Journal of Operation and Automation in Power Engineering
Vol. 2, No. 2, Summer & Fall 2014, Pages: 129-140
http://joape.uma.ac.ir

Simultaneous RPD and SVC Placement in Power Systems for Voltage Stability Improvement Using a Fuzzy Weighted Seeker Optimization Algorithm

F. Namdari*, L. Hatamvand, N. Shojaei, H. Beiranvand
Faculty of Engineering, Lorestan University, Khorram abad, Iran

ABSTRACT
Voltage stability issues are growing challenges in many modern power systems. This paper proposes optimizing the size and location of Static VAR Compensator (SVC) devices using a Fuzzy Weighted Seeker Optimization Algorithm (FWSOA), as an effective solution to overcome such issues. Although the primary purpose of SVC is bus voltage regulation, it can also be useful for voltage stability enhancement and even real power losses reduction in the network. To this aim, a multi-objective function is presented which includes voltage profile improvement, Voltage Stability Margin (VSM) enhancement and minimization of active power losses. Voltage stability is very close to Reactive Power Dispatch (RPD) in the network. Therefore, in addition to voltage regulation with locating SVCs, considering all of the other control variables including excitation settings of generators, tap positions of tap changing transformers and reactive power output of fixed capacitors in the network, simultaneous RPD and SVC placement will be achieved. Simulation results on IEEE 14 and 57-bus test systems, applying Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Seeker Optimization Algorithm (SOA) and FWSOA verify the efficiency of FWSOA for the above claims.

KEYWORDS: Reactive power dispatch, Voltage stability margin enhancement, Voltage deviation reduction, Real power losses minimization.

1. INTRODUCTION

Voltage stability is one of attractive stability aspects in power systems and is considerably affected by Reactive Power Dispatch (RPD) in the network. Flexible AC Transmission System (FACTS) equipments are new fast compensator devices, which increase the power system capacity and make it more capable for controlling the power flow by enhancing the capacity of existing transmission system [1]. These power electronic converters control various electrical parameters in the network, both steady state power flow and dynamic stability. FACTS devices play an important role to overcome power flow and voltage stability problems like Thyristor- Controlled Series Compensator (TCSC), SVC, Unified Power Flow Controller (UPFC), Static Compensator (STATCOM), etc [2-4]. One of the most important of these devices is Static VAR Compensator (SVC). SVC is used widely because of its cheaper and proper operation. SVC is a shunt compensator that can be in an inductive reactor mode that consumes the reactive power or be a capacitive element, which generates reactive power for the system [5].

Many studies have focused on SVC placement in power networks by different analytical techniques [6-9] and many others, employed Evolutionary Algorithms (EAs) like Harmony Search Algorithm (HSA), Genetic Algorithm (GA), Particle Swarm Optimization (PSO), etc [5, 10-12] to achieve various goals.

Reference [5] has proposed HSA to optimize the size and location of shunt VAR compensation devices such as SVC so that improve voltage

Received: 5 Jan. 2014 Revised: 21 June 2014
Accepted: 7 July 2014
*Corresponding author:
F. Namdari (E-mail: namdari.f@lu.ac.ir)

deviation and its stability along with active power losses and cost reduction of mentioned compensators. GA has been used to SVC placement considering all or some of the above objectives in [10-11]. Reference [12] also employed PSO in SVC allocation for voltage regulation along with transient rotor angle stability improvement.

While the primary duty for SVC is bus voltage regulation, this is possible that voltage stability enhancement and real power losses reduction also obtained by optimal placement of SVC [10].

On the other hand, if reactive power well dispatches all over the network, then voltage stability will be guaranteed. This objective will be obtained when all settings related to all control variables of compensator devices are adjusted optimally. Consequently, voltage deviation, VSM and active power losses take proper values in the system. In addition, there are two sets of variables, including continuous and discrete variables in such optimization problems. Considering these reasons, RPD is addressed as a nonlinear optimization problem [13].

Previous classic optimization approaches are based on gradient or mathematical methods. Recently, the EAs like Differential Evolution (DE) [14-16], Hybrid Differential Evolution (HDE) [17], HSA [18], GA [19], PSO [20-23] and Seeker Optimization Algorithm (SOA) [24] for RPD are more attractive because of more efficiency in handling the inequality constraints and discrete values. EAs do not rely on gradient information, so they rarely suffer from being trapped in local minima [25]. However, in the case of some usages, may be slower with respect to gradient-based methods. However, many studies have focused on RPD problems with EAs.

Reference [19] has improved the voltage stability using an improved GA approach. Optimization variables are generator voltages, capacitor bank sizes and tap of transformers. In [20-23] PSO algorithm has been considered for RPD problem. In [20] PSO is used to achieve the optimal reactive power flow in the system. To eliminate premature convergence in PSO, a new learning strategy is presented. Consequently, active power losses reduce, voltage profile improves and VSM increases. In [21] a novel PSO technique based on multi-agent systems (MAPSO) has suggested to RPD problem. Reference [22] also aims to reduce active power losses and voltage deviation by a multi-objective PSO algorithm. Reference [24] performs RPD using SOA that is a global optimization approach. Objectives are active power losses and voltage deviation reduction and increase the voltage stability margin.

