OPTIMAL ALLOCATION AND VOLTAGE STABILITY IN ELECTRICAL NETWORK BY USING A STATCOM

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Abstract *: The main goal of this paper is to define the best location for the STATCOM to improve voltage stability in 59-bus power system network. In daily operation where there are all kinds of disturbances such as voltage fluctuations, voltage sags, swells, voltage unbalances and harmonics, STATCOM is modelled as a controllable voltage source. The Newton-Raphson method algorithm was implemented to solve power flow equations. Particle Swarm Optimization (PSO) and Harmony Search (HS) methods are used to find the optimal location of STATCOM.*

Keywords*: Optimal allocation, Power flow, STATCOM, Newton-Raphson algorithm, PSO, HS.*

1. Introduction

In recent years, increased demands on electric energy transmission and the need to provide access to generating companies and customers have created tendencies toward lower security and reduced quality of supply. The FACTS technology is promising to reduce some of these difficulties by enabling utilities to get more performance from their transmission facilities and to enhance grid reliability [1]. FACTS devices increases power handling capacity of the line and improve transient stability as well as damping performance of the power system [2-3]. According to the specialized literature we find several types of FACTS [4-5], in our work we limited to the study a great disturbance, so the FACTS element used for reactive power compensation both assuring the low cost and high efficiency is STATCOM. The static synchronous compensators (STATCOM) consist of shunt connected voltage source converter through coupling transformer with the transmission line. STATCOM can control voltage magnitude and the phase angle in a very short time and therefore, has ability to improve the system [2-3]. There are some of conventional method i.e. gauss seidal method, newton raphson method for analysis the load flow study but due to continues growth and complexity of power system network soft computing techniques are better than conventional method in which the speed of operation and accuracy are the main advantages. With the advent of artificial intelligence in last recent years. Neural network, fuzzy logic and decision tree like methodology have been applied to the power system problems. Among all the soft computing techniques have shown great promises in power system engineering due to their ability to synthesize the complex mapping, accurately and rapidly. The computational intelligence algorithms have drawn researcher's attention to the area of artificial intelligence as they have become more interested in focusing into the application of these algorithms in Electrical Engineering themes. Among these techniques, Particle Swarm Optimization (PSO) is an optimization method based on swarm intelligence concept. This method can look for more solutions simultaneously. PSO generates random initial particles in the first step and then it applies velocity vectors to update the particles until a process stop condition is satisfied. It requires the test function calculation to determine how a reached solution is good [6]. PSO has been used for solving many power engineering tasks, e.g. UPFC placement and its parameters optimization for possible load increasing, distributed generation placement and sizing optimization with respect to customers' electricity cost or economic dispatch [7-8,9]. During several past years a great effort has been devoted to the research of the optimal STATCOM design and its appropriate placement by means of the PSO strategy [10-11]. PSO algorithms are used in function optimization and are currently applied in several themes related to electrical power system like optimal power flow, power system restoration and load flow study etc.

Recently, another phenomenon-based algorithm, harmony search (HS), which mimics music improvisation process has been proposed [12]. The HS algorithm like other meta-heuristic algorithms employs high level techniques for exploration and exploitation of the huge solution space. Since the discovery of HS algorithm, it has been used extensively with positive results. Its applicability is universal, which is the reason for its high appeal. The

HS algorithm can be considered as universally acceptable, and has many advantages. It is different from other similar algorithms as it can utilize more than one search point at the same time. It is independent of the objective function derivative and can achieve optimum values of such objective functions, both at global or near-global optimization. It can take up high dimensional domains in this regard.

The major objective of this paper is to compare the computational effectiveness and efficiency between two meta-heuristic optimization techniques such as particle swarm optimization (PSO) and Harmony Search (HS) algorithms for analysis the load flow study, find the optimal location of STATCOM in order to improve voltage in power networks. The remainder of the paper is organized as follows. In Section 2, 3 and 4, power flow equation derives the mathematical model of STATCOM based on switching functions. Then the mathematical model is linearized using the method of Jacobian and the controllability for arbitrary operating point of STATCOM is proved, In Section 5, the basic concepts of PSO are explained along with the original formulation of the algorithm in the real number space, as well as the discrete number space,

In Section 6, a brief introduction of the HS is given and the original formulation of the algorithm. Section 7 application and discussions on the experimental results. Finally, the paper is concluded in Section 8.

