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SVC Placement in Unbalanced Distribution Network to Reduce the Neutral Lines Current and Ohmic Losses Using Intelligent Optimization Algorithms

Saeed Rezaeian Marjani, Vahid Talavat
(Department of Electrical Engineering, Urmia University, Urmia, Iran)

Abstract: *Distribution Network (DN) unbalancing and their unfavorable effects such as energy losses is an important challenge in electrical engineering. The system unbalancing problem is highly regarded due to increasing energy costs in DN. In this paper, the use of SVC (Static Var Compensation) is to improve the unbalancing and reducing the energy losses in DN. To handle power flow procedure, a novel circuit solution is presented to modeling the DN unbalancing situations. Furthermore, the nominal active and reactive loads in different phases have been multiplied into a specified value which is defined by the Unbalancing Factor (UF). Intelligent optimization algorithms such as PSO (Particle Swarm Optimization), CSA (Cuckoo Search Algorithm) and FA (Firefly Algorithm) are used to optimal sitting and sizing of the SVC with a three terms objective function, including losses, Neutral Lines Current and SVC installation cost in the distribution networks. The effect of SVC number installation in DN is evaluated. To demonstrate the effectiveness of the proposed method, the modified standard IEEE 123 nodes network has been tested. Simulations are carried out in two options. The results verify the ability of presented method to improve the performance of the unbalance distribution network significantly.*

Keywords: *CSA, Energy Losses, FA, Neutral Lines Current, PSO, SVC, Unbalance Distribution network*

I. Introduction

Power generated in plants delivers to the electricity consumers through the transmission, sub transmission and distribution lines. The consumable loads is always non-uniform and is normally unbalanced due to accidental and un-simultaneous behavior of them in a DN. System unbalance will have adverse effects such as unbalance three Phase voltages, increase energy losses and occupation feeder capacity in DN [1, 2, 3].

It is clear that the minimum energy loss is obtained in balanced three phase currents situation. Moreover, in an unbalancing system, returned flow in neutral wire, increases the Ohmic losses in the neutral conductor and copper and iron losses in distribution transformers [4].

FACTS (Flexible AC Transmission Systems) devices were introduced to increase the capacity of transmission lines and optimal operation of the power system in the recent years [5].

The custom FACTS devices are unsuitable in size and cost for applications in DN. Some of FACTS devices are introduced in suitable capacities to use in DN, such as D-STATCOM and SVC [6, 7]. The number, locations, and ratings of FACTS devices because of installation cost, must be specified carefully to provide the maximum benefit to the network.

In order to solve load balancing and reactive power compensation introduce the method to use SVCs with four-wire three-phase loads [8]. A combined reactive power compensation method of a static Var compensator (SVC) consists of star and delta connected thyristor controlled reactors and a series active filter is described for unbalanced three-phase four-wire distribution feeders with Harmonic distortion presented in [9]. In [10] a mathematical model proposed for computer simulation and control of a delta-connected SVC to achieve the purpose of negative-sequence reduction. In [11] introduced Load Compensate in the unbalanced distributed network by appropriate D-STATCOM design. Determine the appropriate place SVC using genetic algorithm to meet load unbalancing and network in [3]; some works have been proposed to fix an unbalancing load and distribution network problems using D-FACTS In the literature.

Recently, many methods based on artificial intelligence have been developed for solving optimal location of FACTS and D-FACTS devices problems such as tabu search algorithm [12], Particle Swarm optimization [13, 14], Genetic Algorithm, [15] Gravitational Search Algorithm [16], firefly Algorithm [2], Differential Evolution Techniques [13].

DN unbalancing Improvement point of view the maximum decreasing of the Neutral lines current while decreasing the Energy losses by optimal SVC allocation placement distributing networks using three intelligent algorithm consist of cuckoo search algorithm (CSA), PSO and FA has been discussed in this paper.

The paper is organized as follows. Section 2 explains the model of SVC. In Section 3 intelligent Optimization Algorithm is presented. In Section 4, The Proposed SVC Placement Algorithm, including the objective function, The Proposed Method to Modeling the Unbalancing in Distribution Networks and the Four-Wire Modeling in Distribution Networks Power Flow, is developed. In Section 5, Simulation Results and Numerical Studies have been reported. Section 6 contains the Effect of the various SVC Number in system Unbalancing Improvement and Reduction energy Losses according to propped method followed by conclusions.

II. Static Var Compensator (SVC)

SVC is one of various FACTS devices which are connected in parallel to the distribution network nodes and acts as injection or absorbing Static reactive power source. Basically SVC output changes between the inductive or capacitive currents to control various parameters such as network nodes voltage. In the simplest structure SVC consists of a parallel combination of controlled inductor with thyristor valves switches and capacitor banks. In terms of performance it is like a variable parallel reactance which by controlling the firing angle of the thyristors becomes a highly responded capable device [17, 18].

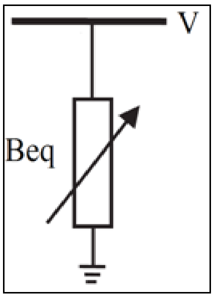

Fig. 1: Circuit model of SVC

Fig. 1 shows an equivalent circuit of SVC. The equipollent reactance to controlled inductor through thyristor can be expressed by:

$$X_L = \frac{\pi X_L}{2(\pi - \alpha) + \sin(2\alpha)} \tag{1}$$

SVC equivalent reactance of the parallel combination of thyristor controlled inductors and capacitor can be obtained by:

$$X_{Leq} = \frac{\pi X_C X_L}{X_C(2(\pi - \alpha) + \sin(2\alpha)) - \pi X_L} \tag{2}$$

Where, X_C is the parallel capacitor reactance and α is the fire angle of the thyristors. Considering (2), SVC equivalent Susceptance that is a function of angle firing of thyristors is obtained in (3):

$$B_{eq} = \frac{\pi X_L - X_C(2(\pi - \alpha) + \sin(2\alpha))}{\pi X_C X_L} \tag{3}$$

According to (3), unlike the capacitor, Susceptance of SVC is a continuous function of the angle fire of the thyristors [17].

