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Artificial Intelligence Techniques for Multi objective Optimum Power Flow with Valve Point Loading Incorporating SVC

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***Abstract*— Multi Objective Optimal Power Flow including FACTS technology is one of the most important issues in power system planning and control. In this paper Artificial Intelligence techniques are used to solve the Multi Objective Optimum Power Flow incorporating FACTS devices with valve point effect. In this paper two objectives loss minimization and minimum voltage deviation are taken into consideration. In proposed algorithm parameters of FACTS can be adjusted according the voltage of generating units and load. This study is implemented on IEEE 5 bus system, 24 bus system and 118 bus system; results are compared with artificial intelligence techniques. Simulation results show the capabilities of different artificial intelligence techniques to solve the multi objective optimum power flow.**

***Keywords*— Artificial Intelligence (AI), Optimal Power Flow (OPF), Flexible AC Transmission systems (FACTS), Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Simulated Annealing (SA), Static Voltage Compensator (SVC)**

I. INTRODUCTION

Flexible Alternating Current Transmission Systems devices (FACTS) [1] are multi functional devices which can be used effectively

- to control the load flow distribution
- to increase power transfer capability
- to reduce active power losses
- to decrease the cost of power production
- to control the power flow in the network.

In this paper FACTS devices are used to control voltage deviation. In the paper FACTS devices are included in the load flow problem [2]-[3] and optimal dispatches are found by artificial intelligence techniques. The major advantage of the artificial intelligence methods is that they are relatively versatile for handling various qualitative constraints. Artificial intelligence methods can find multiple optimal solutions in single simulation run. So they are quite suitable in solving multi-objective optimization problems.

In many cases, they can find the global optimal solution. The advantages of GA methods are: It only uses the values of the objective function and have less chance to get trapped at a local optimum. Higher computational time is its disadvantage. PSO can be used to solve complex optimization problems, which are non-linear, non-differentiable and multi-model. The main merits of PSO are its fast convergence speed. PSO has been mainly used to solve multi-objective generation scheduling, optimal reactive power dispatch and to minimize total cost of power generation. