OPTIMAL PLACEMENT OF TCSC FOR VOLTAGE CONSTRAINED LOSS MINIMIZATION USING SELF-ADAPTIVE FIREFLY ALGORITHM

Selvarasu.R
Research Scholar, Department of EEE, JNTUH, Hyderabad, India.
91944358563, selvarasunaveen@gmail.com
Christober Asir Rajan.C
Associate Professor, Department of EEE, PEC, Puducherry, India.
asir_70@pec.edu
Surya Kalavathi.M
Professor, Department of EEE, JNTUH, Hyderabad.
munagala12@yahoo.co.in

Abstract – Thyristor Controlled Series Compensator *(TCSC) is series compensating Flexible Alternating Current Transmission System (FACTS) Controller in power system network. The objective is to minimize the transmission loss besides keeping the voltage magnitude within the acceptable range. Using proposed strategy, the location of TCSCs and their parameter are optimized simultaneously. Self Adaptive Firefly Algorithm (SAFA) is proposed to solve the above optimization problem for better accuracy. The TCSC placement strategy is tested on three IEEE test systems and their results are presented to demonstrate its effectiveness.*

***Keywords**: Firefly Algorithm, Loss Minimization, TCSC, Voltage Profile*

1. Introduction

In recent years the power systems are forced to operate close to their thermal and stability limits due to exponentially increasing real and reactive power demand, thereby resulting high network loss with poor bus voltages and requiring construction of new generation facilities and transmission networks. However, they involve huge installation cost, environment impact, political, large displacement of population and land acquisition. One of the simplest ways for minimizing the transmission loss rather than constructing new generation systems is through providing optimal quantity of reactive power support at appropriate buses. Fixed and switched capacitors are commonly used for reactive power support.

The power electronics based FACTS devices, developed by N.G.Hingorani [1], have been effectively used for flexible operation and control of the power system through controlling their parameters. They have the capability to control the various electrical parameters in transmission network in order to achieve better system performance. FACTS devices can be divided into shunt connected, series connected and a combination of both [2]. The Static Var Compensator (SVC) and Static Synchronous Compensator (STATCOM) belong to the shunt connected device and are in use for a long time. Consequently, they are variable shunt reactors, which inject or absorb reactive power in order to control the voltage at a given bus. [3]. Thyristor Controlled Series Compensator (TCSC) and Static Synchronous Series Compensator (SSSC) are series connected devices for controlling the active power in a line by varying the line reactance. They are in operation at a few places but are still in the stage of development [4]-[5]. Unified Power Flow Controller (UPFC) belongs to combination of shunt and series devices and is able to control active power, reactive power and voltage magnitude simultaneously or separately [6]. These devices can facilitate the control of power flow, increase the power transfer capability, reduce the generation cost, improve the security and enhance the stability of the power systems.

In recent years, the SVC attracts the system engineers and researchers for providing reactive power support in power systems and its placement has significant influence on network loss and voltage profile. The installation of SVCs can be described as an optimization problem with objectives of simultaneously minimizing network loss and improving the voltage profile while satisfying system constraints.

Different nature inspired meta-heuristic algorithms such as Genetic Algorithm (GA), Simulated annealing (SA), Ant Colony Optimization (ACO), Bees Algorithms (BA), Differential Evolution (DE), and Particle Swarm Optimization (PSO) and Bacterial foraging optimization algorithm etc [7]-[21] have been applied in solving the FACTS placement problems. GA has been proposed to identify the optimal location of multi type FACTS devices in a power system to improve the loadability [9]. PSO has been applied to find the optimal location of FACTS devices considering cost of installation and system loadability. [10]. PSO has been proposed to select the optimal location and parameter setting of SVC and TCSC to mitigate small signal oscillations in multi machine power system [11]. Bees Algorithm has been proposed to determine the optimal allocation of FACTS devices for maximizing the available transfer capability [12]. Bacterial Foraging algorithm has been proposed for loss minimization and voltage stability improvement [13] Bacterial Foraging algorithm has been used to find the optimal location of TCSC devices with objectives of minimizing the losses and improving the voltage profile [14].