There are two deficiencies in GA operation. GA converges precociously and is not enough capable in local search [26]. On the other hand, PSO also suffers from precocious convergence because of dependability on its parameters [27]. However, reference [24] claims that SOA performance is better than GA and PSO in RPD problem.

In this paper, a Fuzzy Weighted Seeker Optimization Algorithm (FWSOA) is proposed to optimize the size and location of SVC as well as the control variables of other compensator devices in the network. Therefore, a simultaneous RPD and optimal SVC placement is obtained.

The objective function includes minimization of active power losses, voltage profile improvement and VSM enhancement. To this aim, all control variables of the network are excitation settings of generators, tap position of tap changing transformers, reactive power output of fixed capacitors and voltage with location of SVCs in the network. RPD is performed by using GA, PSO, SOA and FWSOA. Therefore, in the present study, the effectiveness of GA, PSO, SOA and FWSOA for simultaneous RPD and SVC placement is compared. Simulation results verify that FWSOA is the best solution to solve RPD and therefore voltage stability improvement problem. Furthermore, simulation results show that FWSOA outperforms the GA, PSO and SOA in solving simultaneous RPD and SVC placement problem.

2. PROBLEM FORMULATION

2.1. SVC ideal model

Figure 1 illustrates the general circuit structure of a Static VAR Compensator (SVC). This structure is composed of a fixed capacitor (with susceptance B_C) parallel with a thyristor-controlled reactor (with susceptance B_L). The equivalent susceptance $B_{eq,SVC}$

is determined by the firing angle α of the thyristors. The equivalent susceptance is expressed as follows:

$$B_{eq,SVC} = B_L(\alpha) + B_C \quad (1)$$

where,

$$B_L(\alpha) = -\frac{1}{\omega L}\left(1-\frac{2\alpha}{\pi}\right), \quad B_C = \omega * C \quad (2)$$

The reactive power amount that SVC consumes or generates is:

$$Q_{SVC} = -V_K^2 * B_{eq,SVC} \quad (3)$$

Subject to

$$B_{eq,SVC}^{\min} \le B_{eq,SVC} \le B_{eq,SVC}^{\max} \quad (4)$$

2.2. Objective function

In this section, the overall objective function for simultaneous RPD and SVC placement problem is presented.

2.2.1. Real power losses

First sub-objective function is real power losses minimization, which is defined as follows [24]:

$$\min P_{loss} = f(\vec{x}_1, \vec{x}_2) = \sum_{k \in N_E} g_K (V_i^2 + V_j^2 - 2V_i V_j \cos\theta_{ij}) \quad (5)$$

Subject to

$$\begin{cases} P_{Gi} - P_{Di} = V_i \sum_{j \in N_i} V_j (G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}) & i \in N_0 \\ Q_{Gi} - Q_{Di} = V_i \sum_{j \in N_i} V_j (G_{ij}\sin\theta_{ij} - B_{ij}\cos\theta_{ij}) & i \in N_{PQ} \\ V_i^{\min} \le V_i \le V_i^{\max} & i \in N_B \\ T_k^{\min} \le T_k \le T_k^{\max} & k \in N_T \\ Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max} & i \in N_G \\ Q_{Ci}^{\min} \le Q_{Ci} \le Q_{Ci}^{\max} & i \in N_C \\ V_{SVC_i}^{\min} \le V_{SVC_i} \le V_{SVC_i}^{\max} & i \in N_{SVC} \\ L_{SVC_i} & i \in N_{PQ} \\ Q_{SVC_i}^{\min} \le Q_{SVC_i} \le Q_{SVC_i}^{\max} & i \in N_{SVC} \\ S_l \le S_l^{\max} & l \in N_l \end{cases} \quad (6)$$

where x_1 and x_2 are control and dependent variable vectors, respectively. Control vector includes V_G, K_T, Q_C, V_{SVC} and L_{SVC}. The dependent vector includes V_L and Q_G and Q_{SVC}. V_G and V_{SVC} denote generator and SVC voltages respectively, and are continuous variables. While, K_T, Q_C, L_{SVC} are discrete variables and represent transformer tap position, capacitor size and location of *SVCs*, respectively. g_k is the conductance of branch k, θ_{ij} is difference between voltage angles of bus i and bus j. P_G and P_D are active power generation and power demand respectively. Q_G and Q_D are reactive generation and demand. Q_{svc} also shows the reactive power amount that each SVC absorbs or injects to the network. G is conductance of the transfer branch and B is the susceptance. S_l also is power flow in transmission line l. N_E is the number of all network branches, $N0$ represents each bus except slack bus, N_{PQ}: load buses, N_B: all buses, N_T the number of tap changer transformers, N_G the number of generator buses, N_C the number of possible capacitor installation buses and N_{SVC} means the number of possible *SVCs* installation buses.