2. Power Flow Equation

Basically load flow problem involves solving the set of non-linear algebraic equations which represent the network under steady state conditions. The reliable solution of real life transmission and distribution networks is not a trivial matter and Newton-type methods, with their strong convergence characteristics, have proved most successful. To illustrate the power flow equations, the power flow across the general two-port network element connecting buses k and m shown in Figure 1 is considered and the following equations (1) to (4) are obtained.

The injected active and reactive power at bus-k (P_k and Q_k) is:

$$P_k = G_{kk} V^2_k + (G_{km}\cos\delta_{km} + B_{km}\sin\delta_{km})V_k V_m \quad (1)$$

$$Q_k = -B_{kk} V_k^2 + (G_{km}\sin\delta_{km} - B_{km}\cos\delta_{km})V_k V_m \quad (2)$$

$$P_k = G_{mm} V_m^2 + (G_{mk}\cos\delta_{mk} + B_{mk}\sin\delta_{mk})V_k V_m \quad (3)$$

$$Q_k = -B_{mm} V_k^2 + (G_{mk}\sin\delta_{mk} - B_{mk}\cos\delta_{mk})V_k V_m \quad (4)$$

Where:

P_k: Real power injection at bus k.

Q_k: Reactive power injection at bus k.

V_k : Magnitude of voltage at bus k.

V_m: Magnitude of voltage at bus k.

δ_{km}: Phasor angle of an element of the network admittance matrix.

G_{km}:Element of the real part of network admittance matrix.

B_{km}: Element of the imaginary part of the network admittance matrix.

$\delta_{km} = \delta_k - \delta_m = -\delta_m$

$Y_{kk} = Y_{mm} = G_{kk} + jB_{kk} = Y_{ko} + Y_{km}$

$Y_{km} = Y_{mk} = G_{mk} + jB_{km} = -Y_{mk}$

The nodal power flow equations:

$$P = f(V, \theta, G, B)$$
$$Q = g(V, \theta, G, B) \quad (5)$$

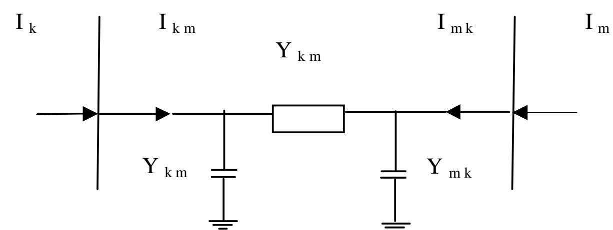

Fig. 1.General two-port network.

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix}^i = [J]^i \begin{bmatrix} \Delta\theta \\ \Delta V \end{bmatrix}^i \quad (6)$$

Where, P and Q are vectors of real and reactive nodal power injections as a function of nodal voltage magnitudes$V$ and angles θ and network conductances G and suceptances B.

$\Delta P = P_{spec} - P_{cal}$ is the real power mismatch vector, $\Delta Q = Q_{spec} - Q_{cal}$ is the reactive power mismatch vector, $\Delta\theta$ and ΔV are the vectors of incremental changes in nodal voltage magnitudes and angles, J is the matrix of partial derivatives of real and reactive power with respect to voltage magnitudes and angle i indicates the iteration number.

Incorporation of FACTS devices in an existing load flow algorithm results in increased complexity of programming due to the following reasons:

New terms owing to the contributions from the FACTS devices need to be included in the existing power flow equations of the concerned buses. These terms necessitate modification of existing power flow codes;

New power flow equations related to the FACTS devices come into the picture, which dictate formulation of separate subroutine(s) for computing them;

The system Jacobian matrix contains entirely new Jacobian sub-blocks exclusively related to the FACTS devices. Therefore, new codes have to be written for computation of these Jacobian sub-blocks.

The increase in the dimension of Jacobian matrix, compared with the case when there are no power system controllers, is proportional to the number and kind of such controllers.

The simultaneous equations for the networks and power system state variables are:

$$f\,(X_{nsys},\, R_{nf}) \qquad (7)$$
$$g\,(X_{nsys},\, R_{nf})$$

Where: X_{nsys} = Network state variables i. e. (voltage magnitudes and phase angles); R_{nf} = Power system controller variables.

3. The Structure of STATCOM

3.1. The voltage converter

The simplest structure of STATCOM is given in Fig.2.

