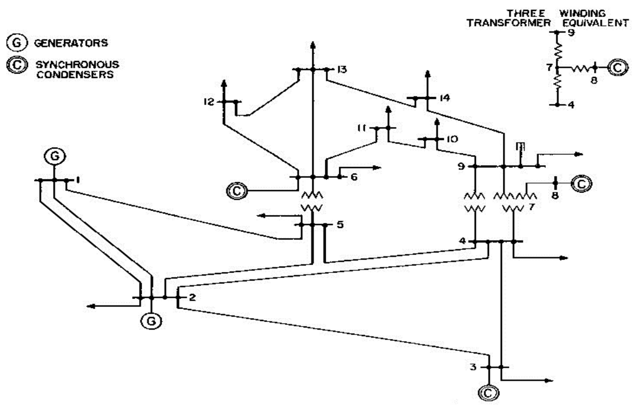

Figure 1. IEEE 14 Bus System

The IEEE 14 bus system is shown in Fig.1. The optimized system data are shown in TABLE II. The table focuses on the comparative results of GA, PSO and ACO after simulation. SVC location, value, power loss, cost per megawatt etc. have been tabled for comparison. The voltage profiles of the IEEE 14 bus system for different algorithms are shown in Fig.2.

TABLE II. IEEE 14 BUS SYSTEM DATA FROM GA, PSO, ACO

Terms	GA	PSO	ACO
Buses	14	14	14
Generators	5	5	5
Loads	11	11	11
Transformers	3	3	3
Total Generation Capacity(MW)	772.4	772.4	772.4
Total generated power (MW)	272.531	272.482	272.31
Power demand(MW)	259.0	259.0	259.0
SVC location	7	5	5
SVC value(MVAR)	24.81	48.32	26.8013
Power loss(MW)	13.452	13.332	13.31
Cost per Megawatt	30.0128	29.9996	29.9968

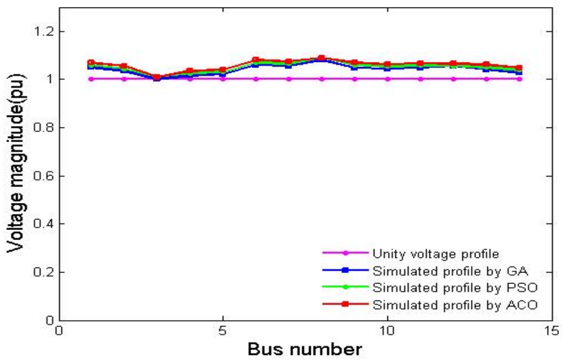

Figure 2. IEEE 14 Bus System Voltage Profile Obtained from GA, PSO, ACO.

B. IEEE 57 Bus System

Fig. 3 shows the IEEE 57 bus system. The optimized system data for IEEE 57 bus system are given in TABLE III. The table focuses on the comparative results of GA, PSO and ACO after simulation. SVC location, value, power loss, cost per megawatt etc. have been tabled for comparison. The voltage profiles of the IEEE 57 bus system for different algorithms are shown in Fig. 4.

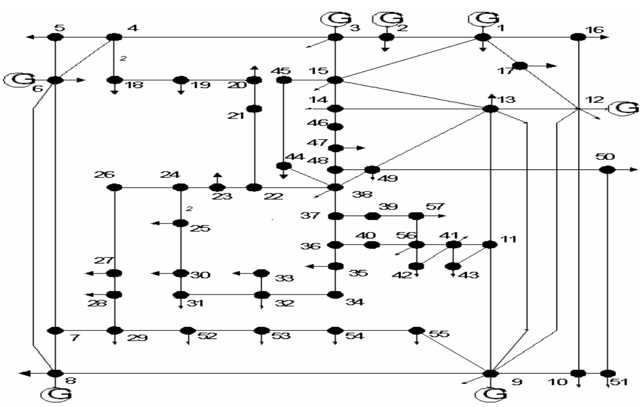

Figure 3. IEEE 57 Bus System

TABLE III. IEEE 57 BUS SYSTEM DATA FROM GA, PSO, ACO

Terms	GA	PSO	ACO
Buses	57	57	57
Generators	7	7	7
Loads	42	42	42
Transformers	17	17	17
Total Generation Capacity(MW)	1975.9	1975.9	1975.9
Total generated power (MW)	1278.331	1278.043	1277.941
Power demand(MW)	1250.8	1250.8	1250.8
SVC location	36	41	38
SVC value(MVAR)	23.8880	48.3912	42.1807
Power loss(MW)	27.531	27.243	27.141
Cost per Megawatt	40.4051	40.3172	40.1271