2.2.2. Voltage deviation

Second sub-objective function is voltage deviation minimization, which is defined as follows [24]:

$$\min \Delta V_L = \sum_{i=1}^{N_L} \left| \frac{V_i - V_i^*}{N_L} \right| \quad (7)$$

ΔV_L is the voltage deviation, N_L represents the number of all load buses, V_i is actual voltage magnitude and V_i^* is the expected corresponding value.

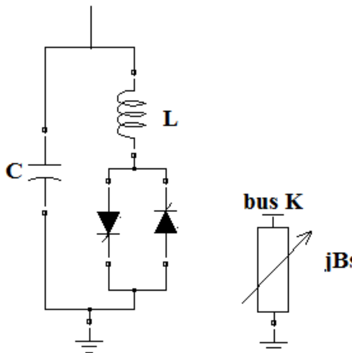

Fig. 1. General circuit structure for SVC [11]

2.2.3. Voltage stability margin

Tertiary sub-objective function is voltage stability margin, which is defined as follows [24]:

$$\max VSM = \max(\min|eig(Jacobi)|) \quad (8)$$

VSM is abbreviated of voltage stability margin and *Jacobi* is the power flow Jacobian matrix and *eig(Jacobi)* means all eigenvalues of Jacobian matrix. Equation (8) expresses that if can maximize the minimum eigenvalue of the power flow Jacobian matrix, in reality VSM increases.

2.2.4. Multi-objective conversion

In this section, f_1, f_2 and f_3 are normalized so as kept within [0, 1]. This fuzzy decision for sub-objective functions is because of each sub-objective function has different range of function values. Note that f_3 function is a maximization optimization problem [24].

$$f1=\begin{cases}0 & if\ Ploss<Ploss_{\min}\\ \dfrac{Ploss-Ploss_{\min}}{Ploss_{\max}-Ploss_{\min}} & if\ Ploss_{\min}\le Ploss\le Ploss_{\max}\\ 1 & if\ Ploss>Ploss_{\max}\end{cases} \tag{9}$$

$$f2=\begin{cases}0 & if\ \Delta V_L<\Delta V_{L\min}\\ \dfrac{\Delta V_L-\Delta V_{L\min}}{\Delta V_{L\max}-\Delta V_{L\min}} & if\ \Delta V_{L\min}\le\Delta V_L\le\Delta V_{L\max}\\ 1 & if\ \Delta V_L>\Delta V_{L\max}\end{cases} \tag{10}$$

$$f3=\begin{cases}0 & if\ \ VSM>VSM_{\max}\\ \dfrac{VSM_{\max}-VSM}{VSM_{\max}-VSM_{\min}} & else\end{cases} \tag{11}$$

where subscripts *min* and *max* denote corresponding expectant minimum and possible maximum values, respectively. Finally, the overall objective function for RPD problem is presented as follows:

$$\min\ f=w1\,f1+w2\,f2+w3\,f3+\lambda V\sum_{N_V^{\lim}}\Delta V_L^2+\lambda Q\sum_{N_Q^{\lim}}\Delta Q_G^2 \tag{12}$$

Dependent variables are constrained using penalty factors while the control variables are self-constrained.

w_i (i= 1, 2, 3) is the user-defined constant which represents the weight of contribution for different sub-objective functions. λ_V and λ_Q are penalty factors. N_V^{lim} is the number of load buses, which violate from the permitted voltage range and N_Q^{lim} is the number of generator buses that violate from permitted reactive power range. ΔV_L, ΔQ_G and ΔQ_{SVC} also are defined as follows:

$$\Delta V_L=\begin{cases}V_{L\min}-V_L & if\ V_L<V_L^{\min}\\ V_L-V_{L\max} & if\ V_L>V_L^{\max}\end{cases} \tag{13}$$

$$\Delta QG=\begin{cases}QG_{\min}-QG & if\ QG<Q_G^{\min}\\ QG-QG_{\max} & if\ QG>Q_G^{\max}\end{cases} \tag{14}$$

$$\Delta QSVC=\begin{cases}QSVC_{\min}-QSVC & if\ QSVC<Q_{SVC}^{\min}\\ QSVC-QSVC_{\max} & if\ QSVC>Q_{SVC}^{\max}\end{cases} \tag{15}$$

3. OPTIMIZATION ALGORITHMS

3.1. PSO and genetic algorithms

Particle swarm optimization algorithm was presented by Kennedy and Eberhart [28]. This algorithm is based on the social behavior of animals like birds or fish, which search the best locations for their food and after finding it, all of them, attack to the food. This seeking behavior is corresponding to the optimization search for solutions that are capable in solving the non-linear problems in a real-valued search space [29].

The main version of GA was proposed by Holland [30]. GA is a search algorithm based on the mechanics of natural genetics and natural selection. The GA is a population search method. A population of strings is kept in each generation. The simulation of the natural process of reproduction, gen crossover and mutation produces the next generation.