Injection or absorbing of reactive power by SVC using (4) is calculated:

$$Q_{SVC} = -V^2 B_{eq} \tag{4}$$

In (4), V is the voltage of the node that SVC is installed.

III. Intelligent Optimization Algorithms

A comprehensive study carried out to optimal SVC allocation using three different types of intelligent optimization algorithms. Main objective is reduction Neutral Lines Current and reduction losses, considering SVC installing cost in network. In this section PSO, CSA and FA optimization Algorithms has been introduced.

3.1 Particle Swarm Optimization (PSO)

PSO is an evolutionary algorithm which was presented in 1995 by Eberhart & Kennedy. This algorithm has strong global search capability and the ability to solve the different optimization problems in the multi-dimensional and nonlinear search space [19].

Simplicity, produce high-quality solutions in less time, Similar flexibility for control, stability study of local and global search space compared with other algorithms, also fast convergence are some advantage of this algorithm in power system [20].

In this algorithm, the population of people with R unknown parameters are used in optimization. In other words, each particle represents a solution of the problem and the appropriate amount of each particle the each iteration is calculated by choice of objective function [21]. Basically, each particle found the best deal by itself and knows its location (pbest) furthermore each particle knows The best obtained value among all the particles (gbest) so the direction and rate of movement of each particle based on previous speed and location is determined by the pbest and gbest . With this amount, the particles are guided in the optimal or near-optimal solutions. This shift can be shown based on speed changing idea. Position vector and velocity vector of the particle can be shown with the help of position and velocity of the particle in the d - dimensional search space as shown $X_i = [x_{i1}, x_{i2} \dots x_{id}]$ and $V_i = [v_{i1}, v_{i2} \dots v_{id}]$ [18, 22].

As a result the speed of the particles changes according to (5):

$$V_i^{k+1} = wV_i^k + c_1 rand1(Pbest - x_i^k) + c_2 rand2(Gbest - x_i^k) \tag{5}$$

In (5), V_i^K is the speed of the particle in kth iteration, w is Constant weight, c_1 and c_2 is Acceleration coefficients that indicate how the particle moves to the best location and best global position, rand is Random number between 0 and 1, and x_i^K is the position of i^{th} particle in kth iteration. Considering (5), particles changes speed the each iteration.

Typically, the particle speed is limited in specified range and the changed position of each particle calculated according to velocity vector as:

$$x_i^{k+1} = x_i^k + V_i^{k+1} \tag{6}$$

Pseudo code of implementation PSO presented as follows [23]:

```
Initialization
Parameters and size of the swarm (S);
Randomly initialize particle position and velocities;
For Each particle,
Let pbest_id = x_id
Calculate f (x_id) of each particle;
Calculate gbest, // the best of pbest_id;

While (maximum iterations or minimum error criteria is not met) {
For (i=1 to S) {

Calculate the new velocity using (5);
Calculate the new position using (6);
Calculate f (x_id) of each particle;
If (f (x_id) <f (pbest_id))
Pbest_id = x_id, // Minimization case;
If (f (pbest_id) <f (gbest_d))
gbest_d = pbest_d;
        }
        }
         Show the best solution found gbest_d;
```

3.2 Cuckoo search algorithm (CSA)

Cuckoo search algorithm (CSA) is one of the most recently defined algorithms by Yang and Deb [24, 25] where inspired by the obligate brood parasitism of some cuckoo species by laying their eggs in the nests of other host birds [27].

Two main operations are building the structure of the CSA, (i) a direct search based on Lévy flights, (ii) a random search based on the probability for a host bird to discover an alien egg in its nest [26], During the search process, CSA is following three idealized rules: (i) each cuckoo lays one egg at a time, and dump its egg in randomly chosen nest; (ii) the best nests with better eggs (better solution) will carry over to the next generations and (iii) available host nests is a constant number, and the egg laid by a cuckoo is discovered by the

host bird with a probability pa ∈ [0, 1]. In this case, the host bird can either throw the egg away or abandon the nest and build a completely new nest [24, 25].
Pseudo code of implementation Cuckoo Search via lévy flights presented as follows [27]:

Begin
Generation t = 1;
Initialized with random vector values, and initialize parameters NP (Number Population), D;
Evaluate fitness for every individual and determine the best individual with the best objective value;
While (stopping criterion is not met)
Get a Cuckoo randomly by lévy flights;
Evaluate fitness for the cuckoo F;
Choose a nest among n (say, j) randomly;
If ($F_i > F_j$)
Replace j by the new solution;
End if
A fraction (pa) of worse nests is abandoned and new ones are built;
Keep the best solution;
Rank the solutions and find the current best;
Update the generation number t = t + 1;
End while
End.

