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SVC Placement for Voltage Profile Enhancement Using Self-Adaptive Firefly Algorithm

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Abstract

Static VAR Compensator (SVC) is one of the shunt type FACTS devices for providing reactive power support in power systems network and its placement representing the location and size has significant influence on enhancement of voltage profile. This paper presents a firefly algorithm based optimization strategy for placement of SVC in power systems with a view of minimizing voltage deviation at the load buses to enhance the load bus voltages. This method uses a self-adaptive scheme for tuning the firefly parameters. The proposed strategy is tested on three IEEE test systems. The obtained results are promising and show the effectiveness of the proposed approach.

Keywords: *firefly algorithm, SVC, voltage profile*

1. Introduction

In recent years, the power system is facing new challenges. The voltage deviation due to continuous load variation and electric power transfer limitations were observed due to reactive power unbalances. Also it causes a high impact on power system security and reliability. Hence this continuously increasing load demand need to be monitored or observed to avoid the transmission lines overloaded and poor load bus voltage profile. Construction of new generation facilities and transmission network will not be an efficient way to solve these challenges. Since it is complicated they involve huge installation cost, environment impact, political, large displacement of population and land acquisition. One of the simplest ways for minimizing the voltage deviation rather than constructing new generation systems is through providing optimal quantity of reactive power support at appropriate buses.

The power electronics based FACTS devices, developed by Hingorani NG [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]. 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 [5]. 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 bus voltage profile. The installation of SVCs can be described as an optimization problem with objectives of simultaneously minimizing the voltage deviations and improving the voltage profile while satisfying system constraints.

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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 [6] 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 [8]. PSO has been applied to find the optimal location of FACTS devices considering cost of installation and system loadability [9]. 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 [10]. Bees Algorithm has been proposed to determine the optimal allocation of FACTS devices for maximizing the available transfer capability [11]. Bacterial Foraging algorithm has been proposed for loss minimization and voltage stability improvement [12] Bacterial Foraging algorithm has been used to find the optimal location of UPFC devices with objectives of minimizing the losses and improving the voltage profile [13].

Firefly Algorithm (FA), which is a nature-inspired meta-heuristic algorithm, has been suggested for solving optimization problems [6-7]. It has been widely applied in solving several optimization problems, to name a few: economic dispatch [14-16], and unit commitment [17] 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. Self Adaptive FA (SAFA) based strategies have been proposed to minimize the transmission loss through placing SVCs [18] and UPFCs [19].

In this paper, a self adaptive firefly algorithm based strategy is proposed for SVC placement with a view of minimizing voltage deviations besides enhancing load bus voltages. The strategy identifies the optimal locations and the SVC 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. Power Flow Model Of SVC

The SVC either injects or absorbs reactive power in order to regulate the voltage magnitude at the point of connection to the AC network and its equivalent circuit of variable susceptance model is shown in Figure 1.

The linearized equation representing the total susceptance B_{svc} as state variable is given by the following equation:

$$\begin{bmatrix} \Delta P_i \\ \Delta Q_i \end{bmatrix}^k = \begin{bmatrix} 0 & 0 \\ 0 & \dfrac{\partial Q_i}{\partial B_{svc}} \end{bmatrix}^k \begin{bmatrix} \Delta \theta_i \\ \Delta B_{svc} \end{bmatrix}^k \quad (1)$$

At each iteration (k), the variable shunt susceptance, B_{svc} is updated.

$$B^{k+1}{}_{svc} = B^k{}_{svc} + \Delta B^k{}_{svc} \quad (2)$$

Based on the equivalent circuit of SVC, the current drawn by SVC is:

$$I_{svc} = jB_{svc}V_i \quad (3)$$

Reactive power drawn by SVC, which is also reactive power injected at bus i, Q_{SVC} is:

$$Q_{svc} = Q_i = -V_i^2 B_{svc} \quad (4)$$

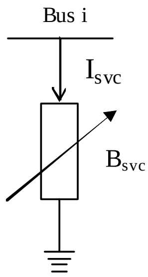

Figure 1. Variable Susceptance Model of SVC

3. Firefly Algorithm

FA is a recent nature inspired meta-heuristic algorithms which has been developed by Xin She Yang at Cambridge University in 2007 [6]. 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 [7].