Firefly Algorithm (FA), which is a nature-inspired meta-heuristic algorithm, has been suggested for solving optimization problems [7]-[8]. It has been widely applied in solving several optimization problems, to name a few: economic dispatch [15]-[17], fault identification [18], scheduling [19] and unit commitment [20]-[21] etc. However, the improper choice of FA parameters affects the convergence and may lead to sub-optimal solutions. There is thus a need for developing better strategies for optimally selecting the FA parameters with a view of obtaining the global best solution besides achieving better convergence.

In this paper, a self adaptive firefly based strategy is proposed for TCSC placement with a view of minimizing transmission loss besides maintaining the voltage magnitude of all the buses with in the lower and upper bounds. The strategy identifies the optimal locations and the TCSC parameters. Simulations are performed on three IEEE test systems using MATLAB software package and the results are presented to demonstrate the effectiveness of the proposed approach.

2. TCSC Model

The Thyristor Controlled Series Compensator (TCSC) is a capacitive reactance compensator. It consists of a series capacitor bank shunted by a thyristor controlled reactor in order to provide a smoothly variable series capacitive reactance [2]. The TCSC can be connected in series with the transmission line to compensate the inductive reactance of the transmission line. The reactance of the TCSC depends on its compensation ratio and the reactance of the transmission line where it is located. The model of TCSC is shown in Fig.1. The TCSC modeled by the reactance, X_{TCSC} is given below,

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

$$X_{TCSC} = \gamma_{TCSC} X_{line} \qquad (2)$$

Where X_{line} =the reactance of the transmission is line and γ_{TCSC} is the compensation factor of the TCSC.

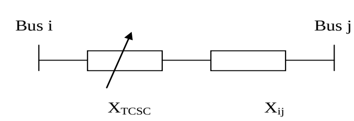

Fig.1.TCSC model

3. Firefly Algorithm

3.1 Classical Firefly Algorithm

FA is a recent nature inspired meta-heuristic algorithms which has been developed by Xin She Yang at Cambridge university in 2007 [7]. The algorithm mimics the flashing behavior of fireflies. It is similar to other optimization algorithms employing swarm intelligence such as PSO. But FA is found to have superior performance in many cases [8].

FA initially produces a swarm of fireflies located randomly in the search space. Initial distribution is usually produced from a uniform random distribution and the position of each firefly in the search space represents a potential solution of the optimization problem. Dimension of the search space is equal to the number of optimizing parameters in the given problem. Fitness function takes the position of a firefly as input and produces a single numerical output denoting how good the potential solution is. Fitness value is assigned to each firefly. The brightness of each firefly depends on the fitness value of that firefly. Each firefly is attracted by the brightness of other firefly and tries to move towards them. The velocity or the drag of a firefly towards another firefly depends on the attractiveness. The attractiveness of firefly depends on the relative distance between the fireflies and it can be a function of the brightness of the fireflies as well. In each iterative step, FA computes the brightness and the relative attractiveness of each firefly. Based on these values, the positions of the fireflies are updated. After a sufficient number of iterations, all fireflies will converge to the best possible position on the search space. The number of fireflies in the swarm is known as the population size, N. The selection of population size depends on the specific optimization problem. Though, typically a population size of 20 to 50 is used for PSO and FA for most applications [10, 16]. Each m^{th} firefly is denoted by a vector x_m as

$$x_m = \left[x_m^1, x_m^2 \cdots, x_m^{nd} \right] \tag{3}$$

The search space is limited by the following inequality constraints

$$x^v(min) \le x^v \le x^v(max) \quad v = 1, 2, \cdots, nd \tag{4}$$

Initially, the positions of the fireflies are generated from a uniform distribution using the following equation

$$x_m^v = x^v(min) + \left(x^v(max) - x^v(min) \right) \times rand \tag{5}$$

Here, $rand$ is a random number between 0 and 1, taken from a uniform distribution. The initial distribution does not significantly affect the performance of the algorithm. Every time the algorithm is executed and the optimization process starts with a different set of initial points. However, in each case, the algorithm searches for the optimum solution. In the case of multiple possible sets of solutions, the proposed algorithm may converge on different solutions each time. Although each of those solutions will be valid as they all will satisfy the requirement.

