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SVC placement for voltage constrained loss minimization using self-adaptive Firefly algorithm

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Abstract: Static Var Compensator (SVC) is a popular FACTS device for providing reactive power support in power systems and its placement representing the location and size has significant influence on network loss, while keeping the voltage magnitudes within the acceptable range. This paper presents a Firefly algorithm based optimization strategy for placement of SVC in power systems with a view of minimizing the transmission loss besides keeping the voltage magnitude within the acceptable range. The method uses a self-adaptive scheme for tuning the parameters in the Firefly algorithm. The strategy is tested on three IEEE test systems and their results are presented to demonstrate its effectiveness.

Key words: Firefly algorithm, loss minimization, SVC, voltage profile

Nomenclature: SVC – Static Var Compensator; FACTS – Flexible Alternating Current Transmission System; FA – Firefly Algorithm; SAFA – Self Adaptive Firefly Algorithm; B_{SVC} – susceptance of SVC; θ_i – voltage phase angle at bus i; I_{SVC} – current drawn by the SVC; nd – number of decision variables; N – maximum number of fireflies; m, n – number of fireflies; I_m – light intensity of the m^{th} Firefly; $\beta_{m,n}$ – attractiveness parameter; γ – absorption parameter; α – random movement factor; $r_{m,n}$ – cartesian distance between m^{th} and n^{th} Firefly; k – number of iterations; $k_{\max}$ – maximum number of iterations; 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; P_{Gi} – real power generation at i^{th} generator; Q_{Gi} – reactive power generation at i_{th} – generator; P_{Di} – Real power drawn by the load at i bus; Q_{Di} – Reactive power drawn by the load at bus i; $Q_{Gi}^{\min}$ and $Q_{Gi}^{\max}$ – minimum and maximum reactive power generation of i^{th} generator respectively; $P_i(V, \delta)$ – set of real power expressions at PV and PQ buses; $Q_i(V, \delta)$ – set of reactive power expressions at PQ buses; Q_{SVC} – VAR output; X_{line} – reactance of the transmission line; L_M – line location of the M^{th} SVC; Φ – augmented objective function; Ψ – a set of load buses.

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 Hingorani N. G [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 [7-20] 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 UPFC devices with objectives of minimizing the losses and improving the voltage profile [14].

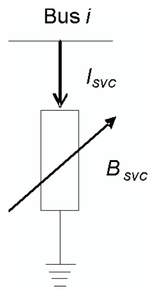
Firefly Algorithm (FA), which is a nature-inspired meta-heuristic algorithm, has been suggested for solving optimization problems [7-8]. It has been widely applied in solving several optimization problems, to name a few: economic dispatch [15-17], fault identification [18], scheduling [19] and unit commitment [20] 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 Algorithm based strategy is proposed for SVC 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 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 generates 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.

Fig. 1. Variable susceptance model of SVC



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

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

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

$$B_{svc}^{k+1} = B_{svc}^{k} + \Delta B_{svc}^{k} . \tag{2}$$

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

$$I_{svc} = jB_{svc}V_i. \tag{3}$$

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

$$Q_{svc} = Q_i = -V_i^2 B_{svc}. \tag{4}$$

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

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

The search space is limited by the following inequality constraints

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

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

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

where

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

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:

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

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 Equation (9). After an adequate number of iterations, each Firefly converges to the same position in the search space and the global optimum is achieved.

3.1.1. 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 which includes α, β and γ. 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 general 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, β 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

$$x_m = \left[x_m^1, \, x_m^2, \ldots, x_m^{nd}, \alpha_m, \beta_{\min,m}, \gamma_m\right]. \tag{12}$$

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. The basic steps of the FA can be summarized as the pseudo code which is depicted in Figure 2.

```
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 Equation (10)
                                Evaluate β_m,n using Equation. (9)
                                Move m^th Firefly towards n^th Firefly through Equation (11)
              end if
        end for n
        end for m
        Rank the fireflies and find the current best
End while
End
```

Fig. 2. Pseudo code for the FA

4. Proposed strategy

The SVCs 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 SVC placement with an objective of minimizing transmission loss besides maintaining the bus voltages within acceptable range.

