Optimal Power flow with STATCOM using Particle Swarm Optimization

V.Harika, Assistant Professor, PVPSIT, Vijayawada & India, vemulapalliharika2312@gmail.com

G. Madhavi, Assistant Professor, PVPSIT, Vijayawada & India, gudavalli.madhavi@gmail.com

Abstract: The FACTS devices can enhance the power transmission capability, reactive power compensation, improvement of power quality, and increase the stability of the power system network. This paper presents optimal power flow (OPF) solution consists of reduction of fuel cost as the objective function. Here we are using STATCOM among all the available shunt FACTS devices to improve the power transfer capability of the line. Particle swarm optimization technique (PSO) is used for optimal power generation with inclusion of STATCOM and for base case. Active power loss, reactive power loss and L-index are calculated. The effectiveness of this method is tested on IEEE-30 bus data consists of 6 generator buses using MATLAB programming.

Keywords — FACTS, PSO, STATCOM, OPF

I. INTRODUCTION

The increasing Industrialization, urbanization of life style has led to increasing the usage of the electrical energy. This has resulted into rapid growth of power requirement. This rapid growth has resulted into few uncertainties. Power commotions and individual power outages are one of the major problems and affect the economy of any country. In contrast to the hasty changes in technologies and the power required by these technologies, transmission systems are being pushed to operate closer to their stability limits and at the same time reaching their thermal limits since the delivery of power have been increasing. Stability and thermal limits violations are the main constraints faced by the power companies.

These constraints affect the Standards of power delivered. However, these constraints can be reduced by enhancing the power system control. One among the most effective methods for reducing these constraints is FACTS devices. With the rapid development of power electronics, Flexible AC Transmission systems (FACTS) devices have been anticipated and applied in power systems. FACTS devices can be operated to control power flow and enhance system stability. Particularly with the deregulation of the electricity market, there is a growing interest in using FACTS devices in the operation and control of power systems. A better use of the existing power systems to increase their capacities and controllability by installing FACTS devices becomes imperative. FACTS devices are cost effective substitutions to new transmission line construction [1].

Reactive power compensation is provided to diminish power transmission losses, to maintain power transmission capability and to maintain the supply voltage. Series compensation is control of line impedance of a transmission line; with the hinge of impedance of a line either inductive or capacitive compensation can be obtained thus facilitating active power transfer or control. The Static Synchronous Compensator (**STATCOM**) is a shunt device of the Flexible AC Transmission Systems (FACTS) family using power electronics to control power flow and progress transient stability on power grids

II. PARTICLE SWARM PTIMIZATION

Particle swarm optimization (PSO) is inhabitants based stochastic optimization technique developed by Dr. Kennedy and Dr. Eberhart in 1995, inspired by social behavior of bird flocking or fish schooling [3]. PSO shares many resemblances with evolutionary computation techniques such as Genetic Algorithm (GA) the system is initiated with a population of random feasible solutions and searches for bests by updating generations. However, contrasting GA, PSO has no evolution operators such as crossover and mutation. PSO algorithm has also been confirmed to perform well on genetic algorithm test function. In PSO, the potential solutions, called particles, glide through the problem space by following the current optimum particles [3].

In a PSO algorithm, Particles change their positions by hovering around in a multi-dimensional search space until a relatively unchanged position has been met, or until computational limitations are exceeded [3]. In social science context, a PSO system consists of a social-only model and a cognition-only model. The social-only component recommends that individuals ignore their own experience and fine tune their behavior according to the successful beliefs of the individual in the neighborhood. On the other hand, the cognition-only component treats individuals as secluded beings. A particle changes its position using these models.

Each particle keeps track of its coordinates in the problem space, which relate to the best solution, fitness, it has achieved so far. The fitness value is also stored. This value is called pbest. Another best value that is tracked by the particle swarm optimizer is the best value, attained so far by any particle in the neighbors of the particle. This location is called lbest. When a particle takes all the population as its topological neighbor's, the best value is a global best and is called gbest. The concept of PSO consists of, at each time step, changing the velocity of (accelerating)

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each particle toward its pbest and lbest locations. Acceleration is weighted by a random term, with separate random numbers being produced for acceleration toward pbest and lbest locations. In past several years, PSO has been effectively applied in many research and application areas. It is proved that PSO gets better results in a faster, cheaper way compared with other methods. As in literature, PSO algorithm has been successfully applied to various problems.