3.2. Seeker optimization algorithm

SOA operates on a set of solutions called search population. The individuals of this population called seeker or searcher. The total population is equally categorized into K subpopulations according to the indexes of the seekers and K=3 is selected in this study [24]. All the seekers in the same subpopulation constitute a neighborhood, which represents the social component for the social sharing of information. Search direction d_{ij} and step length α_{ij} are computed for each seeker i (1≤i≤s, s is the population size), on each dimension j by time step t where $\alpha_{ij}\ge 0$ and d_{ij} belongs to $\{-1, 0, 1\}$. When d_{ij}=1 this means seeker i goes toward positive direction of the coordinate axis on the dimension j, d_{ij}=0 i.e. seeker has no motions and d_{ij}= -1 means negative direction. At each time step or iteration t, the position of each seeker is updated by (16):

$$x_{ij}(t+1) = x_{ij}(t) + \alpha_{ij}(t).\ d_{ij} \tag{16}$$

On the other hand, to prevent of entrapment in local minima, at each iteration, the current positions of the worst two individuals of each subpopulation are combined with the best ones in each of the other two subpopulations, using binomial crossover operator as (17):

$$x_{knj,worst} = \begin{cases} x_{lj,best} & if\ R_j \le 0.5 \\ x_{knj,worst} & else \end{cases} \tag{17}$$

where R_j is a uniformly random real number within [0,1], $x_{knj,worst}$ is j-th dimension of the n-th worst position in the kth subpopulation, $x_{lj,best}$ is the j-th dimension of the best position in the l-th subpopulation, n, k, l=1,2,..., $K-1$ and $k \neq 1$. In result, diversity of the population will increase [24].

3.2.1. Search direction

In SOA, search space can be considered as a gradient field where in the search empirical gradient is determined based on the position change and seeker follows the empirical gradient to guide his search. SOA is not dependent on empirical gradient magnitude and therefore, search direction can be determined by signum function of minus between best and worst positions.

Seeker search directions are determined based on evaluating their current or historical (previous) positions or their neighbors and three kinds of behaviors.

In the first kind i.e. egotistic behavior, each seeker likes to go toward his historical best position $\vec{p}_{i,best}(t)$ and therefore, egotistic direction $\vec{d}_{i,ego}(t)$ is determined by (18):

$$\vec{d}_{i,ego}(t) = sign(\vec{p}_{i,best}(t) - \vec{x}_i(t)) \tag{18}$$

The second case is altruistic behavior where in all seekers in the same neighborhood, are coordinated with each other to achieve desired goal. In this state, two kinds of search direction are defined based on neighbor's historical best position and the other is neighbor's current best position i.e. $\vec{d}_{i,alt_1}(t)$ and $\vec{d}_{i,alt2}(t)$.

$$\vec{d}_{i,alt_1}(t) = sign(\vec{g}_{best}(t) - \vec{x}_i(t)) \tag{19}$$

$$\vec{d}_{i,alt2}(t) = sign(\vec{l}_{best}(t) - \vec{x}_i(t)) \tag{20}$$

In the third kind i.e. pro-activeness behavior, seekers rarely influenced by their environment and they often focus to achieve their desired goal. In addition, next behavior of seeker can be determined by his previous behavior and therefore each seeker is pro-activeness in changing of his search direction. This pro-activeness $\vec{d}_{i,pro}(t)$ is as follows:

$$\vec{d}_{i,pro}(t) = sign(\vec{x}_i(t1) - \vec{x}_i(t2)) \tag{21}$$

where t_1, $t_2 \in$ {t, t−1, t−2}, and $x_i(t_1)$ is better than $x_i(t_2)$.

Finally, the actual search direction $\vec{d}_i(t)$ for each seeker i is determined by a compromise among four mentioned behaviors. Equation (22) shows this parameter:

$$d_{ij} = \begin{cases} 0 & if\ r_j \le p_j^0 \\ +1 & if\ p_j^0 < r_j \le p_j^0 + p_j^{+1} \\ -1 & if\ p_j^0 + p_j^{+1} < r_j \le 1 \end{cases} \tag{22}$$

where r_j is a uniform random number in [0,1], $pj(m^)$ (m∈{0,+1,−1}) is the percentage of the number of "m" from the set{$d_{ij,ego}$, $d_{ij,alt1}$,$d_{ij,alt2}$, $d_{ij,pro}$}on each dimension j of all the four empirical directions, i.e. $p_j^{(m)}$= the number of $m/4$.

3.2.2. Step length

In the optimization problem with continuous search space, usually there is a neighborhood region close to an extremum point. Fitness values of input variables are proportional with their distances from this extremum point. So, near optimal solutions may be found in a neighborhood region with little width (narrow) and lower fitness values or in a spread neighborhood region (broad) containing higher fitness values. Since fuzzy logic is a capable solution in solving of if-then problems, this logic is employed to model the conditional section (if {fitness value is small}) and action part (Then {step length is short}) of the problem. All seeker fitness values are descendingly sorted and converted to consecutive numbers so as fuzzy system be applicable to wide range of optimization problem. A linear membership function is used for conditional part as follow:

$$\mu_i = \mu_{max} - \frac{s - I_i}{s-1}(\mu_{max} - \mu_{min}) \tag{23}$$

where I_i is the sequence number of $x_i(t)$ after sorting the fitness values, μ_{max} is the maximum membership degree value which is equal to or a little less than 1.0.