4.1. Objective function

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

$$\text{Min } P_{loss} = \sum_{l=1}^{nl} G_l \left(V_i^2 + V_j^2 - 2V_i\, V_j \cos\delta_{ij} \right). \tag{13}$$

4.2. Problem constraints

4.2.1. Equality constraints

The equality constraints are the load flow equation given by

$$P_{Gi} - P_{Di} = P_i(V, \delta), \tag{14}$$

$$Q_{Gi} - Q_{Di} = Q_i(V, \delta), \tag{15}$$

4.2.2. Inequality constraints

Voltage Constraints

$$V_i^{\min} \le V_i \le V_i^{\max} \quad \text{for PQ buses} \tag{16}$$

Reactive Power generation limit

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max} \quad \text{for PV buses} \tag{17}$$

SVC Constraints

$$-100\,\text{MVAR} \le Q_{SVC} \le 100\,\text{MVAR}. \tag{18}$$

The Firefly of the proposed SVC placement problem is defined as

$$\begin{aligned} x_m = \{ & (L_1, Q_{SVC1}, \alpha_m, \beta_{\min,m}, \gamma_m)\ldots \\ & (L_M, Q_{SVCM}, \alpha_m, \beta_{\min,m}, \gamma_m)\ldots(L_N, Q_{SVCN}, \alpha_N, \beta_{\min,N}, \gamma_N)\}. \end{aligned} \tag{19}$$

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

$$\text{Max } I_m = \frac{1}{1+\Phi}, \tag{20}$$

where

$$\Phi = P_{loss} + \sum_{i\in\Psi} \left(V_i - V_i^{\lim it}\right)^2, \tag{21}$$

$$V_i^{\text{limit}} = \begin{cases} V_i^{\min} & \text{if } V_i < V_i^{\min} \\ V_i^{\max} & \text{if } V_i > V_i^{\max} \\ V_i & \text{otherwise.} \end{cases} \tag{22}$$

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 Equation (20). Based on the light intensity, each Firefly is moved to the optimal solution through Equation (11) and the iterative process continues till the algorithm converges. The flow of the proposed FA based method is given through the flow chart of Figure 3.

5. Simulation results and discussions

The effectiveness of the proposed SAFA for optimally placing the SVC 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, 22]. 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
	Q_{SVC}(MVAR)	–100	100
Self Adaptive Parameters	α	0	0.5
	β	0.2	1
	γ	0	1

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 before and after placing three SVCs are presented in Table 2. It is clear from this table that SAFA algorithm reduces the loss from 13.3663 MW to 13.2451 MW but the HBOA and BFOA is able to reduce the losses only to 13.2562 MW and 13.2616 MW respectively. This lowest loss value indicates the superior performance of the proposed SAFA.