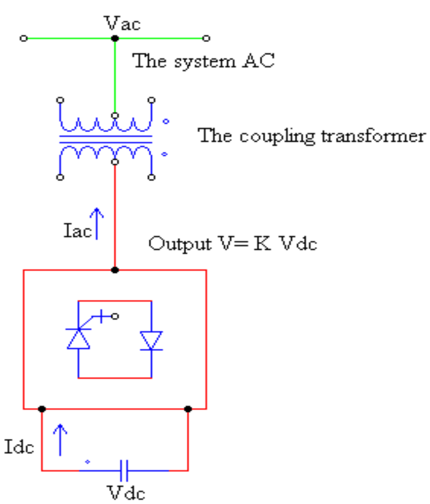

Fig. 2.The model of STATCOM.

The STATCOM consists of a coupling transformer, a voltage converter, and a source of storage for the DC side [13- 14]. The coupling transformer has two roles [13]:

- Linking the system AC with STATCOM

-The link inductor has the advantage that the source DC is not short-circuited

The STATCOM can consist of a power inverter "CSI: current source inverter", but for cost and current is unidirectional, it is preferable to use a voltage converter; virtually is the most used [13-14].

The inverter constituting the STATCOM can be composed of GTO or the IGBT.

3.2. The static characteristic of STATCOM

Fig.3 shows the static characteristic of STATCOM. It is capable of controlling its current estimated maximum regardless of system voltage AC is a medium voltage in case of major system disturbances. Fig. 3 shows the ability of STATCOM to maintain as the capacitive current at voltages very low system [15-16]. The estimated value of the current spike in the inductive side is greater than the rated capacitive switching is the natural GTO used in the inductive side, it is limited by the current of the diode, but in the side this capacitive current is determined by switching drilled GTO used [17- 18].

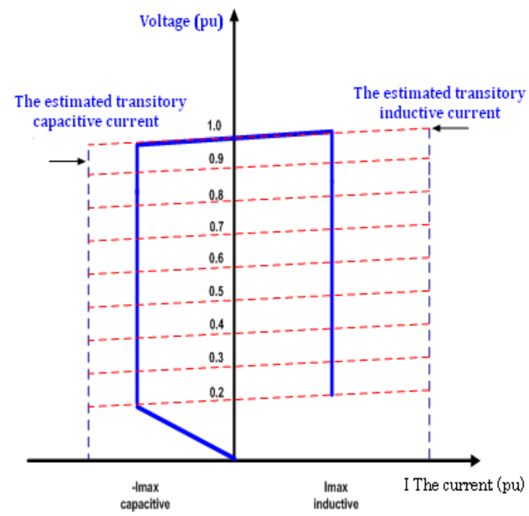

Fig. 3.The static characteristic of STATCOM.

4. Power System with STATCOM

Fig. 4 shows the circuit model of a STATCOM connected to Bus *k* of an *N*-Bus power. The STATCOM is modeled as a controllable voltage source (E_{stat}) in series with impedance. The real part of this impedance represents the ohmic losses of the power electronics devices and the coupling transformer, while the imaginary part of this impedance represents the leakage reactance of the coupling transformer. Assume that the STATCOM is operating in voltage control mode. This means that the STATCOM absorbs proper amount of reactive power from the power system to keep $|V_k|$ constant for all power system loading within reasonable range.

The ohmic loss of the STATCOM is accounted by considering the real part of Y_{stat} in power flow calculations. The net active/reactive power injection at Bus k including the local load, before addition of the STATCOM, is shown by P_k+jQ_k.

The power flow equations of the system with STATCOM connected to Bus *k*, can be written as:

$$P_k = P_{stat} + \sum_{j=1}^{N} |V_k||V_j||Y_{kj}| \cos(\delta_k - \delta_j - \theta_{kj}) \quad (8)$$

$$Q_k = Q_{stat} + \sum_{j=1}^{N} |V_k||V_j||Y_{kj}| \sin(\delta_k - \delta_j - \theta_{kj}) \quad (9)$$

$$P_{stat} = \mathrm{G}_{stat} + |V_k|^2 - |V_k||E_{stat}||Y_{stat}| \cos(\delta_k - \delta_{stat} - \theta_{stat}) \quad (10)$$

$$Q_{stat} = B_{stat} + |V_k|^2 - |V_k||E_{stat}||Y_{stat}| \sin(\delta_k - \delta_{stat} - \theta_{stat}) \quad (11)$$

Where, $|E_{stat}|$, δ_{stat}, $|Y_{stat}|$ and θ_{stat} are shown in Fig. 4.