3.1. Classical Firefly Algorithm

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 [9, 15]. Each m^{th} firefly is denoted by a vector x_m as:

$$x_m = \left[x_m^1, x_m^2 \cdots, x_m^{nd} \right] \tag{5}$$

The search space is limited by the following inequality constraints.

$$x^v(min) \le x^v \le x^v(max) \qquad v = 1, 2, \cdots, nd \tag{6}$$

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

$$x_m^v = x^v(min) + \left(x^v(max) - x^v(min) \right) \times rand \tag{7}$$

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:

$$I_m = Fitness\ (x_m) \tag{8}$$

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

$$\beta_{m,n} = (\beta_{\max,m,n} - \beta_{\min,m,n}) \exp(-\gamma_m r_{m,n}{}^2) + \beta_{\min,m,n} \tag{9}$$

Where $r_{i,j}$ is Cartesian distance between i-th and j-th firefly.

$$r_{m,\mathrm{n}} = \left\| x_m - x_n \right\| = \sqrt{\sum_{v=1}^{nd} \left(x_m^k - x_n^k \right)^2} \tag{10}$$

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:

$$x_m(\mathrm{k}) = x_m(\mathrm{k}-1) + \beta_{m,\mathrm{n}} \left(x_n(\mathrm{k}-1) - x_m(\mathrm{k}-1) \right) + \alpha \left(rand - 0.5 \right) \tag{11}$$

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 to 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. Generally the absorption coefficient γ is chosen in the in the range of 0 to 10. Indeed, the choice of these parameters affects the final solution and the convergence of the algorithm. 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:

$$x_m = \left[x_m^1, x_m^2 \cdots, x_m^{nd}, \alpha_m, \beta_{\min,\mathrm{m}}, \gamma_m \right] \tag{13}$$

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 Equations. (9) and (11) using the parameters available in the firefly of Equation. (13), thereby enhancing the convergence of the algorithm.

4. Proposed Strategy

The SVCs are to be installed at appropriate locations with optimal parameters that minimize the voltage deviations to enhance the load bus voltage profile. This paper aims to develop a methodology that performs SVC placement to enhance the load bus voltage profile.

4.1. Objective Function

The load bus voltage can be brought to the normal value of 1.0 per unit through tailoring the objective function for minimizing the sum of deviations of all load bus voltages from the nominal voltage of 1.0 per unit. The objective function is formulated as:

$$\text{Minimize } \Phi(x, u) = \sum_{i=1}^{nload} |V_i - 1| \tag{14}$$

Where,

nload is the number of load buses.
V_i is the Voltage magnitude at bus i.

4.2. Problem Constraints
4.2.1. Equality Constraints

The equality constraints are the load flow equation given by:

$$P_{Gi} - P_{Di} = P_i(V, \delta) \quad \text{for PV and PQ buses} \tag{15}$$

$$Q_{Gi} - Q_{Di} = Q_i(V, \delta) \quad \text{for PQ buses} \tag{16}$$

Where P_{Gi} and Q_{Gi} represent the real and reactive power injected by the generator at bus i, 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

$$V_i^{\min} \le V_i \le V_i^{\max} \quad \text{for PQ buses} \tag{17}$$

Reactive Power generation limit

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max} \quad \text{for PV buses} \tag{18}$$

Where $Q_{Gi}^{\min}$ and $Q_{Gi}^{\max}$ are the upper and lower limit of reactive power source i.

SVC Constraints

$$-100MVAR \le Q_{SVC} \le 100MVAR \tag{19}$$

Where,

Q_{SVC} = Reactive power injected at SVC placed bus in p.u

The firefly of the proposed SVC placement problem is defined as:

$$x_m = \{(L_1, Q_{SVC1}, \alpha_m, \beta_{\min,m}, \gamma_m)....(L_M, Q_{SVCM}, \alpha_m, \beta_{\min,m}, \gamma_m)...........(L_N, Q_{SVC,N}\, \gamma_{TCSC,N,}, \alpha_N, \beta_{\min,N}, \gamma_N)\} \tag{20}$$

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 voltage deviation function and the voltage constraint into I_m function as:

$$Max \quad I_m = \frac{1}{1+\Phi} \tag{21}$$

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 (11) and the iterative process continues till the algorithm converges.