The light intensity of the m^{th} firefly, I_m is given by

$$I_m = Fitness\ (x_m) \tag{6}$$

The attractiveness between m^{th} and n^{th} firefly, $\beta_{m,n}$ is given by

$$\beta_{m,n} = (\beta_{\max,m,n} - \beta_{\min,m,n}) \exp(-\gamma_m r_{m,n}{}^2) + \beta_{\min,m,n} \tag{7}$$

Where

$$r_{m,\text{n}} = \left\| x_m - x_n \right\| = \sqrt{\sum_{v=1}^{nd} \left(x_m^k - x_n^k \right)^2} \tag{8}$$

$r_{m,\text{n}}$ =Cartesian distance between m^{th} and n^{th} firefly.

γ = Absorption parameter.

k = Number of Iterations.

The value of $\beta_{\min}$ is taken as 0.2 and the value of $\beta_{\max}$ is taken as 1. γ is another constant whose value is related to the dynamic range of the solution space. The position of firefly is updated in each iterative step. If the light intensity of n^{th} firefly is larger than the intensity of the m^{th} firefly, then the m^{th} firefly moves towards the n^{th} firefly and its motion at the k^{th} iteration is denoted by the following equation:

$$x_m(\text{k}) = x_m(\text{k}-1) + \beta_{m,\text{n}} \left(x_m(\text{k}-1) - x_m(\text{k}-1) \right) + \alpha \left(rand - 0.5 \right) \tag{9}$$

The random movement factor α is a constant whose value depends on the dynamic range of the solution space. At each iterative step, the intensity and the attractiveness of each firefly is calculated. The intensity of each firefly is compared with all other fireflies and the positions of the fireflies are updated using (9). After an adequate number of iterations, each firefly converges to the same position in the search space and the global optimum is achieved.

3.2 Self Adaptive Firefly Algorithm

In the above narrated FA, each firefly of the swarm travel around the problem space taking into account the results obtained by others and still applying its own randomized moves as well. Performance of the FA can be improved by tuning three parameters. The random movement factor (α) is very effective on the performance of FA whose value is commonly chosen in the range 0 and 1. A large value of α makes the movement to explore the solution through the distance search space and smaller value of α tends to facilitate local search.

The influence of other solutions is controlled by the value of attractiveness of equation (9), which can be adjusted by modifying two parameters $\beta_{\max}$ and γ. In general the value of $\beta_{\max}$ is chosen in the range of (0,1) and two limiting cases can be defined: The algorithm performs cooperative local search with the brightest firefly strongly determining other fireflies positions, especially in its neighborhood, when $\beta_{\max}$ = 1 and only non-cooperative distributed random search with $\beta_{\max}$ = 0. On the other hand, the value of γ determines the variation of attractiveness with increasing distance from communicated firefly In this paper, the parameters α, $\beta_{\min}$ and γ are tuned through a self-adaptive mechanism.

Each firefly for a problem with nd control variables will be defined to encompass nd +3 decision variables in the proposed formulation involving self-adaptive technique. The additional three decision variables represent α_m, $\beta_{\min,m}$ and γ_m. A firefly is represented as

$$x_m = \left[x_m^1, x_m^2 \cdots, x_m^{nd}, \alpha_m, \beta_{\min,\mathrm{m}}, \gamma_m \right] \quad (10)$$

Each firefly possessing the solution vector, α_m, $\beta_{\min,m}$ and γ_m undergo the whole search process. During iterations, the FA produces better off-springs through (7) and (9) using the parameters available in the firefly of (10), thereby enhancing the convergence of the algorithm. The basic steps of the FA can be summarized as the pseudo code which is depicted in Fig. 1.

4. Proposed Strategy

The TCSCs are to be installed at appropriate locations with optimal parameters that minimize the transmission loss for better utilization of the existing power system. This paper aims to develop a methodology that performs TCSC placement with an objective of minimizing transmission loss besides maintaining the bus voltages within acceptable range.

```
Read the Power System Data
Select the population size N and Maximum number of Iterations for convergence check
Generate the initial population
while (termination requirements are not met) do
    for m =1: N
        Alter the system data,α, β_min and γ according to m -th firefly values
        Run the load flow
        Compute the Real power loss
        Calculate I_m
    For n =1: N
        Alter the system data according to n -th firefly values
        Run the load flow
        Compute the Real power loss
        Calculate I_n
        If I_m < I_n
                Compute r_m,n using (8)
                Evaluate β_m,n using (7)
                Move m^th firefly towards n^th firefly through (9)
        end if
    end for n
    end for m
    Rank the fireflies and find the current best
End while
End
```