Addition of STATCOM introduces two new variables $|E_{stat}|$ and δ_{stat}; however, $|V_k|$ is now known. Thus, one more equation is needed to solve the power flow problem.

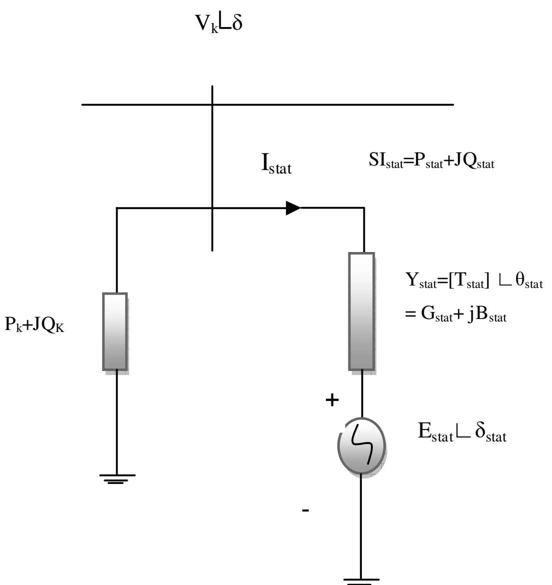

Fig. 4. Steady state model of STATCOM

Equation (11) is found using the fact the power consumed by the source $E_{stat}(P_{Estat})$ must be zero in steady state. Thus the equation for P_{Estat} is can written as:

$$p_{E_{stat}} = \mathrm{Real}\left[E_{stat} I^{*}_{stat}\right] = -G_{stat}|E_{stat}|^2 + |V_k||E_{stat}||Y_{stat}| \cos(\delta_k - \delta_j - \theta_{stat}) = 0 \quad (12)$$

Using these power equations, the linearized STATCOM model is given below:

$$\begin{bmatrix} \Delta P_k \\ \Delta Q_k \\ \Delta P_{stat} \\ \Delta Q_{stat} \end{bmatrix} = \begin{bmatrix} \frac{\partial P_k}{\partial \theta_k} & \frac{\partial P_k}{\partial V_k} V_k & \frac{\partial P_k}{\partial \theta_{stat}} & \frac{\partial P_k}{\partial V_{stat}} V_{stat} \\ \frac{\partial Q_k}{\partial \theta_k} & \frac{\partial Q_k}{\partial V_k} V_k & \frac{\partial Q_k}{\partial \theta_{stat}} & \frac{\partial Q_k}{\partial V_{stat}} V_{stat} \\ \frac{\partial P_{stat}}{\partial \theta_k} & \frac{\partial P_{stat}}{\partial V_k} V_k & \frac{\partial P_{stat}}{\partial \theta_{stat}} & \frac{\partial P_{stat}}{\partial V_{stat}} V_{stat} \\ \frac{\partial Q_{stat}}{\partial \theta_k} & \frac{\partial Q_{stat}}{\partial V_k} V_k & \frac{\partial Q_{stat}}{\partial \theta_{stat}} & \frac{\partial Q_{stat}}{\partial V_{stat}} V_{stat} \end{bmatrix} \begin{bmatrix} \Delta \theta_k \\ \frac{\Delta V_k}{V_k} \\ \Delta \theta_{stat} \\ \frac{\Delta V_{stat}}{V_{stat}} \end{bmatrix} \quad (13)$$

5. Particle swarm optimization (PSO)

Two scientists namely Dr. Kennedy and Dr. Eberhart developed a PSO algorithm based on the behavior of individuals (i.e., particles or agents) of a swarm in the year 1995 [19]. PSO has its roots in artificial life and social psychology as well as in engineering and computer science. It utilizes a “population” of particles that fly through the problem hyperspace with given velocities. At each iteration, the velocities of the individual particles are stochastically adjusted according to the historical best position for the particle itself and the neighborhood best position. Both the particle best and the neighborhood best are derived according to a user defined fitness function. The movement of each particle naturally evolves to an optimal or near-optimal solution.

5.1. PSO Principle

PSO is an iterative process. On each iteration in PSO, current velocity of each particle is first updated based on three parameters:

i. the particle’s current velocity
ii. the particle’s local information
iii. global swarm information.