Another reason that PSO is striking is that there are fewer parameters to adjust. One version, with slight variations, works well in a wide variation of applications. Particle swarm optimization has been used for approaches that can be used across a wide variety of applications, as well as for definite applications focused on a specific requirement.

In a PSO algorithm, the population has n particles that signifies candidate solutions. Each particle is a k-dimensional real-valued vector, where k is the number of the optimized parameters [3]. Therefore, each optimized parameter signifies a dimension of the problem space. The PSO technique steps can be defined as below.

***Step 1*: Initialization**: Set i=0 and produce random n particles, $\{X_j(0), j=1,2,\ldots,n\}$. Each particle is considered to be a solution for the problem and it can be pronounced as $X_j(0)=\{xi,1(0); xi,2(0);\ldots\ldots.xi,k(0)\}$.Each control variable has a range $[X_{min}, X_{max}]$. Each particle in the initial population is estimated using the objective function f. If the candidate solution is a feasible solution, i.e., all problem constraints have been met, then go repeat to step-2 else repeat this step.

***Step 2:* Counting Updating**: Update the counter i=i+1.

***Step 3*: Compute the objective function**

Step 4: Velocity updating: Using the global best and individual best, the j^{th} particle velocity in the k^{th} dimension in this study (integer problem) is updated according to the following equation.

V(k,j,i+1) = w*V(k,j,i) + C1*rand*(pbestx(j,k) – x(k,j,i)) + C2*rand*(gbest(k) – x(k,j,i))

Where, i is the iteration number

j is the particle number

k is the k^{th} control variable

w is the inertia weighting factor

c1,c2 are acceleration constant

rand ( ) is an uniform random variable belongs to the range of [0,1] V(k,j,i) is the velocity of particle j

at iteration 1 x(k,j,i) is the current position of particle j at iteration j.

Then, check the velocity limits. If the velocity violates its limit, set it at its suitable limit. The second term of the equation represents the cognitive part of the PSO where the particle changes its velocity based on its own thinking and memory. The third term represents the social part of the PSO where the particle changes its velocity based on the social-psychological adaptation of knowledge.

***Step 5:* Position updating:** Based on the updated velocity, each particle changes its position according to the equation given below

x(k,j,i+1) = x(k,j-1,i) + v(k,j,i)

***Step 6:* Individual best updating**: Each particle is assessed and updated according to the update position.

Step 7: Search for the minimum value in the individual best and its solution, if it has ever been matched in any iteration and considered the minimum.

***Step 8:* Stopping criteria:** If one of the ending criteria is satisfied, then halt otherwise go to step 2.

B. STATCOM

A static synchronous compensator (STATCOM), also known as a static synchronous condenser, is a regulating device used on alternating current electricity transmission networks. It is constructed on a power electronics voltage-source converter and can act as either a source or sink of reactive AC power to an electricity network. If connected to a source of power, it can also deliver active AC power. It is a fellow of the FACTS family of devices. It is intrinsically modular and electable. These compensators are also usable to diminish voltage fluctuations

A STATCOM is a voltage source converter (VSC) constructed device, with the voltage source behind a reactor. The voltage source is formed from a DC capacitor and therefore a STATCOM has very little active power capability. However, its active power capability can be enhanced if a suitable energy storage device is coupled across the DC capacitor. The reactive power at the terminals of the STATCOM rest on the amplitude of the voltage source. For example, if the terminal voltage of the VSC is higher than the AC voltage at the point of connection, the STATCOM harvests reactive current; on the other hand, when the amplitude of the voltage source is inferior than the AC voltage, it absorbs reactive power. The response time of a STATCOM is smaller than that of a static VAR compensator (SVC), mainly due to the fast switching times provided by the IGBTs of the voltage source converter. The STATCOM also delivers better reactive power support at low AC voltages than an SVC, since the reactive power from a STATCOM declines linearly with the AC voltage.