In the CSA each solution is shown as egg in a nest, and a cuckoo egg represent a new solution. The object is to use the potentially better solutions (cuckoos egg) to replace non-dominate solution in the nests. Similar to many other meta-heuristic search methods, in the initial process, each solution is generated randomly, The initial population of the host nests is set to best value of each nest $Xbest_d$ (d = 1,…, D). The cuckoo randomly chooses the nest position to lay egg, in other words the next newly generated solution form D dimension optimization problem is expressed as:

$$X_d^{t+1} = X_d^t + stepsize \times \alpha \times randn\,(D) \tag{7}$$

Where in (7) α is a random number generated between [−1, 1], and

$$Stepsize = 0.01 \times step \times (X_d^t - Xbest_d) \tag{8}$$

Where

$$Step = \frac{randn\,(D) \times Levy(\lambda)}{randn\,(D)^{1/\lambda}} \tag{9}$$

The randn [D] function generates a Gaussian distribution between [1, D]. Levy (λ) obtain from (10)

$$Levy(\lambda) = \left| \frac{\Gamma(1+\lambda) \times \sin(\frac{\pi \times \lambda}{2})}{\Gamma(\frac{1+\lambda}{2}) \times \lambda \times 2^{\frac{(\lambda-1)}{2}}} \right|^{\frac{1}{\lambda}} \tag{10}$$

Where λ is a constant (1 < λ ≤ 3) and Γ is gamma function. A Lévy flight is a random walk. After producing the new solution based on above procedure, it will be compared to the X_d^t, if the introduced objective function value of the new solution is smaller than the objective function value of X_d^t, the new solution is accepted. Otherwise X_d^t remains as the best solution.

For the newly obtained solution, its lower and upper limits should be satisfied according to [26]:

$$X_{di}^{t+1} = \begin{cases} Ub & if \;\; X_{di}^{new} > Ub \\ Lb & if \;\; X_{di}^{new} < Lb \\ X_{di}^{t+1} & \end{cases} \tag{11}$$

The other part of cuckoo search is to place some nests by constructing a new solution. The egg is discovered by the host bird by comparing randomly (i.e. probability Pa ∈ [0, 1]). If the host bird discovers the alien egg, the host bird can either throw the egg away or abandon the nest, and build a completely new this crossover operator is shown as Follows [24, 28]:

$$X_d^{dis} = \begin{cases} X_d^t + rand \times (Ub - Lb) & rand_i < P_a \\ X_d^t & otherwise \end{cases} \tag{12}$$

It can be concluded, CSA good converge behavior is related to three control parameters namely cuckoo nest population size, maximum generation. Optimally setting of these parameters leads to yield better solution and lesser computational time.

3.3 Firefly Algorithm (FA)

Firefly algorithm (FA) is a novel nature-inspired meta-heuristic and powerful algorithm that solves the continuous constrained optimization problems. This algorithm was first developed by Xin-She Yang in late 2007 and 2008 at Cambridge University which was based on the social behavior of fireflies [2, 29].

FA uses the three idealized rules. These three rules are given as follows: (a) One firefly is be attracted to other fireflies with assumption unisexual mode for them; (b) Attractiveness and brightness decrease as their distance increases. For any two flashing fireflies if there is no brighter one than a particular firefly, it will move randomly otherwise the less bright one will move towards the brighter one, and (c) Each firefly represents a solution. Solution quality is specified by firefly brightness Based on the landscape of the objective function [29].

According to above rules, In FA the variation in light intensity, I, and the formulation of the attractiveness β are two important parameters. In the simplest form and considering a fixed light absorption coefficient γ, light intensity I, which is the function of distance r, can be expressed as (13):

$$I(r) = I_0 e^{-\gamma r^2} \tag{13}$$

Where I_0 is the light intensity at r = 0 [2].

As a firefly's attractiveness is proportional to the light intensity seen by adjacent fireflies, define the variation of attractiveness β with the distance r by (14):

$$\beta(r) = \beta_0 e^{-\gamma r^2} \tag{14}$$

Where β_0 is the attractiveness at r = 0 [29].

The distance between any two fireflies i and j can be calculated using the Euclidean distance as:

$$r_{ij} = \left\| x_i - x_j \right\| = \sqrt{\sum_{d \in D} (x_{i,d} - x_{j,d})^2} \tag{15}$$

Where $x_{i,d}$ is the d^{th} component of the spatial coordinate x of the i^{th} firefly and D is the dimension of the problem [2]. Therefore, the movement of firefly i to another more attractive (brighter) firefly j determined by (16):

$$x_i^{k+1} = x_i^k + \beta_0 e^{-\gamma r_{ij}^{k^2}} (x_j^k - x_i^k) + \alpha \xi_i \tag{16}$$

Where α is the randomization parameter and ξ is a vector of random numbers drawn from a Gaussian distribution or uniform distribution. [29].

Pseudo code of implementation FA presented as follows [2]:

Begin
Insert the objective function f(x), $x=(x_1, x_2 \ldots x_d)^T$;
Initialize the fireflies population xi, i=1, 2… n;
Determine the light intensity Ii at xi using f (xi);
Set light absorption coefficient γ, randomize coefficient α;
While (t < MaxGeneration)
For i=1: n   all n fireflies
For j=1: n
If ($I_i < I_j$), Move firefly I toward j; end if

Vary attractiveness with distance r via exp [-γr^2];
Evaluate new solutions and update light intensity;
End for j
End for i
Rank the fireflies and find the current global best;
End while
End.

IV. The Proposed SVC Placement Algorithm

In this paper, the SVCs are located to improve the unbalancing situation and ohmic loss reduction in distribution network. As well an innovative method is proposed to create different unbalancing status in distribution network. Comprehensive objective function is defined as sum of three terms consist of the total Neutral Lines Current, active power loss and SVC installation cost. Optimization results have been carried out with PSO, CSA and FA methods.

4.1 Problem Formulation

The SVC placement problem in DN is formulated as a general objective function to minimize ohmic losses, Neutral Lines Currents and SVC installation cost. The proposed objective function is given by:

$$Objective\,Function = \beta_1 F_1 + \beta_2 F_2 + \beta_3 F_3 \tag{17}$$

Where F_1 is the losses in distribution network which is expressed as:

$$F_1 = P_{losses} \tag{18}$$

As well as F_2 indicates the total Neutral Lines Current as is following:

$$F_2 = \sum_{i=1}^{N_{LINE}} \left| I_{Ri} + I_{Si} + I_{Ti} \right| \tag{19}$$

In (19), N_{Line} is lines number of distribution network and I_{Ri}, I_{Si} and I_{Ti} are the current phasors in different phases of i^{th} line.