For action part the Bell membership function $\mu(x)=e^{-x2/2\delta 2}$ in Fig. 2 is used. One dimension is considered, membership degree values of the input variables are between [-3δ, 3δ] and other values are neglected. Parameter δ in Bell function is presented as:

$$\vec{\delta} = \omega * abs(\vec{x}_{best} - \vec{x}_{rand}) \tag{24}$$

where ω is weight parameter, $\vec{x}_{best}$ and $\vec{x}_{rand}$ are best seeker and a randomly selected seeker of the same subpopulation, respectively.

The parameter μ_i is changed to vector $\vec{\mu}_i$ by (25) to produce of randomicity on each dimension and improve local search capability. Finally action part α_{ij} will be presented by (26).

$$\mu_{ij} = RAND(\mu_i, 1) \tag{25}$$

$$\alpha_{ij} = \delta_j \sqrt{-\ln(\mu_{ij})} \tag{26}$$

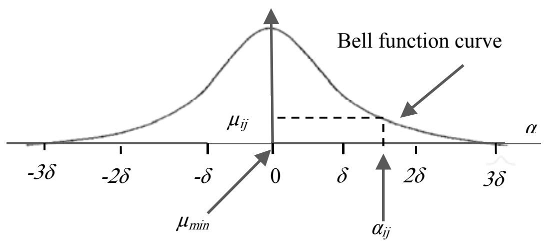

Fig. 2. The action part of the Fuzzy reasoning

3.3. Fuzzy weighted SOA

In the number of evolutionary algorithms like PSO and SOA a weight parameter (ω in (24)) is defined which decreases linearly by iteration increment. The parameter ω is used to decrease the step length with time step increasing so as to gradually improve the search precision [24]. So, the probability to find a better solution in adjacent of the recent optimal point increases. If the algorithm cannot find a proper solution at the last iterations, this update role may cause the early stagnation during the stochastic search. A rational decision is to select the parameter ω according to the evaluated fitness of the search space. So, in this paper, a fuzzy procedure is proposed to calculate the parameter ω effectively. Thus, here, a Fuzzy Weighted SOA (FWSOA) algorithm is presented. The proposed FWSOA is detailed in the following paragraph.

We define an Average Fitness (AF) value of the search space at iteration t as an index of the quality of the obtained results of the algorithm so far. This AF index will be used as the input of the fuzzification part. Desired Fitness (DF) value of an objective function is the ideal solution of an engineering optimization problem and the Worst Fitness (WF) at the first iteration in the search space are used to form the sigmoid fuzzy membership function in the inference engine. The control rule as "If AF value is small, then parameter ω is small" is applied to the fuzzy inference system. Figure 3 illustrates the sigmoid fuzzy membership function.

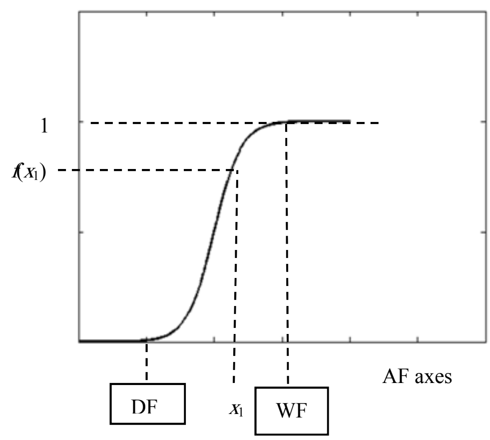

Fig. 3. Sigmoid membership function used in fuzzy inference system.

The output of the defuzzification part of the fuzzy inference system is the fuzzified weight ω. In the defuzzification part, ω will be extracted as a number in [0.1, 0.9] as follows:

$$\omega_t = 0.8 f(x_t) + 0.1 \tag{27}$$

$$f(x_t) = \frac{1}{1 + a e^{(b - x_t)}} \tag{28}$$

where f is the sigmoid function, x is the AF index at iteration t. Parameters a and b depend on DF and WF. The DF index has to be set for each optimization problem separately and WF index will be calculated at start of optimization process automatically.

3.4. FWSOA for simultaneous RPD and SVC placement

Here, there are follow steps in FWSOA employment for simultaneous RPD and SVC placement (Fig. 4):

Four mentioned algorithms are employed for simultaneous RPD and SVC placement problem and simulation results for IEEE 14 and 57-bus test systems will be presented.