Fig.1. Pseudo Code for the FA

4.1 Objective Function

The objective is to minimize transmission loss, which can be evaluated from the power flow solution, and written as follows:

$$\text{Min } P_{loss} = \sum_{l=1}^{nl} G_l (V_i^2 + V_j^{\,2} - 2V_i V_j \cos\delta_{ij}) \quad (11)$$

Where P_{loss} =Net transmission loss, nl =Total number of transmission lines, l =Number of transmission of lines, G_l =Conductance of l^{th} line , V_i V_j =Voltage magnitudes at bus i and j respectively, δ_{ij} =Voltage angle at bus i and j .

4.2 Problem Constraints

The optimal placement of TCSC on problem can be subjected to the following equality and inequality constraints.

4.2.1 Equality Constraints

The equality constraints are the load flow equation given by

$$P_{Gi} - P_{Di} = P_i(V,\delta) \quad (12)$$

$$Q_{Gi} - Q_{Di} = Q_i(V,\delta) \quad (13)$$

Where P_{Gi} and Q_{Gi} represent the real and reactive power generation at i^{th} generator respectively. P_{Di} and Q_{Di} represent the real and reactive power drawn by the load at bus i, respectively.

4.2.2 Inequality Constraints

Voltage Constraints

$$V_i^{\min} \le V_i \le V_i^{\max} \text{ for PQ buses} \quad (14)$$

Reactive Power generation limit

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max} \quad \text{for PV buses} \quad (15)$$

Where

$Q_{Gi}^{\min}$ & $Q_{Gi}^{\max}$ -Minimum and maximum reactive power generation of i^{th} generator respectively, Q_{SVC} =VAR output , X_{line} is the reactance of the transmission line and γ_{TCSC} is the compensation factor of the TCSC.

TCSC Constraints

$$-0.8X_{line} \le X_{TCSC} \le 0.2X_{line} \quad (16)$$

The firefly of the proposed TCSC placement problem is defined as

$$x_m = \{(\mathrm{L}_1,\gamma_{TCSC,1},\alpha_m,\beta_{\min,m},\gamma_m)....(\mathrm{L}_M,\gamma_{TCSC,\mathrm{M}},\alpha_m,\beta_{\min,\mathrm{m}},\gamma_m)......$$
$$..(\mathrm{L}_N,\gamma_{TCSC,\mathrm{N}},\alpha_N,\beta_{\min,\mathrm{N}},\gamma_N)\} \quad (17)$$

Where L_M =Line location of the M^{th} TCSC.

The Self Adaptive FA (SAFA) searches for optimal solution by maximizing the light intensity I_m, like the fitness function in any other stochastic optimization techniques. The light intensity function can be obtained by transforming the power loss function and the voltage constraint into I_m function as

$$Max \quad I_m = \frac{1}{1+\Phi} \quad (18)$$

Where

$$\Phi = P_{loss} + \sum_{i\in\Psi}\left(V_i - V_i^{\mathrm{limit}}\right)^2 \quad (19)$$

$$V_i^{\mathrm{limit}} = \begin{cases} V_i^{\min} & if\ V_i < V_i^{\min} \\ V_i^{\max} & if\ V_i > V_i^{\max} \\ V_i & otherwise \end{cases} \quad (20)$$

Φ -Augmented objective function; Ψ -A set of load buses.

It is to be noted that the reactive power generation limits are controlled within the load flow technique and need not be controlled through the light intensity function. A population of fireflies is randomly generated and the intensity of each firefly is calculated using (18). Based on the light intensity, each firefly is moved to the optimal solution through (9) and the iterative process continues till the algorithm converges. The flow of the proposed FA based method is given through the flow chart of Fig.3.