Then, each particle’s position is updated using particle’s new velocity. The two updated equations are:

$$v_i^{(k+1)} = \underbrace{\omega v_i^{(k)}}_{\text{Previous Velocity}} + \underbrace{c_1 r_1 \times \left(Pbest_i^{(k)} - x_i^{(k)}\right)}_{\text{Cognitive Component}} + \underbrace{c_2 r_2 \times \left(gbest_i^{(k)} - x_i^{(k)}\right)}_{\text{Social Component}} \quad (14)$$

$$x_i^{(k+1)} = x_i^{(k)} + v_i^{(k+1)} \quad (15)$$

In equation (14), index $x_i^{(k)}$ is current position of particle i at iteration k, which has velocity $v_i^{(k)}$ and $v_{\min} \le v_i^{(k)} \le v_{\max}$ and the $pbest_i$ is the historical best position of $x_i^{(k)}$ and $gbest_i$ is the global best position in the population’s history. The parameter ω is the inertia weight factor, c_1 and c_2 are acceleration constants and r_1 and r_2 are uniform random numbers between 0 and 1. The parameter v_{max} determines the resolution with which region between the present position and target position is searched. If v_{max} is too high, particles may fly past the good solutions. If v_{max} is too small, particles may not explore sufficiently beyond local solutions. The constants c_1 and c_2 represent the weighting of the stochastic acceleration terms that pull each particle toward *pbest* and *gbest* positions. Low values makes particles to roam far from target regions before being tugged back. On the other hand, high values result in abrupt movements toward, or past, the target regions. It can be proved that for convergence c_1+c_1 must be less than or equal to 4. The inertia weight ω provides a balance between global and local exploration and exploitation, and on average results in less iterations required to find a sufficiently good solution. It is typically set according to the following equation:

$$\omega = \omega_{\max} - \frac{(\omega_{\max} - \omega_{\min})}{k_{\max}} \times k \qquad (16)$$

$\omega_{\min}$, $\omega_{\max}$: initial and final inertia factor weights.
k_{max}: maximum iteration number.
k: current iteration number.

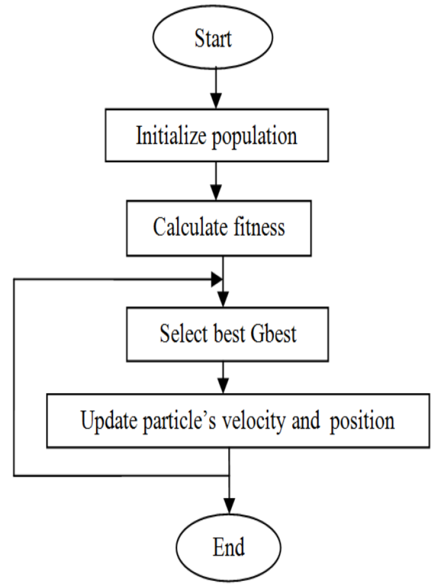

Fig. 5. Flowchart of the Basic PSO

5.2. PSO Algorithm

In the flowing, the basic steps of PSO:

Step1: Initialization the swarm i.e position, and velocity, maximum number of iterations (*itermax)*

Step2: Identify the *pbest* among .The *pbest* is also *gbest*. Initialize iteration counter, *iter*=1.

Step3: If *iter*>*itermax*, go to step 6 otherwise for each particle update velocity, update position. Compute objective function. Update the *pbest*.

Step4: Update the *gbest*.

Step5: Increment iter=*iter*+1 and go to step3.

Step6: Print the optimal solution of *gbest*.

The basic steps of the PSO algorithm are shown in Fig. 5.

6. Harmony search (HS)

Harmony search it is one of the most recent heuristic methods. Since it was introduced in 2001 and due to its simplicity, harmony search has been implemented to solve different optimization problems. The algorithm was originally developed in 2005 for discrete optimization and later expanded for continuous optimization [20].

Harmony Search (HS) is based on improvising musicians search for good sounding harmonies [21].

The design parameters of the HS algorithm are:

1. Harmony is the set of the values of all the variables of the objective function. Each harmony is a possible solution vector.
2. Harmony memory (HM) is the location where harmonies are stored.
3. Harmony memory size (HMS) is the number of solution vectors in the harmony memory.
4. Harmony memory considering rate (HMCR) is the probability of selecting a component from the HM members.
5. Pitch adjusting rate (PAR) determines the probability of selecting a candidate from the HM.