C. Problem Formation:

The objective of an ELD problem is to determine the optimal combination of power generations that reduces the total generation cost while satisfying an equality constraint and inequality constraints. The fuel cost curve for any unit is expected to be approximated by segments of quadratic functions of the active power output of the generator. For a given power system network, the problem may be defined as optimization (minimization) of total fuel cost as F_T under a set of operating constraints.

$$F_T = \sum_{i=1}^{n} F(P_i) = \sum_{i=1}^{n} (a_i P_i^2 + b_i P_i + c_i)$$

where is total fuel cost of generation in the system ($/hr), a_i, b_i and c_i are the cost coefficient of the generator, P_i is the power generated by the i^{th} unit and n is the number of generators. F_T is the cost is minimized subjected to the following generator capacities and active power balance constraints.

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$$P_{i,\min} \le P_i \le P_{i,\max} \; for i = 1, 2, \ldots n$$

Where $P_{i,\min}$ and $P_{i,\max}$ are the minimum and maximum power output of the i^{th} unit.

$$P_D = \sum_{i=1}^{n} P_i + P_L$$ where P_D is the total power demand and P_L is total transmission loss.

Here P_L is calculated by using Newton Raphson method [6,8] and the Stability index of each bus is calculated by using L-index formula.

Voltage stability index L: -

The voltage stability analysis involves determination of an index known as voltage collapse proximity indicator [9]. This index is an approximate measure of the closeness of the system to voltage collapse [7]. There are numerous methods of determining the voltage collapse proximity indicator. One such method is the L-index method projected by Kessel and Glavitsch. It is built from load flow analysis. Its value changes from 0 (no load condition) to 1 (voltage collapse). The bus with the highest L-index value will be the most vulnerable bus in the system be expressed by the following expression:

$$I_{bus} = Y_{bus} . V_{bus}$$

By segregating the load buses (PQ) from generator buses (PV), above Equation can write as

$$\begin{bmatrix} I_G \\ I_L \end{bmatrix} = \begin{bmatrix} Y_{GG} & Y_{GL} \\ Y_{LG} & Y_{LL} \end{bmatrix} \begin{bmatrix} V_G \\ V_L \end{bmatrix}$$

where I_G, I_G and V_G, V_L represent currents and voltages at the generator buses and load buses.

Rearranging the above equation, we get:

$$\begin{bmatrix} V_L \\ I_G \end{bmatrix} = \begin{bmatrix} Z_{LL} & F_{LG} \\ K_{GL} & Y_{GG} \end{bmatrix} \begin{bmatrix} I_L \\ V_G \end{bmatrix}$$

$$F_{LG} = -[Y_{LL}]^{-1}[Y_{LG}]$$

The L-index of the *j*th node is given by the expression

$$L_j = \left| 1 - \sum_{i=1}^{N_g} F_{JI} \frac{V_i}{V_j} \angle \left(\theta_{ji} + \delta_i - \delta_j \right) \right|$$

The stability index is given by lowest value of jacobian.

III. MODELLING EQUATIONS OF STATCOM

The power flow equations for the STATCOM are derived from first principles and assuming the following voltage source representation

$$E_{vR} = V_{vR}(\cos \delta_{vR} + j \sin \delta_{vR})$$

After performing some complex operations, the following active and reactive power equations [10] are obtained for the converter and bus k, respectively

$$P_{vR} = V_{vR}^2 G_{vR} + V_{vR} V_k [G_{vR} \cos(\delta_{vR} - \theta_k) + B_{vR} \sin(\delta_{vR} - \theta_k)]$$
$$Q_{vR} = -V_{vR}^2 B_{vR} + V_{vR} V_k [G_{vR} \sin(\delta_{vR} - \theta_k) - B_{vR} \cos(\delta_{vR} - \theta_k)]$$
$$P_k = V_k^2 G_{vR} + V_{vR} V_k [G_{vR} \cos(\theta_k - \delta_{vR}) + B_{vR} \sin(\theta_k - \delta_{vR})]$$
$$Q_k = -V_k^2 G_{vR} + V_{vR} V_k [G_{vR} \sin(\theta_k - \delta_{vR}) - B_{vR} \cos(\theta_k - \delta_{vR})]$$