The annual SVC installation cost in $/kVAr is determined by (20) [30]:

$$F_3 = \sum_{i=1}^{N_{SVC}} (0.0003 Q_i^2 - 0.3051 Q_i + 127.38) \tag{20}$$

Where N_{SVC} is the number of SVCs and Q_i is the reactive power capacity of i^{th} SVC in MVAr.

It should be pointed out that the terms of objective function in (17) have not the same units, thus Normalized Weight coefficients, β_1, β_2 and β_3 are defined as follows:

$$\beta_1 = \frac{1}{3 P_{\max\,loss}} \tag{21}$$

$$\beta_2 = \frac{1}{3 \sum_{i=1}^{N_{LINE}} \left| I_{Ri\max} + I_{Si\max} + I_{Ti\max} \right|} \tag{22}$$

$$\beta_3 = \frac{1}{3 \sum_{i=1}^{N_{SVC}} (0.0003 Q_{i\max}^2 - 0.3051 Q_{i\max} + 127.38)} \tag{23}$$

Where P_{max} loss is the maximum losses, I_{Rimax}, I_{Simax}, I_{Timax} are the three-phase lines current in distribution network without SVCs and Q_{imax} is the nominal SVC reactive power.

4.2 The Proposed Method to Modeling the Unbalancing in Distribution Networks

The Neutral Lines Current values in unbalanced distribution networks are not neglected. This is because of the single-phase loads and unequal drawn currents by various phases of load points in the real distribution network. Furthermore, the non-zero Neutral lines currents increase losses in the networks.

For a more comprehensive study on the unbalanced network, a novel method is used to modeling the unbalancing situation in distribution network.

For this purpose, in the proposed method, the nominal active and reactive loads in different phases have been multiplied into a specified value which is defined by the unbalancing factor (UF). The specified factor, which is shown in (24), is randomly developed in five diverse ranges of 0 to 1, 0.25 to 1, 0.5 to 1, 0.75 to 1 and 0.9 to 1.

$$\begin{aligned} &Unbalancing\ Factor = x + (x-1)\times r \\ &x = 0,\ 0.25,\ 0.5,\ 0.75,\ 0.9 \end{aligned} \tag{24}$$

Where, r is a random number between 0 and 1.

4.3 The Four-Wire Modeling in Distribution Networks Power Flow

Due to detailed analysis and study of the DNs and calculate the unknown voltage and currents of DN, the method in [31] has been used. Forasmuch as the mentioned method is used for non-neutral network, the modified method as in followed.

In order to obtain the lines currents and nodes voltage of the distribution network, four-wire segment of the DN has been shown in Fig. 2.

In the above section, the relationship between nodes voltage and branches current is obtained from (25): [32]

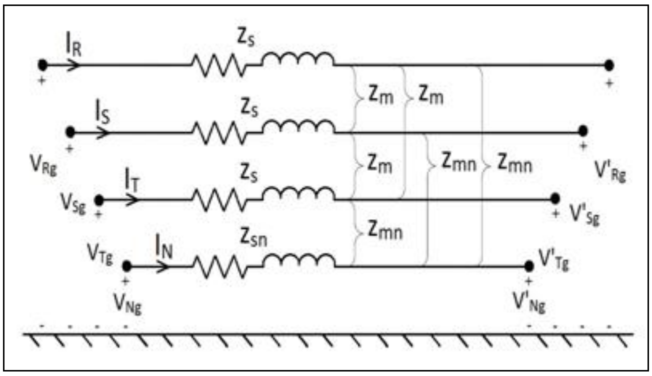

Fig. 2: Circuit model of the four-wire line DN

$$\begin{bmatrix} V_{RN} \\ V_{SN} \\ V_{TN} \end{bmatrix} = \begin{bmatrix} V'_{RN} \\ V'_{SN} \\ V'_{TN} \end{bmatrix} + Z_{RST} \begin{bmatrix} I_R \\ I_S \\ I_T \end{bmatrix} \tag{25}$$

Where Z_{RST} obtain from (26)

$$Z_{RST} = \begin{bmatrix} z_s + Z_S & z_m + Z_S & z_m + Z_S \\ z_m + Z_S & z_s + Z_S & z_m + Z_S \\ z_m + Z_S & z_m + Z_S & z_s + Z_S \end{bmatrix} \tag{26}$$

Where, z_s and z_m are the self-impedance of each line and the mutual-impedance between lines respectively.

Based on definition, Z_S is defined as follows:

$$Z_S = z_{sn} + 2z_{mn} \tag{27}$$

Where, z_{sn} and z_{mn} are the self-impedance of Neutral lines and the mutual-impedance between Neutral lines and other lines respectively.

In this study Forward-backward power flow has been employed [32].

V. Simulation Results and Numerical Studies

In order to evaluate the efficiency of the proposed method, the modified standard IEEE 123-node radial DN illustrated in Fig. 3, has been studied. In this network, the forth wire has been added in lines to modeling the Neutral lines of distribution networks. The nominal voltage of the outlined networks is 4.16 KV and the installed SVCs in various phases is differs from 0 to 600 kVAr.

According to the SVC structure, two working modes can be defined for it, voltage control and reactive power control. In this study has been used reactive power control mode of SVC.

The simulation results are presented in two options with three optimization algorithms such as PSO, CSA and FA which is the following:

1) Three items objective function with identical weight coefficients for all x values

2) Single item objective function for x=0 and x=0.9

The parameters used for optimization algorithms shown in Tables 1 to 3.