5. Simulation Results and Discussions

The effectiveness of the proposed SAFA for optimally placing the TCSC devices to minimize the transmission loss in the power system has been tested on IEEE-14, -30 and -57 bus test systems using MATLAB 7.5. The line data and bus data for the three test systems are taken from [21]. The results of the SAFA are compared with that of the Honey Bee Optimization Algorithm (HBOA) and Bacterial Foraging Optimization Algorithm (BFOA). The limits for the control and dependant variables and the chosen range for self adaptive parameters are given in Table-1. The population size, N for all the test systems is taken as 30 and the number of iterations, K_{max}, is considered as 200.

Table 1
Control Variables

		Minimum	Maximum
Power system variables	VM (per unit)	0.95	1.1
	γ_{TCSC}	-0.8	0.2
Self Adaptive Parameters	α	0	0.5
	β	0.2	1
	γ	0	1

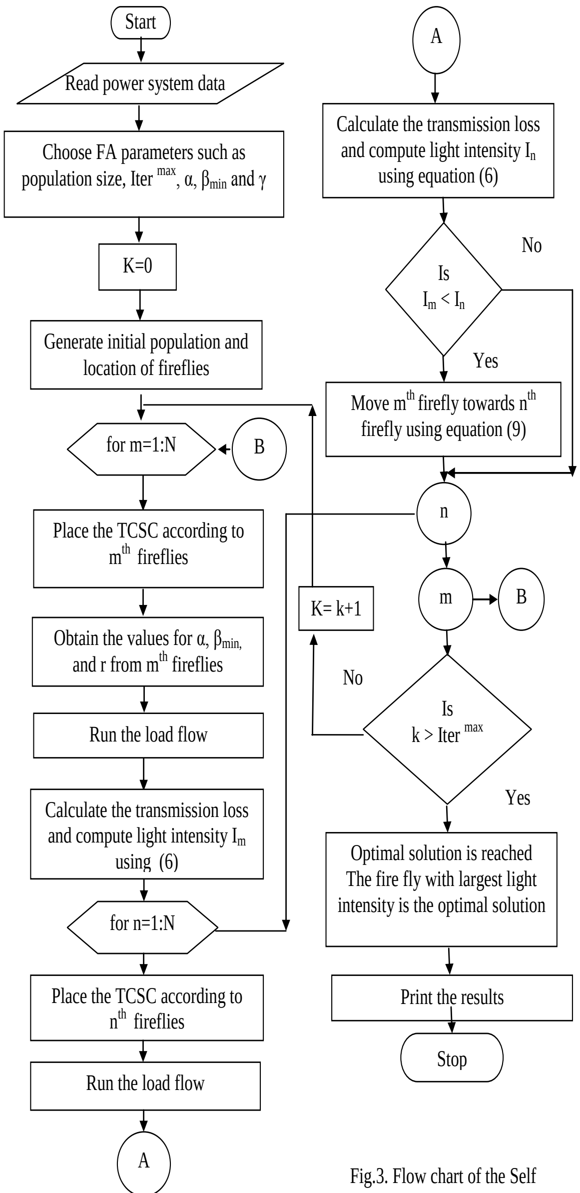

Fig.3. Flow chart of the Self Adaptive FA

IEEE 14 bus system: The system comprises 20 transmission lines, five generator buses (bus no 1,2,3,6 and 8) and nine load buses. Simulations are carried out with different numbers of TCSCs and it is found that three TCSCs are sufficient to realize the satisfactory performance. The results before and after placing three TCSCs are presented in Table-1. It is clear from this table that SAFA algorithm reduces the loss from 13.3663 MW to 13.2903 MW but the HBOA and BFOA is able to reduce the losses only to 13.2905 MW and 13.2912 MW respectively. This lowest loss value indicates the superior performance of the proposed SAFA.

Table 2
Optimal Location, Parameter of TCSC and Real Power Loss for IEEE 14- Bus System

Method	Real power loss (MW)	Locations (Line No)	γ_{TCSC} (p.u)
Without TCSC	13.3663	-	-
Proposed Method	13.2903	15 16 17	-0.800 -0.800 -0.798
Honey Bee	13.2905	17 9 15	-0.800 -0.233 -0.800
Bacterial Foraging	13.2912	15 20 17	-0.800 -0.200 -0.800

IEEE 30 bus system: The system has 41 transmission lines and six generator buses (bus no 1, 2, 5, 8, 11 and 13). The simulation study is performed with four TCSCs, as they can produce adequate performance for 30 bus test system. The results in terms of the locations and the TCSC parameters and the resulting loss of the proposed SAFA are compared with that of HBOA and BFOA in Table-2. It is seen from this table that the real power loss is considerably reduced from 17.5028 MW to 17.4338 MW by the SAFA. But the loss is reduced to 17.4437 MW and 17.4519 MW by HBOA and BFOA respectively. This lowest loss value of the SAFA affirms the superior performance of the proposed SAFA.