Using these power equations, the linearized STATCOM model is specified below, where the voltage magnitude V_{vR} and phase angle δ_{vR} are taken to be the state variables

$$\begin{bmatrix} \Delta P_k \\ \Delta Qk \\ \Delta P_{vR} \\ \Delta P_{vR} \end{bmatrix} = \begin{bmatrix} \frac{\partial P_k}{\partial \theta_k} & \frac{\partial P_k}{\partial V_k} V_k & \frac{\partial P_k}{\partial \delta_{vR}} & \frac{\partial P_k}{\partial V_{vR}} V_{vR} \\ \frac{\partial Q_k}{\partial \theta_k} & \frac{\partial Q_k}{\partial V_k} V_k & \frac{\partial Q_k}{\partial \delta_{vR}} & \frac{\partial Q_k}{\partial V_{vR}} V_{vR} \\ \frac{\partial P_{vR}}{\partial \theta_k} & \frac{\partial P_{vR}}{\partial V_k} V_k & \frac{\partial P_{vR}}{\partial \delta_{vR}} & \frac{\partial P_{vR}}{\partial V_{vR}} V_{vR} \\ \frac{\partial Q_{vR}}{\partial \theta_k} & \frac{\partial Q_{vR}}{\partial V_k} V_k & \frac{\partial Q_{vR}}{\partial \delta_{vR}} & \frac{\partial Q_{vR}}{\partial V_{vR}} V_{vR} \end{bmatrix} \begin{bmatrix} \Delta \theta_k \\ \frac{\Delta V_k}{V_k} \\ \Delta \delta_{vR} \\ \frac{\Delta V_{vR}}{V_{vR}} \end{bmatrix}$$

PSO Algorithm Application to OPF

The PSO algorithm applied to OPF can be explained in the following steps.

Step 1: Read the parameters of system and specify the lower and upper boundaries of each control variable.

n= number of generator buses, itr=100, $P_{i,\min}, P_{i,\max}$

Step 2: The particles are randomly generated between the maximum and minimum operating boundaries of the generators.

$$P_{i,\min} \le P_i \le P_{i,\max} \; for i = 1, 2, \ldots n \quad P_D = \sum_{i=1}^{n} P_i + P_L$$

Step 3: Compute the value of each particle using objective function.

$$F_T = \sum_{i=1}^{n} F(P_i) = \sum_{i=1}^{n} (a_i P_i^2 + b_i P_i + c_i)$$

Step 4: Evaluate the fitness value of objective function of each particle. x_{ibest} is set as the i th particle's initial position; x_{gbest} is set as the best one of x_{ibest}. The current evolution is t =1.

Step 5: Initialize learning factors c_1, c_2, inertia weight w_i and the initial velocity v_1.

Step 6: Modify the velocity v of each particle

x(k,j,i+1) = x(k,j-1,i) + v(k,j,i)

Step 7: Modify the position of each particle. If a particle violates its position limits in any dimension, set its position at suitable limits. Calculate each particle's new fitness; if it is better than the previous x_{gbest}, the current value is set to be x_{gbest}.

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Step 8: To each particles of the population, use the basic Newton-Raphson load flow to calculate power flow and the transmission loss.

Step 9: Update the time counter $t = t + 1$.

Step 10: If one of the ending criteria is satisfied regarding the number of iterations then go to step 11. Otherwise go to step 6.

Step 11: The particle that generates the latest p_{gbest} is the global optimum.