Optimization Process was carried out more than 20 times. Results are given in Tables 4 to 7.

Table 1: PSO parameters

parameter	value
Number of Particles	60
Inertia Weight	50
Acceleration constants	C1=1.5 C2=2.5
Maximum Iteration	200

Table 2: CSA parameters

parameter	Value
Number of nest	60
Discover rate of alien eggs	0.25
Levy coefficient, λ	1.25
Maximum Iteration	200

Table 3: FA parameters

parameter	Value
Number of Fireflies	60
gamma	1
Initial Beta	0.2
alpha	0.5
Maximum Iteration	200

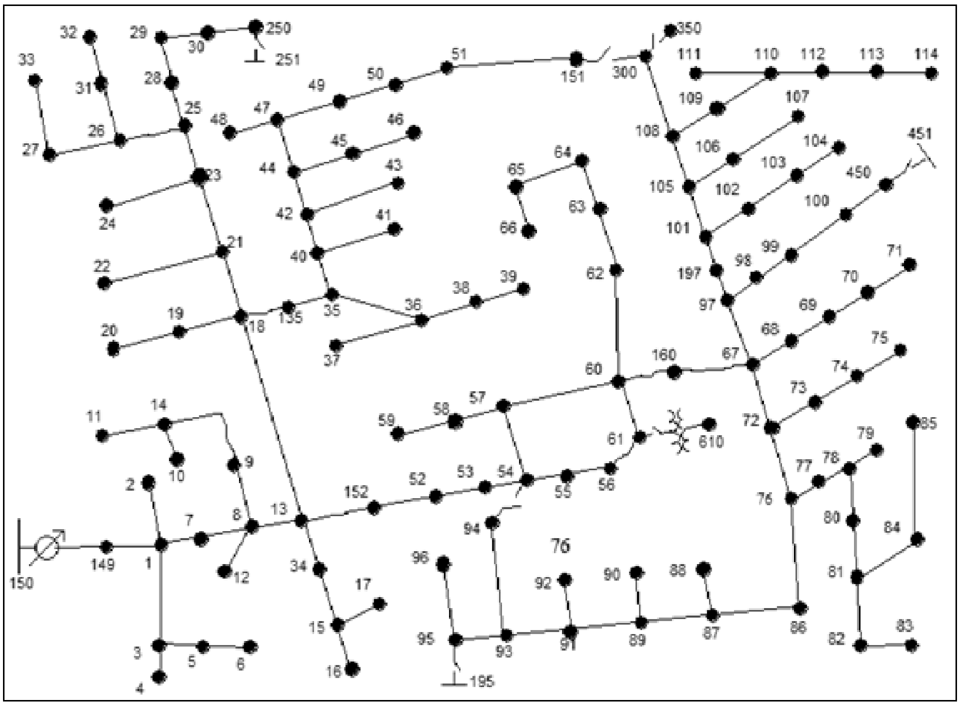

Fig. 3: The modified standard IEEE 123-node radial distribution system

5.1 Three Items Objective Function

In this case, the complete form of objective function contains ohmic loss, Neutral Lines Currents and SVC installation cost has been used and the simulation results illustrate the effects of SVCs installation in three optimization algorithms.

According to the non-zero Neutral lines current values of lines, the injected reactive powers in various phases of the SVCs are different.

Based on the unbalancing situation, the x values differs From zero and 0.9, the simulation results has been presented in Table 4 and 5 in x=0 and x=0.9 respectively.

Table 4: simulation result in x=0

	Without SVC	With SVC					
Optimization Algorithms	-	PSO		CSA		FA	
SVCs number	-	3		2		3	
		Location	Size (kVAr)	Location	Size (kVAr)	Location	Size (kVAr)
SVC1	-	52	97.10 97.65 86.29	86	96.06 83.16 57.16	48	99.25 82.75 117.72
SVC2	-	44	130.16 127.94 168.21	1	100.16 47.79 91.86	76	104.88 92.18 63.28
SVC3	-	77	92.70 78.94 50.50	-	-	34	85.51 87.77 81.86
Feeder current of phase R (A)	534.31	484.12		485.13		484.81	
Feeder current of phase S (A)	557.61	503.41		512.91		504.35	
Feeder current of phase T (A)	504.93	452.73		459.76		453.46	
Total Neutral Lines Current(A)	1016.9	477.78		476.65		409.67	
Loss (kW)	148.44	123.19		124.02		122.81	
Cost ($)	-	118430		60669		103860	

Table 5: simulation result in x=0.9

	Without SVC	With SVC					
Optimization Algorithms	-	PSO		CSA		FA	
SVCs number	-	3		3		3	
		Location	Size (kVAr)	Location	Size (kVAr)	Location	Size (kVAr)
SVC1	-	2	22.02 28.89 42.02	53	86.561 85.862 98.978	60	103.05 111.11 124.50
SVC2	-	1	193.85 186.30 169.48	86	45.897 34.524 55.772	50	116.67 117.71 119.65
SVC3	-	60	104.68 112.66 124.95	76	160.49 175.14 154.15	15	117.03 117.22 117.54
Feeder current of phase R (A)	973.5	915.96		905.54		918.38	
Feeder current of phase S (A)	969.29	910.7		901.82		912.7	
Feeder current of phase T (A)	978.6	920.27		911.39		921.61	
Total Neutral Lines Current(A)	109.58	72.794		77.128		54.216	
Loss (kW)	490.02	461.6		424.74		452.7	
Cost ($)	-	125490		114340		133080	

In the above tables the best location and size of SVCs, feeder top current in R, S and T phases, the total current through the Neutral lines and network loss considering the cost of SVC.