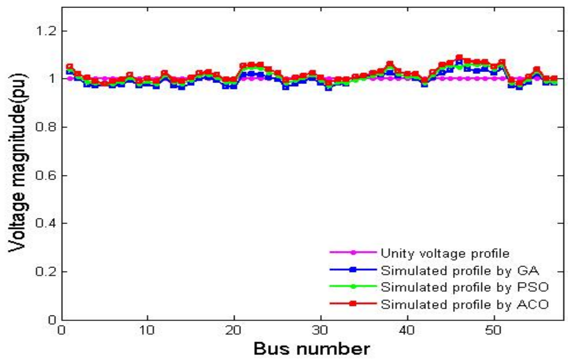

Figure 4. IEEE 57 Bus System Voltage Profile Obtained from GA, PSO, ACO.

C. Convergence Characteristic

The performance comparison of computational fastness for GA, PSO and ACO can be observed from convergence characteristics curve in the Fig. 5.

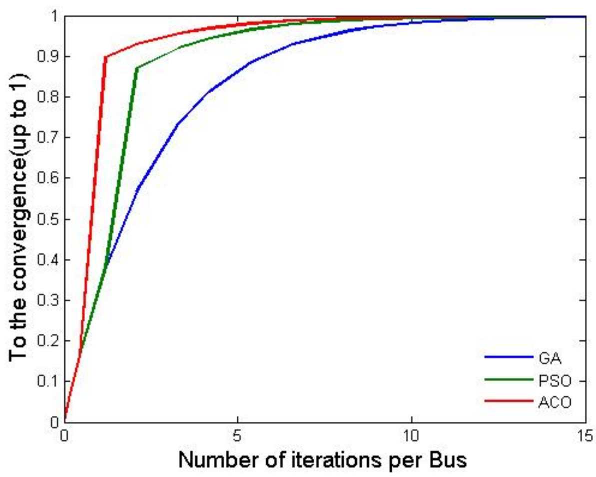

Figure 5. Convergence Characteristic of GA, PSO, ACO

D. Discussions

From the simulation results, it is observed that ACO gives the best performance among the three algorithms. Tables indicate that for both bus systems, ACO gives the lowest cost and loss than the others. However, PSO gives lesser loss and cost than GA. The voltage profile for IEEE 14 bus system is above unity for GA, PSO and ACO. But, for IEEE 57 bus system ACO gives excellent voltage profile whereas PSO gives moderate and GA gives worst voltage profile. For lower number of buses, algorithms show about same performance. But, in the case of higher number of buses, the comparative performance is obvious. Again, In Fig. 5 in case of meeting convergence, ACO shows its superior performance. However, PSO is faster than GA.

V. CONCLUSION

In this paper, GA, PSO and ACO have been used to find the optimal location and size of SVC device for the purpose of minimizing loss, cost and improving voltage profile. Simulations have been performed on IEEE 14 bus and IEEE 57 bus systems using MATLAB. From the obtained results and Graphs, it is clear that, overall, ACO is the best algorithm. It's also fastest. In fact, with the increase in bus numbers the difference in performance of the algorithms becomes clearer.

REFERENCES

[1] N. G. Hingorani, "Power electronics in electrical utilities: role of power electronics in future power systems", Proceedings of the IEEE, Vol. 76 No. 4, pp.481-482, Apr. 1988.

[2] Sode-Yome, A., N. Mithulananthan and K.Y. Lee, 2005. "Static voltage stability margin enhancement using STATCOM, TCSC and SSSC.", Proceedings of the IEEE/PES Transmission and Distribution Conference and Exhibition: Asia and Pacific, Aug.M18-18, IEEE Xplore Press, Dalian, pp: 1-6. DOI: 10.1109/TDC.2005.1547141.

[3] Reza Sirjani, Azah Mohamed, Hussain Shareef, "Optimal placement and sizing of Static Var Compensators in power systems using Improved Harmony Search Algorithm", PRZEGLĄD ELEKTROTECHNICZNY (Electrical Review), ISSN 0033-2097, R. 87 NR 7/2011

[4] M.Noroozian, L. Angquist, M. ghandhari, and G.Andersson, " Use of UPFC for optimal power flow control", IEEE Trans. Power Deliv., vol. 12, no. 4, pp. 1629-1634, Oct. 1997.