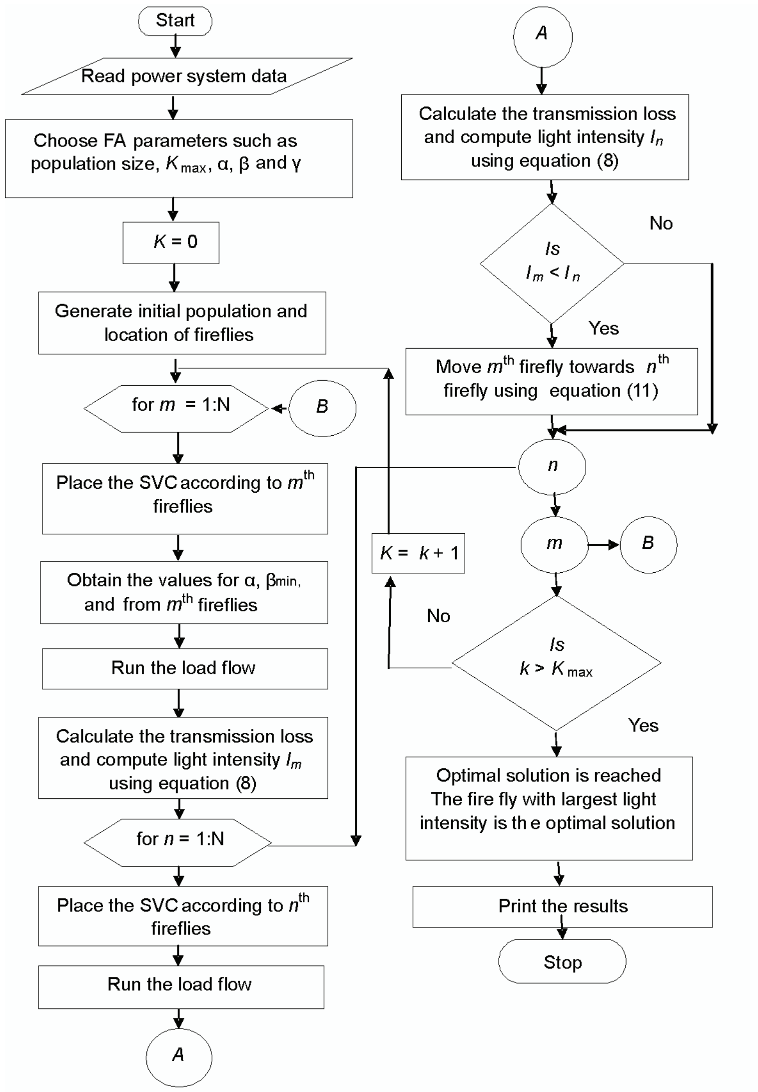


Fig. 3. Flow chart of the self adaptive FA

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 and the resulting loss of the proposed SAFA are compared with that of

HBOA and BFOA in Table 3. It is seen from this table that the real power loss is considerably reduced from 17.5028 MW to 17.1601 MW by the SAFA. But the loss is reduced to 17.1890 MW and 17.1906 MW by HBOA and BFOA respectively. This lowest loss value of the SAFA affirms the superior performance of the proposed SAFA.

Table 2. Optimal location, parameter of SVC and real power loss for IEEE 14-bus system

Method	Real power loss (MW)	Locations (Bus No)	Q (MVAR)
Without SVC	13.3663	–	–
Proposed Method	13.2451	7 9 13	25.889 6.021 8.155
Honey Bee	13.2562	13 4 10	11.110 11.101 9.871
Bacterial Foraging	13.2616	7 13 10	11.211 5.555 11.606

Table 3. Optimal location, parameter of SVC and real power loss for IEEE 30-bus system

Method	Real power loss (MW)	Locations (Bus No)	Q (MVAR)
Without SVC	17.5028	–	–
Proposed Method	17.1601	21 3 25 4 10 19	13.156 14.447 5.473 16.297 8.652 6.077
Honey Bee	17.1890	21 3 27 4 10 19	19.026 6.561 5.138 13.616 11.185 4.941
Bacterial Foraging	17.1906	15 21 19 3 27 16	1.760 16.163 3.881 29.775 9.003 9.543

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 and the resulting loss with seven SVCs are presented in Table 4. It is seen from this table that the real power loss is considerably reduced from 27.2233 MW to 26.8098 MW by the SAFA. But the loss is reduced to 26.9566 MW and 26.9702 MW by the HBOA and BFOA respectively after SVC placement. This SAFA is able to reduce the loss to the lowest possible value, which exhibits its superior performance.

Table 4. Optimal location, parameter of SVC and real power loss for IEEE57-bus system

Method	**Real power loss (MW)**	**Locations (Bus No)**	**Q (MVAR)**
Without SVC	27.2233	–	–
Proposed Method	26.8098	11 36 4 7 39 29 24	12.896 1.907 0.685 24.777 0.151 6.403 0.582
Honey Bee	26.9566	15 21 24 10 28 52 32	0.100 0.102 0.111 27.085 9.401 1.608 0.121
Bacterial Foraging	26.9702	44 38 4 30 21 49 37	0.100 5.430 0.101 0.747 1.665 1.173 0.104

The minimum and maximum voltage magnitude at load buses before and after placement of SVC is given in Table 5. It is observed from this table that the voltage profile lies within the minimum and maximum acceptable limits.

Table 5. Comparision of bus voltage profile before and afetr SVC placement

System	**V_{min}/V_{max}(p.u)**			
	Before SVC placement	After SVC placement		
		PM	HBOA	BFOA
IEEE 14	1.014/1.057	1.006/1.050	1.008/1.056	1.007/1.058
IEEE 30	0.989/1.082	1.010/1.047	0.990/1.056	0.991/1.064
IEEE 57	0.936/1.061	0.987/1.045	0.987/1.045	0.940/1.051

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 transmission loss besides maintaining the voltage magnitude of all the buses with in the lower and upper bounds. Simulations results in terms of locations, SVC parameters and the resulting loss 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 reduce the loss to the lowest possible value and the developed algorithm is suitable for practical applications.

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