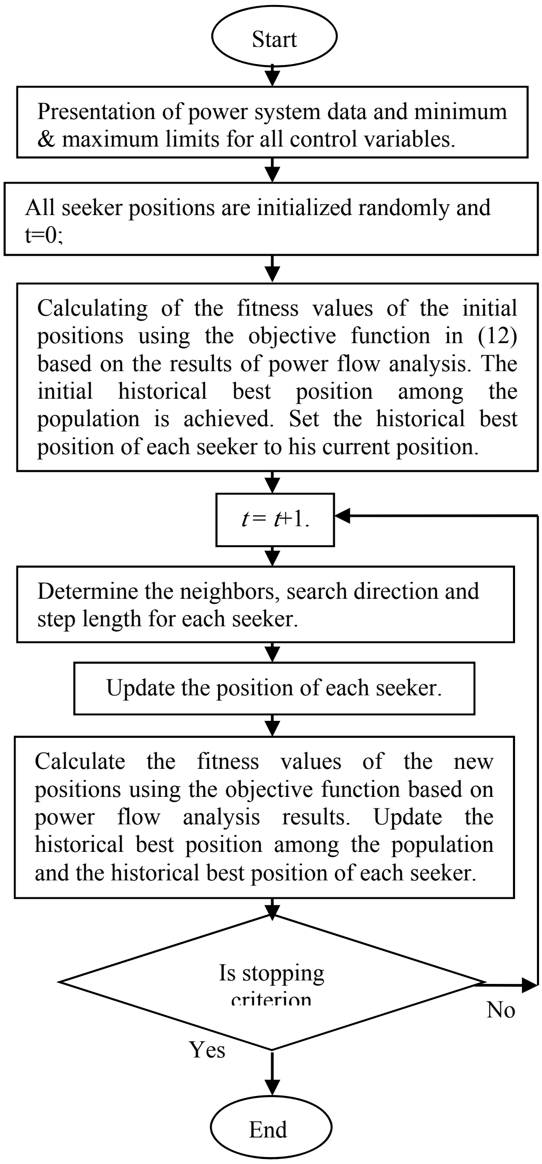

Fig. 4. The flowchart of FWSOA employment

4. SIMULATION RESULTS

4.1. IEEE 14- bus test system

The IEEE 14-bus test system has five generators, 20 transmission lines and three tap changing transformers. One capacitor placed at bus 9 [31]. One SVC also has been considered in the present study IEEE 14-bus test system. This is recommended that in this paper, SVCs are allocated to place in non-generator buses. Because the voltages of generator buses are regulated by excitation system. All variable limits have taken from [32]. The population size is 30 for IEEE 14-bus system, total 30 runs and the maximum generations of 25. Optimization parameters are w_1=0.6, w_2=0.2, w_3=0.2 [24], $Ploss_{min}=0.07$, $Ploss_{max}=0.2$, $\Delta V_{Lmin}=0$, $\Delta V_{Lmax}=1.5$, $VSM_{min}=0.05$, $VSM_{max}=2$, $\lambda_V=500$, $\lambda_Q=500$. Real power losses, voltage deviation and VSM are listed in Table 1. Table 2 includes all variable limitations that will be used for optimization process.

Table 1. Sub-objective function values, P_G and Q_G for IEEE 14- bus test system before optimization.

Real power losses (p.u.)	0.1339
Voltage deviation (p.u.)	0.0754
VSM(p.u.)	0.5489
$\sum P_G$ (MW)	272.3933
$\sum Q_G$ (MVAR)	82.4375

Table 2. Control variable limits for IEEE 14- bus test system.

Variable	Min variable	Max variable
Generator bus voltages (p.u.)	0.95	1.1
Q_{C9} (MVAR)	0	19
All taps (p.u.)	0.9	1.1
Q_{SVC} (MVAR)	-50	50

Best Function Value (BFV), Average Function Value (AFV) and Standard Deviation (STD) indices for IEEE 14- bus test system are listed in Table 3. These indices are obtained from 30 successive runs for each optimization algorithm. Real power losses (*Ploss*), voltage deviation (ΔV_L) and *VSM* objectives for the best solution are listed in Table 4.

BFV, AFV and STD indices are very important. These parameters show the efficiency and robustness of an optimization algorithm in achieving global or near global optimal solution. BFV, AFV and STD indices of FWSOA are smaller than GA, PSO and SOA. From Table 3 it can be understood that FWSOA is better than GA, PSO and SOA in solving simultaneous RPD and SVC placement problem.

Table 3. Optimization indices by four algorithms for IEEE 14-bus test system.

Indices	GA	PSO	SOA	FWSOA
AFV	0.4600	1.2793e3	0.4542	0.4509
BFV	0.4097	0.4099	0.4091	0.4068
STD	0.0338	7.0038e3	0.0286	0.0271

Table 4. Sub-objective function values by four algorithms for IEEE 14-bus test system.

Indices	GA	PSO	SOA	FWSOA
Ploss	0.1317	0.1300	0.1254	0.1250
ΔV_L	0.0120	0.0271	0.0362	0.0416
VSM	0.5281	0.5289	0.5556	0.5621

The aim of the optimization is to further reduction in real power losses and voltage deviation and further increment in voltage stability margin. These objectives are listed in Table 4. However, increment or reduction in these objectives, depend quietly on the selection of weighted factors (w_i) in the overall objective function. So, these objectives may not validate the effectiveness of an optimization algorithm directly. For instance, by choosing the mentioned values for w_i for IEEE 14-bus test system, it is seen that ΔV_L becomes 0.0416 which is greater than GA, PSO and SOA, while Table 3 strictly represents the effectiveness of the FWSOA.

Figures 5 and 6 represent the voltage profile (before and after optimization) and convergence curve of FWSOA method for IEEE 14-bus system, respectively. Table 5 and Table 6 include control and dependent variables respectively, by FWSOA optimization method. Because of reduction in voltage deviation, voltage profile has been improved.