6.1. HS Algorithm

The general steps of the procedure of HSA are follows as [22]:

Step 1: Initialize the optimization problem and algorithm parameters

In this step the optimization problem is specified as follows:

Minimize $f(x)$

Subject to $x_i \in X_i$, $i = 1, 2, ..., N$

where $f(x)$ is the objective function; x is a candidate solutions consisting of N decision variables (x_i); X_i is the set of possible range of values for each decision variable, that is, ${}_L xi \leq Xi \leq {}_U x_i$ for continuous decision variables where ${}_L x_i$ and ${}_U x_i$ are the lower and upper bounds for each decision variable, respectively and N is the number of decision variables.

Step 2: Initialize the Harmony Memory (HM)

In this Step, the HM matrix is filled with as many randomly generated solution vectors as the HMS.

$$HM = \begin{bmatrix} x_1^1 & x_2^1 & \cdots & x_{N-1}^1 & x_N^1 \\ x_1^2 & x_2^2 & \cdots & x_{N-1}^2 & x_N^2 \\ \vdots & \cdots & \ddots & \vdots & \cdots \\ x_1^{HMS-1} & x_2^{HMS-1} & \cdots & x_{N-1}^{HMS-1} & x_N^{HMS-1} \\ x_1^{HMS} & x_2^{HMS} & \cdots & x_{N-1}^{HMS} & x_N^{HMS} \end{bmatrix} \quad (17)$$

Step 3: Improvise a new harmony from the HM

A New Harmony vector is generated from the HM based on memory considerations, pitch adjustments, and randomization. For instance, the value of the first decision variable for the new vector can be chosen from any value in the specified HM range Values of the other decision variables can be chosen in the same manner. There is a possibility that the new value can be chosen using the HMCR parameter, which varies between 0 and 1 as follows:

$$x_i^{'} = \begin{cases} x_i^{'} \in \{x_i^1, x_i^2, \cdots \cdots\} With \quad probabilit \quad y \; HMCR \\ x_i^{'} \in X_i With \quad probabilit \quad y(1 - HMCR \quad) \end{cases}$$

The HMCR sets the rate of choosing one value from the historic values stored in the HM and (1-HMCR) sets the rate of randomly choosing one feasible value not limited to those stored in the HM. For example, a HMCR of 0.9 indicates that the HS algorithm will choose the decision variable value from historically stored values in the HM with the 90% probability or from the entire possible range with the 10% probability. Each component of the new Harmony vector is examined to determine whether it should be pitch adjusted. This procedure uses the PAR parameter that sets the rate of adjustment for the pitch chosen from the HM as follows:

Pitch adjusting decision for

$$x_i^{'} = \begin{cases} With \quad probabilit \quad y \; HMCR \\ With \quad probabilit \quad y(1 - HMCR \quad) \end{cases}$$

A PAR of 0.3 indicates that the algorithm will choose a neighboring value with 30% × HMCR probability.

Step 4: Update harmony memory

For each new value of harmony the value of objective function, $f(x^{'})$ is calculated. If the new harmony vector is better than the worst harmony in the HM, the new harmony is included in the HM and the existing worst harmony is excluded from the HM.

Step 5: Check stopping criterion

If the stopping criterion (maximum number of improvisations) is satisfied, computation is terminated. Otherwise, Steps 3 and 4 are repeated. Finally the best harmony memory vector is selected and is considered as best solution.

The steps in the procedure of algorithm harmony search are shown in Fig. 6.

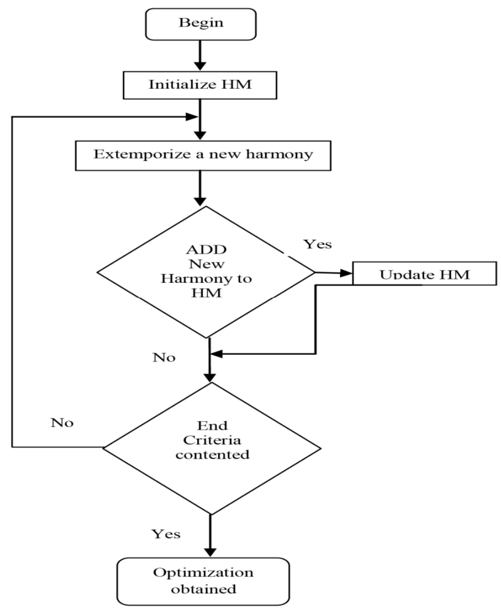

Fig. 6. Flowchart of HS

6. Application

The test system consists of 59 buses, 83 branches (lines and transformers) and 10 generators. The apparent power S_{base} is 100MVA.