According to Table 4, the total current of Neutral lines with SVCs placement decrease from 1016.9A to 409.67A about 59.7% in FA optimization algorithm. The ohmic Loss decrease from 148.4 kW to 122.81 kW about 17.24% in FA optimization algorithm.

The simulation results indicate the PSO and FA algorithms use three SVCs and CSA algorithm use two location for SVCs. Cost of SVCs allocation Point of view, the optimal solution obtained by employing CSA.

However, with this amount of investment the total current of Neutral lines decrease about 53.12%. The ohmic Loss decrease about 16.5%. According to Table 5, the optimum value of main objective function optimization obtained by CSA. It is observed that reduced the total Neutral lines current about 29.61 % and network loss about 13.32%, while the annual SVCs installation cost is 114340 dollars.

On the other hand, the total current of Neutral lines with SVCs placement decrease from 109.58A to 54.216A about 50.5% in FA optimization algorithm. The ohmic Loss decrease from 490.02 kW to 452.7 kW about 7.62% in FA optimization algorithm. The simulation results indicate the PSO, CSA and FA algorithms use the same number of location of SVCs. Figs. 4 and 5 shown the Neutral lines current values in DN branches, without and with SVC by employing various optimization algorithms for x=0 and x=0.9 unbalancing situation.

It is observed that the Neutral lines current magnitude improved in the majority branches with placing SVCs in appropriate nodes of the network.

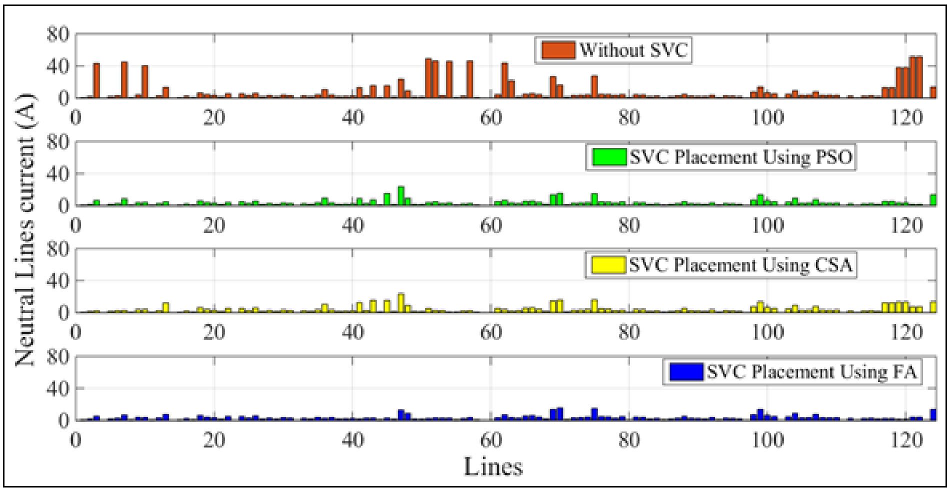

Fig. 4: Neutral Lines current magnitude with and without SVC in x=0 by applying PSO, CSA, FA

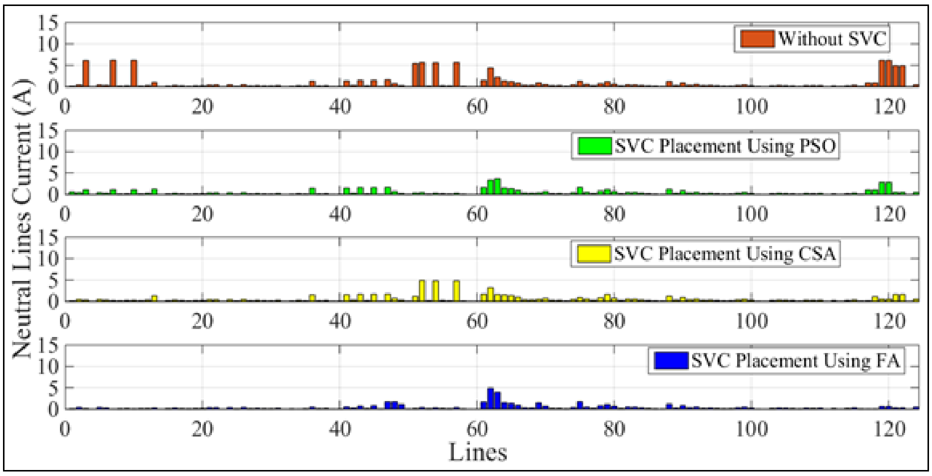

Fig. 5: Neutral Lines current magnitude with and without SVC in x=0.9 by applying PSO, CSA, FA

Performance and convergence comparison of the various optimization algorithms during 200 iteration and the same initializing populations, is given in Figs 6 to 7.

5.2 Single Item Objective Function

In order to evaluate efficiencies of PSO, CSA and FA methods to Single-terms optimization, Further consideration, implementation to SVCs allocation based on consist of just losses and just total neutral Lines current in the x=0 and x=0.9 status. Simulation results are presented in Tables 6 and 7. In Table 6, the loads values are in high unbalancing situation and single term objective function has been used. The simulation results show that the PSO algorithm shown minimum loss with SVCs allocation in losses optimization.

Under this condition The PSO and CSA algorithms find three number of SVCs and FA algorithm find four candidates of SVC places. Furthermore in the Neutral lines current optimization point of view, the FA

algorithm is the best result in the total Neutral lines current minimization. Under this condition The PSO and FA algorithms find four number of SVCs and CSA algorithm find three candidates of SVC places.
As well as, Table 7, the loads values are in low unbalancing situation has been used.