IEEE 57 bus system: The system has 80 transmission lines and seven generator buses (bus no 1, 2, 3,6,8,9 and 12). The simulation results in terms of the locations and the TCSC parameters and the resulting loss with five TCSCs are presented in Table III. It is seen from this table that the real power loss is considerably reduced from 27.1531 MW to 26.9013 MW by the SAFA. But the loss is reduced to 27.1712MW and 27.1947MW by the HBOA and BFOA respectively after TCSC placement. This SAFA is able to reduce the loss to the lowest possible value, which exhibits its superior performance.

Table 3
Optimal Location, Parameter of TCSC and Real Power Loss for IEEE 30- Bus System

Method	Real power loss (MW)	Locations (Line No)	γ_{TCSC} (p.u)
Without TCSC	17.5028	-	-
Proposed Method	17.4338	41 37 4 7 9 30	0.184 -0.159 -0.470 0.200 0.200 -0.618
Honey Bee	17.4437	28 18 25 4 14 7	-0.527 -0.175 -0.800 -0.680 -0.785 0.200
Bacterial Foraging	17.4519	9 41 26 21 4 33	0.147 -0.361 -0.754 -0.005 -0.628 -0.314

Table 4
Optimal Location, Parameter of TCSC and Real Power Loss for IEEE 57- Bus System

Method	Real power loss (MW)	Locations (Line No)	γ_{TCSC} (p.u)
Without TCSC	27.2233	-	-
Proposed Method	27.1531	66 59 42 55 36 41	-0.030 0.095 -0.648 -0.268 -0.342 -0.648
Honey Bee	27.1712	30 59 42 49 50 46	-0.011 0.122 -0.664 -0.277 -0.305 -0.643
Bacterial Foraging	27.1947	69 59 44 68 36 41	-0.169 0.145 -0.307 -0.192 -0.601 -0.109

The minimum and maximum voltage magnitude at load buses before and after placement of TCSC is given in Table-4. It is observed from this table that the voltage profile lies within the minimum and maximum acceptable limits.

Table 5
Comparison of Bus Voltage Profile before and after TCSC placement

System	V_{min}/V_{max}(p.u)			
	Before	After TCSC Placement		
		PM	HBOA	BFOA
IEEE 14	1.014/1.057	1.010/1.049	1.012/1.050	1.014/1.053
IEEE 30	0.989/1.082	1.002/1.050	0.990/1.062	0.991/1.068
IEEE 57	0.936/1.061	0.989/1.048	0.972/1.049	0.968/1.054

It is very clear from the above discussions that the proposed SAFA is able to reduce to the loss to the lowest possible by optimally placing and determining the parameters of TCSC when compared to other optimization algorithms. In addition the self adaptive nature of the algorithm avoids repeated runs for fixing the optimal FA parameters by a trial and error procedure and provides the best possible parameters values.

6. Conclusions

The optimal location of FACTS devices play a vital role in achieving the proper functioning of these devices. However this paper made an attempt to identify the optimal location and parameter of TCSC which minimizes the transmission loss besides keeping the bus voltages within the acceptable limits in the power system network using Self Adaptive Firefly algorithm. Simulations results are presented for IEEE14-bus IEEE30- bus and IEEE57- bus systems. Results have shown that the identified location of TCSC minimize the transmission loss in the power system network. With the above proposed algorithm it is possible for utility to place TCSC devices in transmission network such that proper planning and operation can be achieved with minimum system losses.

References

1. Hingorani, G, Gyugyi, I.: *Understanding FACTS:Cconcepts and technology of Flexible AC Transmission S*ystems.New York:IEEE Press, 2000.