[5] Noroozian, M. Angquist, L. , Ghandhari, M. ; Andersson, G, "Improving power system dynamics by series-connected FACTS devices", Power Delivery, IEEE Transactions on (Volume:12 , Issue: 4), pp. 1635-1641, Oct 1997.

[6] C.R. Fuietre-Esquivel, E. Acha, and H. Ambriz-Perez, "A thyristor controlled series compensator model for the power flow solution of practical power networks", IEEE Trans. Power Syst., vol 15, no. 1, pp. 58-64, Feb.2000.

[7] E. Acha, C.R. Fuietre-Esquivel, H. Ambriz-Perez, FACTS modelling and simulation in power networks, England: John Wiley & Sons Ltd, 2004, pp. 200-215.

[8] A.M. Vural and M. Tumay, " Mathematical modelling and analysis of a unified power flow controller: A comparison of two approaches in power flow studies and effect of UPFC location", Electr. Power Energy Syst., vol.29, pp. 617-629, 2007.

[9] Bhowmick S., Das B. and Narendra Kumar, "An indirect UPFC model to enhance reusability of Newton power-flow codes," IEEE Trans. On Power Delivery, vol. 23, no. 4, pp.2079-2088, Oct. 2008.

[10] Rafael Mihalic and Uros Gabrijel, "Transient stability assessment of system comprising phase-shifting FACTS devices by direct methods", Elect. Power and Energy Syst., vol.26, pp.26, pp.445-453,2004.

[11] S. Gerbex, R. Cherkaoui, and A.J. Germond, "Optimal location of multi-type FACTS devices in a power system by means of genetic algorithms," IEEE Trans. Power Syst., vol.16, no.3, pp. 537-544, Aug. 2001.

[12] D.J. Gotham and G.T. Heydt, "Power flow control and power flow studies for systems with FACTS devices", IEEE Trans. Power Syst., vol. 13, no. 1, pp. 60-65, Feb. 1998.

[13] Y. Lu and A.Abur "Static Security enhancement via optimal utilization of thyristor-controlled series capacitors", IEEE Trans. Power Syst., vol.17, no.2, pp. 324-329, May 2002.

[14] L. Ippolito and P. Sinao, "Selection of optimal number and location of thyristor-controlled phase shifters using genetic based algorithms", Proc. Inst. Elect. Eng. Gen. Transm. Distrib, vol.151, no. 5, pp. 630-637, Sep. 2004.

[15] S. Rahimzadeh, M. Tavakoli Bina, and A.H. Viki, "Simultaneous application of multi-type FACTS devices to the restructured environment: achieving both optimal number and location", IET Gener. Transm. Distrib., vol. 4, no. 3, pp. 349-362, 2010.

[16] Tiwari, R., Niazi, K.R., Gupta, V., "Optimal Location of FACTS Devices for Improving Performance of the Power Systems", Power and Energy Society General Meeting, 2012 IEEE, pp. 1-8, 22-26 July 2012.

[17] Malakar, T., Sinha, N., Goswami, S.K., Saikia, L.C., "Optimal location and size determination of FACTS devices by using multiobjective optimal power flow", TENCON 2010 - 2010 IEEE Region 10 Conference, pp. 474-478, 21-24 Nov. 2010.

[18] S. Panda, and N.P. Padhy, "Optimal location and controller design of STATCOM for power system stability improvement using PSO", Journal of Frank Inst., vol. 345, pp. 166-181, 2008.

[19] Kalaivani, R. and V. Kamaraj, "Enhancement of Voltage Stability by Optimal Location of Static Var Compensator Using Genetic Algorithm and Particle Swarm Optimization", American J. of Engineering and Applied Sciences 5 (1): 70-77, 2012.

[20] S. M. Rakiul Islam, Md. Alimul Ahsan, and Bashudeb Chandra Ghosh, "Optimization of Power System Operation with Static Var Compensator applying ACO Algorithm," *Proceedings of IEEE 1st International Conference on Electrical Information and Communication Technology*, pp. 66–71, ISBN IEEE Xplore Compliant: 978-1-4799-2299-4/13, 12-15 February 2014, Khulna, Bangladesh.