5. Simulation Results and Discussions

The effectiveness of the proposed SAFA for optimally placing the SVC devices to minimize the voltage deviation in the power system has been tested on IEEE-14, IEEE-30 and IEEE-57 bus test systems using MATLAB 7.5. The line data and bus data for the three test systems are taken from [20]. 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.

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 SVCs and it is found that three SVCs are sufficient to realize the satisfactory performance. The results in terms of the locations and the SVC parameters are given in Table 2. The bus voltages before and after placing three SVCs are presented in Table3. It is clear from this table that SAFA algorithm identifies the optimal placement of SVC to enhance the bus voltage profile. The Comparison of load bus voltages with and without SVC placement is shown in Figure 2.

Table 1. Control Variables

		Minimum	Maximum
Power system variables	VM (per unit)	0.95	1.1
	Q_{SVC} (MVAR)	-100	100
Self Adaptive Parameters	α	0	0.5
	β	0.2	1
	γ	0	1

Table 2. Optimal Location, Parameter of SVC for IEEE 14- Bus System

Number of SVC	Locations (Line Number)	Q (MVAR)
3	17	-17.947
	19	-32.052
	15	-50.00

Table 3. Bus Voltages of IEEE 14- Bus System

Bus No	Bus Voltages	
	Without SVC	With SVC
1	1.060	1.060
2	1.040	1.040
3	1.005	1.005
4	0.984	0.999
5	1.000	1.001
6	1.065	1.065
7	0.998	1.007
8	1.085	1.085
9	1.002	0.998
10	1.005	1.000
11	1.031	1.018
12	1.004	1.000
13	1.025	1.013
14	0.998	0.999

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 six SVCs, as they can produce adequate performance for 30 bus test system. The results in terms of the locations and the SVC parameters are given in Table 4. The bus voltages before and after placing three SVCs are presented in Table 5. It is seen from this table that the identified placement of SVC enhance the bus voltage profile. The Comparison of load bus voltages with and without SVC placement is shown in Figure 3.

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 SVC parameters are presented in Table-6.The bus voltages before and after placing three SVCs are presented in Table 7. It is seen from this table that the identified placement of SVC enhance the bus voltage profile. The Comparison of load bus voltages with and without SVC placement is shown in Figure 4.

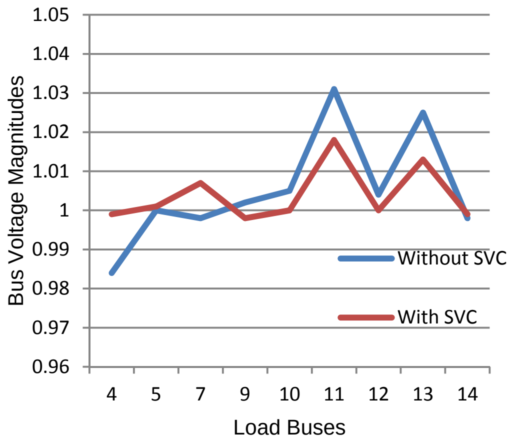

Figure 2. Comparison of Load Bus Voltage Magnitudes of IEEE 14 Bus System

Table 4. Optimal Location, Parameter of SVC for IEEE 30- Bus System

Number of SVC	Locations (Line Number)	Q (MVAR)
6	26	11.619
	33	7.931
	24	7.442
	14	-40.237
	18	-37.021
	19	-11.632

Table 5. Bus Voltages of IEEE 30- Bus System

Bus No	Bus Voltages Without SVC	Bus Voltages with SVC	Bus No	Bus Voltages Without SVC	Bus Voltages with SVC
1	1.060	1.060	16	1.033	1.003
2	1.043	1.043	17	1.023	1.001
3	1.021	1.013	18	1.016	0.997
4	1.012	1.003	19	1.011	0.999
5	1.010	1.010	20	1.014	1.001
6	1.012	1.004	21	1.014	0.998
7	1.013	1.008	22	1.015	1.000
8	1.010	1.010	23	1.017	0.998
9	1.042	1.008	24	1.009	0.999
10	1.026	1.008	25	1.010	1.002
11	1.082	1.082	26	0.993	0.996
12	1.052	1.013	27	1.020	1.012
13	1.073	1.073	28	1.010	1.002
14	1.036	1.001	29	1.000	0.998
15	1.030	1.000	30	0.989	0.997