2. Mathur,R.M.,Varma,R.K.: *Thyristor-based FACTS controllers for e lectrical t ransmission* systems. Piscataway: IEEE Press,2002.
3. Ambriz-perez,H., Acha, E., Fuerte-Esquivel, C.R.: *Advanced SVC models for newton raphson load flow and newton optimal power flow studies*. IEEE Trans. on Power Syst.,vol.15,2000, p. 129-136.
4. Orfanogianni, T.: *A Flexible software environment for steady state power flow optimization with series FACTS devices*.DScTech Diss,2000, ETH, Zurich.
5. Larsen, E.V.,Clark.,Miske S.A.,*Urbanek.:Characteristic and rating considerations of thyristor controlled series compensation*. IEEE Transaction Power Delivery. (1994),Vol. 9, p.992-1000.
6. Gyugyi L.: *Unified power flow controler concept for Flexible AC Transmission System.* IEE proceedings.(1994),Vol. 139,No.4, p.323-331.
7. Yang, X.S. *Nature-Inspired Meta-Heuristic Algorithms,* 2nd ed., Beckington, Luniver Press,2010.
8. Yang, X.S.: *Firefly algorithms for multimodal optimization, Stochastic algorithms: Foundations and applications,* SAGA 2009, LNCS, Berlin, Germany: Springer-Verlag, 5792:169-178, 2009.
9. Gerbex, S., R., Germond, A. J.: *Optimal location of multi type FACTS devices in power systems by means of genetic algorithms*. IEEE Trans. on Power Syst., (2001), Vol.16, No.3, p.537-544.
10. Saravanan, M., Mary Raja Slochanal, S., Venkatesh P., Abraham, J. P. S.: *Application of particle swarm optimization technique for optimal location of FACTS devices considering cost of installation and system loadability*. Electrical Power System Research.(2007),No. 77, p. 276-283.
11. Mondal D., Chakrabarti A., Sengupta A., *Optimal placement and parameter setting of SVC and TCSC using PSO to mitigate small signal stability problem*. International Journal of Electrical Power & Energy Systems, (2012), Vol. 42(1), p. 334–340.
12. Mohamid Idris, R., Khairuddin, A., Mustafa M.W.: *Optimal allocation of FACTS devices for ATC enhancement using Bees algorithm*. World Academy of science Engineering and Technology. (2009), No. 3, p. 313-320.
13. Tripathy, M., Mishra, S.: *Bacteria foraging based solution to optimize both real power loss and voltage stability limit*. IEEE Trans. on Power Syst, (2007), Vol. 22, No. 1,p. 240-248.
14. Senthil Kumar M., Renuga P., *Application of UPFC for enhancement of voltage profile and minimization of losses using fast voltage stability index (FVSI)*. Archives of Electrical Engineering Journal. (2012), Vol. 61, No.2, p. 239-250.
15. Apostolopoulos, T., Vlachos, A.: *Application of the Firefly algorithm for solving the economic emissions load dispatch problem.* International Journal of Combinatorics. (2011) No.523806, p.23.
16. Taher Niknam., Rasoul Azizipanah-Abarghooee., Alireza Roosta.: *Reserve Constrained Dynamic Economic Dispatch:A New Fast Self-Adaptive Modified Firefly Algorithm.* IEEE System Journal. (2012), Vol 6, No.4, p. 635-646.
17. Yang, X S., Hosseini, S.S., Gandomi, A. H.: *Firefly algorithm for solving non- Convex economic dispatch problems with valve loading effect*. Applied Soft Computing. (2012), vol.12, No.3, p. 180- 186.
18. Falcon, R., Almeida, M., Nayak A.: *Fault identification with binary adaptive fireflies in parallel and distributed systems*. In: proceedings of. IEEE Congress on Evolutionary Computation. 2011, p. 1359-1366.
19. Chandrasekaran, K., Simon, S. P.: *Demand response scheduling in SCUC problem for solar integrated thermal system using firefly algorithm,* In: proceedings of iET Conference on Renewable Power Generation (RPG 2011).2011,p 1-8.
20. Chandrasekaran, K., Simon, S.P.: *Network and reliability constrained unit commitment problem using binary real coded firefly algorithm.* International Journal of Electrical Power and Energy Systems. (2012), Vol.43,No.1,p. 921–932.
21. http://www.ee.washington.edu/research/pstca/ Accessed May 2012.