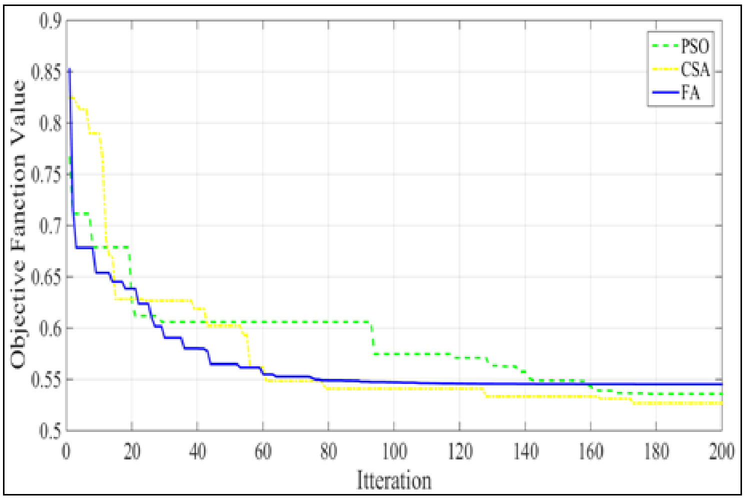

Fig. 6: PSO, CSA, FA Convergence plot in x=0

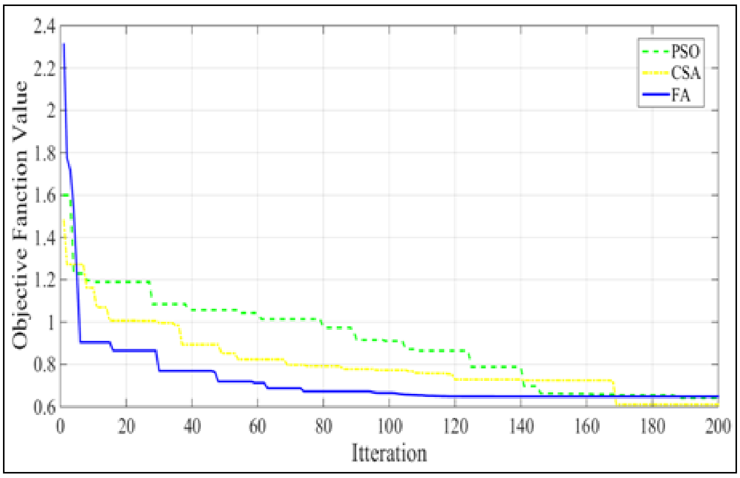

Fig. 7: PSO, CSA, FA Convergence plot in x=0.9

Table 6: SVC placement based on Single – terms optimization in x=0

case	losses						Total Neutral lines current					
Optimization algorithm	PSO		CSA		FA		PSO		CSA		FA	
SVC number	3		3		4		4		3		4	
SVC1(location & number)	67	101.03 102.64 86.39	97	101.39 105.31 88.11	23	77.49 62.47 70.76	30	72.24 72.81 80.97	48	119.47 106.49 139.92	57	69.08 85.95 69.11
SVC2(location & number)	47	90.96 86.29 109.64	44	45.72 48.55 100.14	62	71.72 94.19 78.01	86	105.07 92.39 63.33	57	107.38 117.59 55.69	48	102.71 84.28 115.98
SVC3(location & number)	52	57.57 67.23 36.88	13	142.16 118.12 79.50	72	87.34 85.95 67.22	9	75.80 74.31 64.59	67	139.38 123.48 110.05	37	60.43 67.06 70.04
SVC4(location & number)		-	-	-	44	84.01 62.45 74.9	48	111.85 85.43 130.07	-	-	76	100.72 83.91 57.92
Losses(kW)	122.25		122.37		122.4		123.58		124.23		123.04	
Total Neutral Lines Current(A)	769.41		845.29		767.04		402.73		405.52		403.36	
Cost($)	94107		105620		116770		132360		129900		123230	

Table 7: SVC placement based on Single – terms optimization in x=0.9

case	losses						Total Neutral lines current					
Optimization algorithm	PSO		CSA		FA		PSO		CSA		FA	
SVC number	3		3		3		2		3		3	
SVC1(location & number)	52	199.94 199.95 200	40	189.26 168.10 173.96	67	148.53 142.64 152.81	60	57.317 66.79 78.34	48	119.47 106.49 139.92	15	104.84 105.06 105.34
SVC2(location & number)	44	157.1 156.75 157.5	8	141.22 183.45 157.8	47	147.83 130.20 129.59	48	116.34 117.90 120.3	57	107.38 117.38 55.69	60	114.27 122.42 135.81
SVC3(location & number)	67	142.92 143.14 144.17	67	146.80 150.98 151.25	53	116.83 146.67 132.74	-	-	67	139.38 123.49 110.08	42	99.33 100.2 102.23
SVC4(location & number)		-	-	-	-	-	-	-	-	-	-	-
Losses(kW)	416.3		416.7		416.93		467.02		418.33		452.98	
Total Neutral Lines Current(A)	100.5		134.16		184.56		53.621		50.66		54.04	
Cost($)	191340		186410		159000		70966		216150		126080	

According to Table 7, losses optimization point of view, the PSO, CSA and FA algorithms find the same number of location of SVCs. allocation SVCs by employing PSO, CSA and FA algorithms, Leads to the ohmic losses decrease about 15.04%, 14.96% and 14.92% respectively. However the total neutral lines current Condition not seems appropriate.

As well as, the total neutral lines current optimization point of view, the CSA and FA algorithms use three and FA algorithm use two location for SVCs. allocation SVCs by employing PSO, CSA and FA algorithms, Leads to the total neutral lines current decrease about 51.07%, 53.77% and 50.68% respectively. However ohmic losses decrease about 4.69%, 14.63% and 7.56% respectively.