The flowchart corresponding to the objective function is presented in the below figure

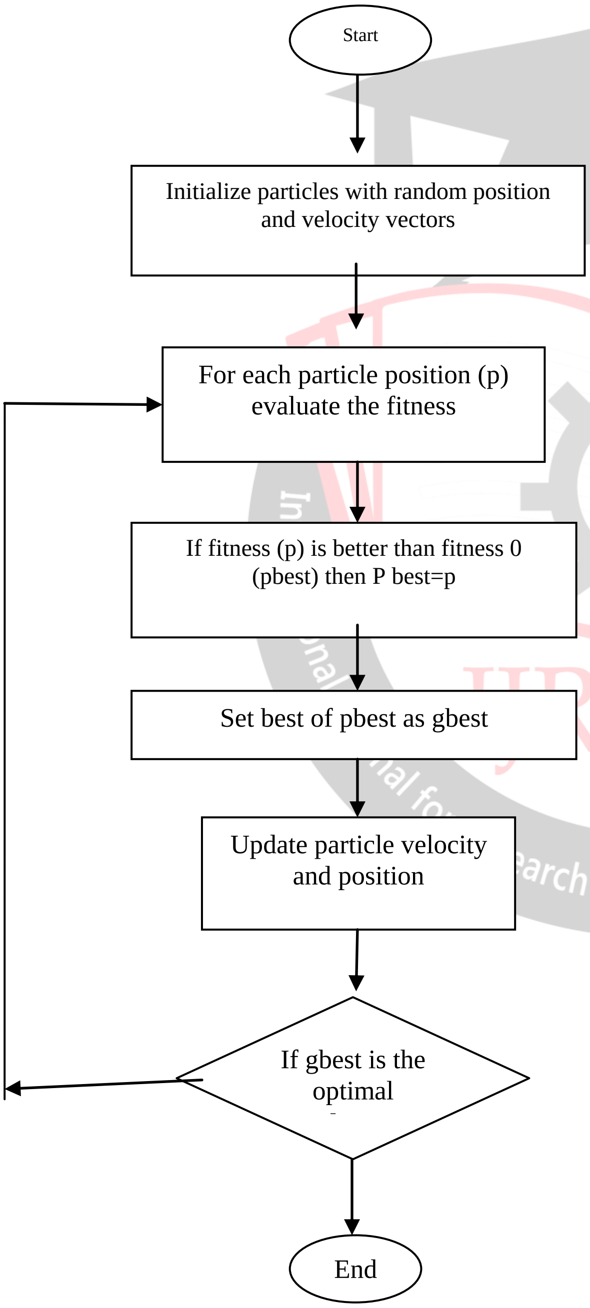

Figure 1: Flowchart for proposed algorithm

Test system:

In this paper IEEE 30 bus system with 6 generators having a maximum demand of 2.84 P. U is considered. The STACOM is placed at 29 bus because in this system bus 29 is identified as the weak bus by performing the basic Newton Raphson program and by calculating L-index at each load bus. The system is tested both with and without STATCOM by performing basic Newton Raphson for load flow and PSO for generating the powers of generator buses. The following are the considered values of various parameters.

The number particles =6

Number of populations =20

C1=2, C2=2 and R=10 for PSO

Number of iterations for Newton Raphson are 100

The results obtained were quite encouraging by placing the STATCOM and PSO to minimize the operating cost.

IV. RESULTS AND DISCUSSION

To prove the usefulness of the proposed PSO based algorithm with inclusion of STATCOM, it was applied to IEEE 30 bus system for both including of STATCOM and without including of STATCOM. The considered test system is simulated on MATLAB 2013 with i3 core processor and the results are taken after performing 10 iterations to get accurate results

The corresponding operating cost, generated powers and real and reactive power losses are tabulated below both with and without STATCOM. By observing the results, we can conclude that the operating cost is reduced to 824.8$ from 826.46$ with the incorporation of the STATCOM.

Quantity	Cost ($)	PLoss	QLoss
With out	826.4669	0.1822	0.0625
With STATCOM	824.8229	0.166	0.0129

The following graph shows the variation of operating cost and the corresponding fitness graph before the incorporation of STATCOM.