4.2. IEEE 57- bus test system

The IEEE 57- bus test system has seven generators, 80 transmission lines and 15 tap changer transformers. Three capacitors are placed at buses 18, 25, 53 [31]. Three SVCs are also considered in the present study for IEEE 57- bus test system. All variable limits have been taken from [25]. The population size is 60, total 30 runs and the maximum generations of 300 [24]. Optimization parameters are w_1=0.6, w_2=0.2, w_3=0.2, $Ploss_{min}=0.2$, $Ploss_{max}=0.5$, $\Delta V_{Lmin}=0$, $\Delta V_{Lmax}=1$, $VSM_{min}=0.05$, $VSM_{max}=0.4$, $\lambda_V=500$, $\lambda_Q=500$. All these limits are taken from [24]. Real power loss, voltage deviation and VSM, are in Table 7. Table 8 includes all variables that will be used for optimization process.

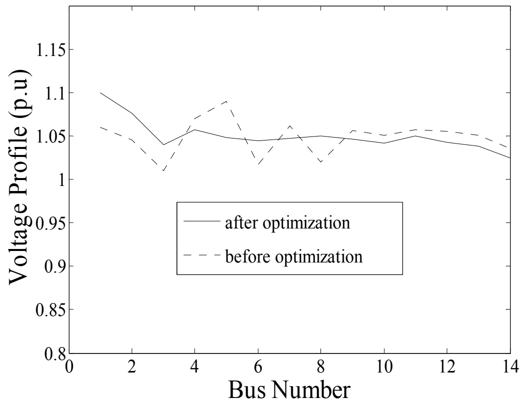

Fig. 5. Voltage profile for IEEE 14- bus test system before and after optimization.

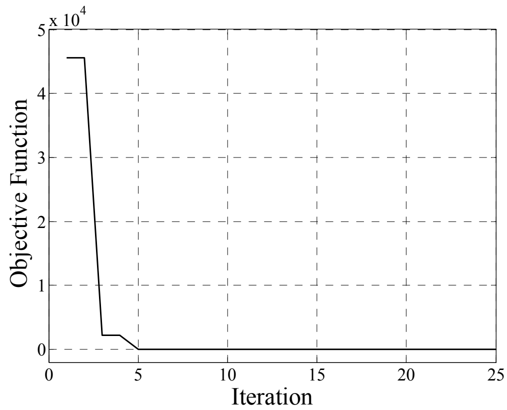

Fig. 6. Convergence curve of FWSOA method for IEEE 14-bus system

Table 5. Control variables of FWSOA optimization method for IEEE 14-bus system.

Control variables	Before optimization	After optimization
V_1	1.0600	1. 10
V_2	1.0450	1.08
V_3	1.0100	1.04
V_6	1.0177	1.06
V_8	1.0195	1.05
Q_{C9}	19	2.75
T_{4-7}	0.978	0.996
T_{4-9}	0.969	0.998
T_{5-6}	0.932	0.971
L_{SVC}	-	11
V_{SVC11}	-	1.05

Table 6. Dependent variables of FWSOA optimization method for IEEE 14-bus system.

$\sum Q_G$ (MVAR)	70.5607
Q_{SVC11}(MVAR)	4.3230

Table 7. Sub-objective function values, P_G and Q_G for IEEE 57- bus test system before optimization.

Real power losses (p.u.)	0.2786
Voltage deviation (p.u.)	0.0272
VSM (p.u.)	0.2101
$\sum P_G$ (MW)	1278.6638
$\sum Q_G$ (MVAR)	321.0800

Table 8. Control variable limits for IEEE 57- bus test system.

Variable	Min variable	Max variable
All voltages (p.u.)	0.94	1.06
Q_{C18} (MVAR)	0	10
Q_{C25} (MVAR)	0	5.9
Q_{C53} (MVAR)	0	6.3
All taps (p.u.)	0.9	1.1
Q_{SVCs} (MVAR)	-100	100

BFV, AFV and STD indices for IEEE 57- bus test system are listed in Table 9. These indices are obtained from 30 successive runs for each optimization algorithm. Real power losses *(Ploss*), voltage deviation (ΔV_L) and *VSM* objectives for the best solution are listed in Table 10.

Table 9. Optimization indices by four algorithms for IEEE 57-bus test system.

Indices	GA	PSO	SOA	FWSOA
AFV	0.2171	0.4195	0.2193	0.2036
BFV	0.1972	0.2091	0.1829	0.1794
STD	0.0120	0.6536	0.0204	0.0117

Table 10. Sub-objective function values by four algorithms for IEEE 57-bus test system.

Indices	GA	PSO	SOA	FWSOA
Ploss	0.2494	0.2547	0.2437	0.2424
ΔV_L	0.0209	0.0197	0.0224	0.0255
VSM	0.2352	0.2325	0.2413	0.2432

BFV, AFV and STD indices are very important. These parameters show the efficiency and robustness of an optimization algorithm in achieving global or near global optimal solution. BFV, AFV and STD indices of FWSOA are smaller than GA, PSO and SOA. From Table 9 it can be understood that FWSOA is better than GA, PSO and SOA in solving simultaneous RPD and SVC placement problem.