To compare between various unbalancing situation where created in a distributing network, Standard Deviation indicator is presented for three optimization methods. The index indicates rating of current dispersion through the neutral lines from the average value of currents in two modes by SVC in each five unbalancing situations.

$$SD_j = \sqrt{\frac{1}{N_{LINE}-1}\sum_{i=1}^{N_{LINE}}(A_i - \bar{A}_i)^2} \tag{28}$$

$$j = 1,\ 2,\ 3,\ 4,\ 5$$

Where A_i and $\bar{A}_i$ obtain by (29):

$$A_i = \frac{Neutral\ Current_i}{\sum_{i=1}^{N_{LINE}} Neutral\ Current_i} \quad ,\ i = 1,\ldots, N_{LINE} \tag{29}$$

$$\bar{A}_i = \frac{Average\ Neutral\ Current_i}{\sum_{i=1}^{N_{LINE}} Average\ Neutral\ Current_i} \tag{30}$$

Using (30) the results for a different unbalancing situation is shown in Fig. 8.

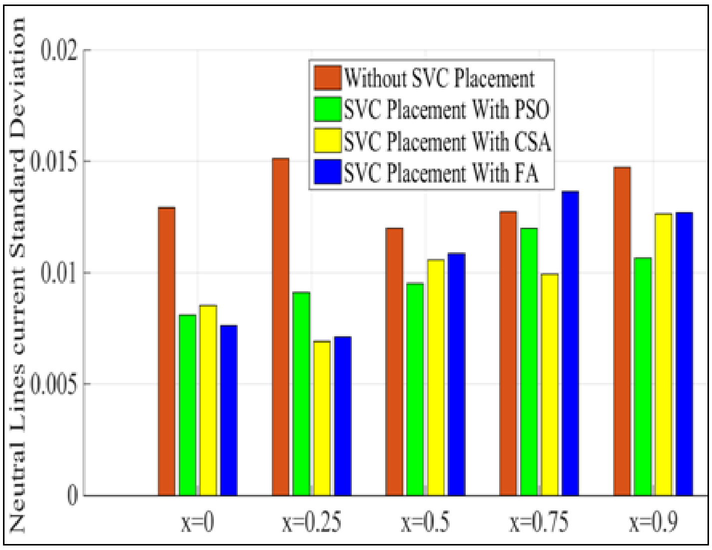

Fig. 8: comparison of normalized SD factor for different values of x with PSO, CSA, FA

VI. The Effect of Increasing the Number of SVC in Improvement Unbalancing and Reduction Losses in the Distribution Network

In order to analysis placed SVC's number efficacy on the improvement of unbalancing network and reduction of losses in unbalancing state for x=0 Serve as the worst unbalancing situation for network using PSO, CSA and FA.

Results have been investigated for 1 to 8 three-phase SVC placement with these algorithms, which is shown in Fig. 9.

In the case of unbalancing, comparing the total Neutral line current with respect to the value shown in Fig. 9. It reveals that the increasing the number of SVC's has not a significant impact on reducing the Neutral lines current. As well to reduce the losses more than three 3-phases SVC's can be used which at economic point of view may not be affordable.

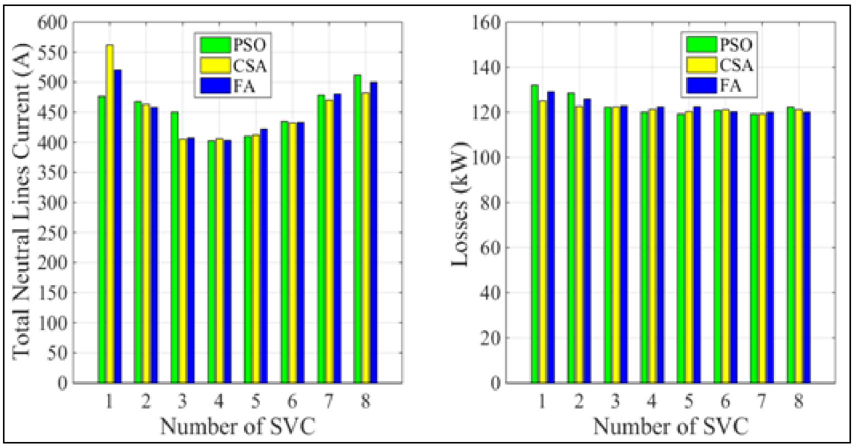

Fig. 9: the Effect of more number of SVC on Neutral lines current and losses reduction with PSO, CSA, FA

VII. Conclusion

In this paper, to distribution network unbalancing improvement point of view reduction Neutral Lines Current and energy loss, three phase SVC optimal allocation with non-identical values is performed.

A novel method for modeling the unbalanced DN is introduced, so the nominal active and reactive loads in different phases have been multiplied into a specified value which is defined by the unbalancing factor (UF).

Simulation results have been carried out on The IEEE Standard 123 node network for five random unbalance situations. Optimal location, sizing and number of SVC specified using PSO, CSA and FA algorithms. The simulation results presented in two options: 1) Three items objective function with identical weight coefficients for all x values, 2) Single item objective function for x=0 and x=0.9, were shows reduction network unbalancing and network losses with the lowest investment.

The used optimization algorithms were compared point of view optimal SVCs allocation and Convergence speed in different UF value under proposed method.

It can be concluded from the simulation results that in point of view of main objective function optimization and convergence speed, CSA is more efficient in the proposed method. But this does not mean the performance of the two other algorithms is Inefficient. Because, in point of view of single term analysis of main objective function and Single item objective function optimization, FA and PSO also have shown better solution. This paper presented a comprehensive study about efficiency of various optimization algorithms in proposed method.

In addition, the effect of raising the number of installed SVC's in network is evaluated on reducing network unbalancing and losses. So it can be seen usage of the SVC in DNs as an efficient and updated manner to improve the DNs operation, which will increase the performance of networks efficiently.

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