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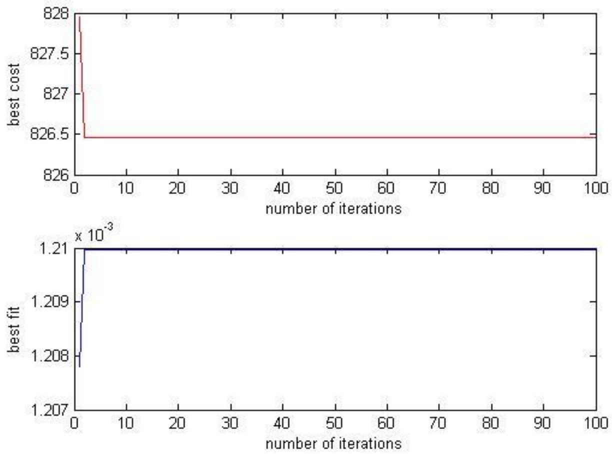

Figure 2: cost and fitness graph without STATCOM

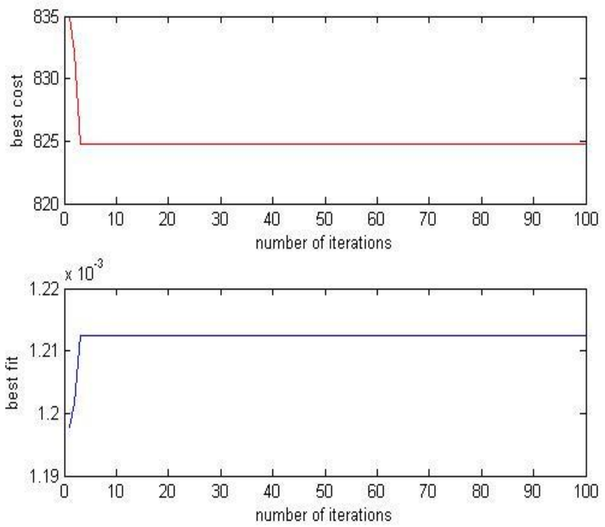

Figure 3: cost and fitness graph with STATCOM

Figure 3 shows the variation of operating cost and the corresponding fitness values after incorporating STATCOM.

The values of generated powers in p.u with and without STATCOM as tabulated below

Bus Number	Generated Power (Xg)	
	Without STATCOM	With STATCOM
1	1.859	1.7162
2	0.4889	0.4531
3	0.1335	0.1634
4	0.1240	0.2252
5	0.1730	0.2308
6	0.2121	0.1846

The real and reactive power losses are reduced with the incorporation of the STATCOM which we can observe from the above tables.

Bus number/L-index value	Without STATCOM	With STATCOM
7	0.0226	0.0226
8	0.0156	0.0156
9	0.0428	0.0427
10	0.0799	0.0797
11	0.0184	0.0184
12	0.0511	0.051
13	0.0163	0.0163
14	0.0743	0.0743
15	0.0799	0.0798
16	0.0715	0.0714
17	0.0836	0.0835
18	0.098	0.0978
19	0.1039	0.1038
20	0.0992	0.099
21	0.0941	0.094
22	0.0935	0.0934
23	0.0955	0.0954
24	0.1061	0.106
25	0.1036	0.1036
26	0.1219	0.1219
27	0.0931	0.0931
28	0.0217	0.0217
29	0.1233	0.1234
30	0.1443	0.1443

The values of L index for the test system with and without STATCOM are calculated. By observing the results, we can conclude that stability of the system is improved with the incorporation of the STATCOM at weak bus.

V. CONCLUSION

In this paper optimal power flow with minimization of operating cost as the objective function is tested on IEEE 30 bus with and without incorporating STATCOM. By observing the results, we can conclude that by placing the STATCOM we can increase the Stability of the system, reduce the active power losses, reactive power losses and, we can also reduce the operating cost of the system. We can extend this results to hydrothermal scheduling, and we can also place other facts devices which can improve the system performance.

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