For each possible location of the STATCOM, a power flow based on the Newton-Raphson method is calculated.

The objective function $Fobj$ is calculated as the square root of the sum of all voltage deviations squared as follows.

$$Fobj = \left(\sum_{i=1}^{Nbus} (V_i - 1)^2 \right)^{1/2} \quad (18)$$

Where:

V_i : is the value of the voltage at bus i in p.u.

Nbus: Number of bus.

6.1. Different types of inertia weight in PSO

In theory, three approaches are considered for the inertia constant:

i. Fixed inertia weight: as in standard PSO definition.

ii. Linearly decreased inertia weight: the purpose is to improve the convergence of the swarm by reducing the inertia weight from 0.9 to 0.1 in even steps over the maximum number of iterations.

iii. Randomly decreased inertia weight: introduces a random factor in the previous approach to avoid the swarm to get trapped in a local minimum

$$w_i = rand \cdot \left(0.9 - 0.8 \cdot \frac{iter - 1}{\max\_ \, iter - 1}\right) \qquad (19)$$

Where:

rand is a random number between 0 and 1.

iter is the iteration number.

max_iter is the maximum number of iterations.

In our study we have use this last approach in optimization process.

Table1presents the best location of STATCOM (optimal location) found by both optimization method (PSO and HSA).

The STATCOM is connected at 19th bus and injects reactive power given in table 2 to improve voltage profile of the system and avoids future voltage collapse.

Table2

STATCOM parameters (size and location).

STATCOM Bus	Vstat pu	Angle Degree	Qstat pu
19	0.9223	9.4417	0.7771

Table1

The best location of STATCOM (optimal location) found by both optimization method (PSO and HSA)

Bus N°	V(p.u.) without Statcom	V(p.u.) with Statcom	Bus N°	V(p.u.) without Statcom	V(p.u.) with Statcom
1	1.0600	1.0600	31	1.0999	1.0284
2	1.0400	1.0400	32	1.0980	1.0193
3	1.0500	1.0500	33	1.0547	0.9921
4	1.0283	1.0283	34	1.0978	1.0274
5	1.0276	1.0194	35	1.0328	0.9688
6	1.0560	1.0375	36	0.9433	0.8681
7	0.9931	0.9959	37	1.0273	1.0273
8	0.9848	0.9730	38	1.0072	1.0062
9	0.9901	0.9808	39	1.0006	0.9910
10	1.0746	1.0749	40	1.0762	1.0765
11	0.9962	0.9883	41	1.0966	1.0966
12	1.0139	1.0103	42	1.0340	1.0440
13	1.0961	1.0517	43	1.0318	0.9648
14	0.9725	0.9617	44	1.0117	1.0082
15	1.0596	0.9907	45	1.0454	1.0440
16	1.0917	1.0211	46	1.0040	0.9993
17	0.9918	0.9836	47	0.9599	0.9635
18	1.0956	1.0168	48	0.9228	0.8675
19	**1.0947**	**1.0000**	49	0.9698	0.9746
20	1.0438	1.0236	50	1.1035	1.0303
21	1.0721	1.0146	51	1.1025	1.0270
22	1.0913	1.0110	52	1.0713	1.0003
23	1.0156	1.0137	53	1.1051	1.0313
24	1.0105	1.0173	54	1.0585	0.9939
25	1.0062	0.9939	55	1.0396	1.0359
26	1.0195	1.0186	56	0.9742	0.9790
27	1.0266	1.0266	57	1.0165	1.0233
28	1.0195	0.9743	58	1.0329	1.0353
29	1.0297	1.0168	59	1.0352	1.0421
30	1.0561	1.0415			

The 59-bus test system was used to demonstrate the effectiveness of the proposed algorithms. The results of the proposed HSA algorithm were compared with those of PSO algorithm. Table 3 presents optimal values found by PSO and HSA.

Table3
Comparison results between HSA and PSO

	Objective function value (Fobj)	Optimal location (bus_optim)	Simulation time seconds
HS	0.3110	19	473.991
PSO	0.3110	19	1447.276

Based on several simulation studies, the optimal control parameters values of the proposed HSA and PSO are presented in Table 4.