The aim of the optimization is to further reduction in real power losses and voltage deviation and further increment in voltage stability margin. These objectives are listed in Table 10. However, increment or reduction in these objectives, depend quietly on the selection of weighted factors (w_i) in the overall objective function. So, these objectives may not validate the effectiveness of an optimization algorithm directly. For instance, by choosing the mentioned values for w_i for IEEE 57-bus test system, it is seen that ΔV_L becomes 0.0255 which is greater than GA, PSO and SOA, while Table 9 strictly represents the effectiveness of the FWSOA.

Figures 7 and 8 represent the voltage profile (before and after optimization) and convergence curve of FWSOA method for IEEE 57-bus system, respectively.

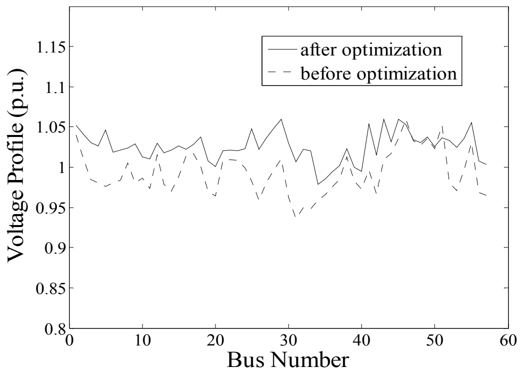

Fig. 7. Voltage profile for IEEE 57- bus test system before and after optimization.

Because of reduction in voltage deviation, voltage profile has been improved.

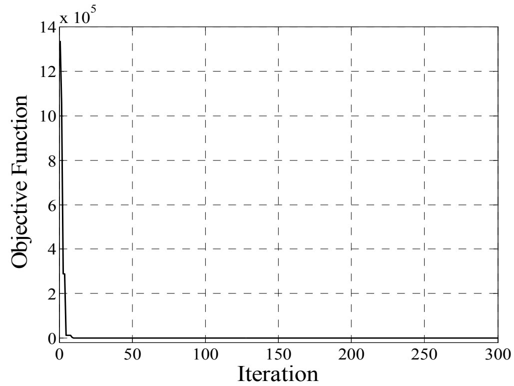

Fig. 8. Convergence curve of FWSOA method for IEEE 57-bus test system.

Tables 11 and 12 include control and dependent variables respectively, by FWSOA optimization method.

Table 11. Control variables by FWSOA optimization method for IEEE 57-bus test system.

Control variables	Before optimization	After optimization
V_1	1.04	1.05
V_2	1.01	1.04
V_3	0.985	1.03
V_6	0.98	1.03
V_8	1.005	1.05
V_9	0.98	1.02
V_{12}	1.015	1.02
Q_{C18}	10	7.52
Q_{C25}	5.9	5.90
Q_{C53}	6.3	6.30
$T_{4\text{-}18}$	0.97	1.02
$T_{4\text{-}18}$	0.978	0.991
$T_{20\text{-}21}$	1.043	1.02
$T_{24\text{-}26}$	1.043	0.999
$T_{7\text{-}29}$	0.967	0.968
$T_{32\text{-}34}$	0.975	0.927
$T_{11\text{-}41}$	0.955	0.900
$T_{15\text{-}45}$	0.955	0.964
$T_{14\text{-}46}$	0.9	0.983
$T_{10\text{-}51}$	0.93	0.974
$T_{13\text{-}49}$	0.895	0.974
$T_{11\text{-}43}$	0.958	0.949
$T_{40\text{-}56}$	0.958	0.999
$T_{39\text{-}57}$	0.98	0.962
$T_{9\text{-}55}$	0.94	0.960
L_{SVC}	-	50
L_{SVC}	-	49
L_{SVC}	-	46
V_{SVC50}	-	1.03
V_{SVC49}	-	1.04
V_{SVC46}	-	1.05

Table 12. dependent variables by FWSOA optimization method for IEEE 57-bus test system.

$\sum Q_G$ (MVAR)	211.8758
Q_{SVC50} (MVAR)	9.5144
Q_{SVCs49}(MVAR)	19.7419
Q_{SVCs46} (MVAR)	36.0037
$\sum Q_{SVCs}$ (MVAR)	65.2600

5. CONCLUSIONS

Voltage stability is very close to RPD in the power network. Thus, via optimization for included control variable settings in RPD problem, adequate and proper voltage stability margin, voltage deviation and real power losses reduction can be obtained. Therefore, in this paper, simultaneous RPD and SVC placement were investigated and optimization algorithms including GA, PSO, SOA and FWSOA were implemented to achieve these goals. The priority of this paper comparing with other researches is focusing on RPD with control variables including excitation settings of generators, tap positions of tap changing transformers, reactive power output of fixed capacitors and voltages with locations of SVCs in the network, simultaneously. Finally, by comparison, between performances of GA, PSO, SOA and FWSOA algorithms, the efficiency of the FWSOA based RPD and SVC placement approach in the present study was well verified.

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