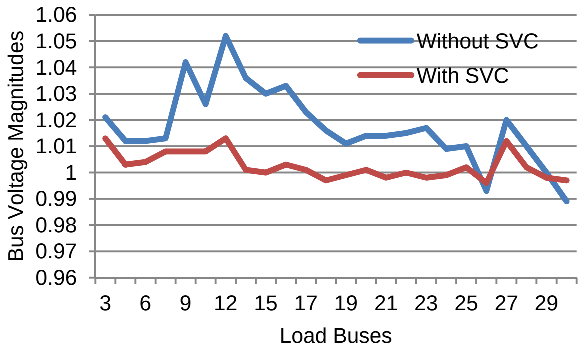

Figure 3. Comparison of Load Bus Voltage Magnitudes of IEEE 30 Bus System

Table 6.Optimal Location, Parameter of SVC for IEEE 57- Bus System

Number of SVC	Locations (Line Number)	Q (MVAR)
7	26	11.619
	33	7.931
	24	7.442
	14	-40.237
	18	-37.021
	19	-11.632

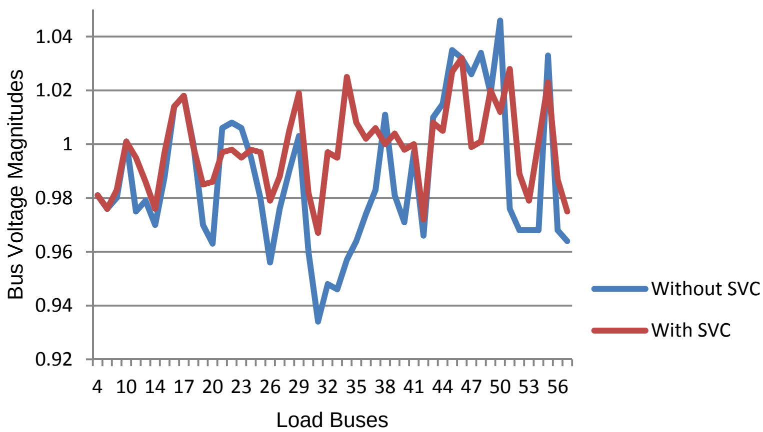

Figure 4. Comparison of Load Bus Voltage Magnitudes of IEEE 57 Bus System

Table 7. Bus Voltages of IEEE 57- Bus System

Bus No	Bus Voltages Without SVC	Bus Voltages with SVC	Bus No	Bus Voltages Without SVC	Bus Voltages with SVC
1	1.040	1.040	30	0.960	0.982
2	1.010	1.010	31	0.934	0.967
3	0.985	0.985	32	0.948	0.997
4	0.981	0.981	33	0.946	0.995
5	0.976	0.976	34	0.957	1.025
6	0.980	0.980	35	0.964	1.008
7	0.978	0.983	36	0.974	1.002
8	1.005	1.005	37	0.983	1.006
9	0.982	0.982	38	1.011	1.000
10	1.001	1.001	39	0.981	1.004
11	0.975	0.995	40	0.971	0.998
12	1.015	1.015	41	0.997	1.000
13	0.979	0.986	42	0.966	0.972
14	0.970	0.976	43	1.010	1.008
15	0.988	0.997	44	1.015	1.005
16	1.014	1.014	45	1.035	1.027
17	1.018	1.018	46	1.032	1.032
18	1.000	0.999	47	1.026	0.999
19	0.970	0.985	48	1.034	1.001
20	0.963	0.986	49	1.019	1.020
21	1.006	0.997	50	1.046	1.012
22	1.008	0.998	51	0.976	1.028
23	1.006	0.995	52	0.968	0.989
24	0.995	0.998	53	0.968	0.979
25	0.980	0.997	54	0.968	1.001
26	0.956	0.979	55	1.033	1.023
27	0.976	0.988	56	0.968	0.987
28	0.990	1.005	57	0.964	0.975
29	1.003	1.019			

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 SVC 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. Conclusion

In this paper a new SAFA has been proposed to identify the optimal locations of SVC and their parameter with a view of minimizing the voltage deviations to enhance the load bus voltage profile. Simulations results in terms of locations, SVC parameters and the bus voltages have been presented for three IEEE test systems. It has been found that the identified location and SVC parameters by the SAFA are able to enhance the bus voltage profile and the developed algorithm is suitable for practical applications.

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