Table4
HS and PSO algorithm parameters

HS Parameters			
HMS	maxiter	HMCR	PAR
3	100	0.95	0.7
PSO Parameters			
Number of particles	maxiter	c1	c2
10	100	3.25	4-c1

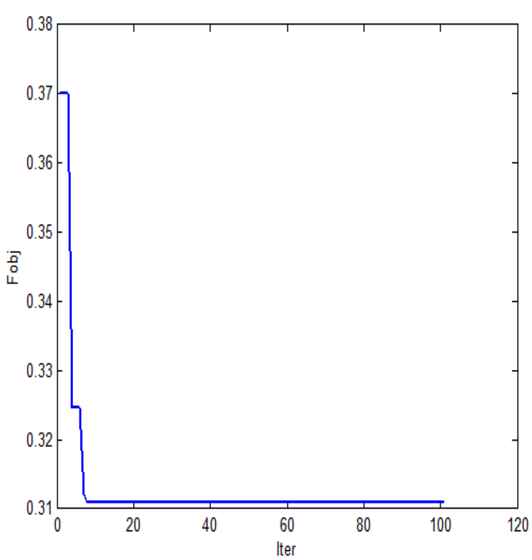

Fig. 7. The objective function history of HSA.

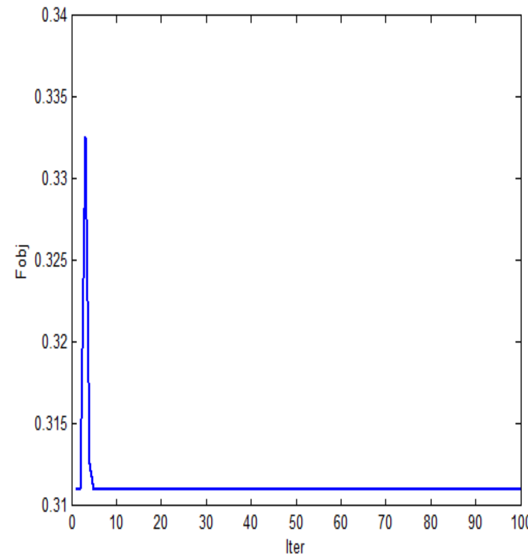

Fig. 8. The objective function history of PSO

6.2. Discussion

This study has shown application of the Particle Swarm Optimization and Harmony search algorithm methods to solve the problem of optimal placement of STATCOM in the 59-bus test system. PSO algorithm is easy to implement and it is able to find multiple optimal solutions to this constrained multi-objective problem, giving more flexibility to take the final decision about the location of the STATCOM units. The settings of the PSO parameters are shown to be optimal for this type of application; the algorithm is able to find the optimal solutions with a relatively small number of iterations, therefore with a reasonable computational effort and the calculation in PSO algorithm is very simple. Harmony search algorithm needs a small HMS to obtain the optimal solutions. In recent years, HS was applied to many optimization problems, demonstrating its efficiency compared to other heuristic algorithms and other Meta mathematical optimization techniques. HS is good at identifying the high performance regions of the solution space at a reasonable time. From the simulation results presented in Table 1 show that the bus 19 is the best place to install STATCOM respectively, it was observed from the results that the HSA has advantages in finding the best solution over the PSO algorithm in this specific optimization problem.

We can conclude that installing the STATCOM at bus 19, the voltage stability is improved. We see also that HSA method is more effective than PSO method in term of computation time. Fig. 7 and Fig. 8 illustrate history of the objective function (for HS and PSO respectively).

8. Conclusion

The results are obtained with and without compensation using matlab/simulink environment.

STATCOM was implemented in 59-bus system using Newton-Raphson load flow algorithm.

In this paper we have used the PSO and HS techniques to find the optimal allocation of a STATCOM in a 59-bus of a power system. The techniques are able to find the best location for the STATCOM in order to optimize the system voltage profile. Based on a voltage source converter, the STATCOM regulates system voltage by absorbing or generating reactive power. Newton-Raphson algorithm was used to calculate the load flow of the power system.

PSO and HS have proved themselves to be an effective meta-heuristics to solve the problem of optimal allocation of STATCOM in complex power system (59 buses).

It is observed that, in terms of computational time, HS approach is faster and has been proven more effective than using the PSO.

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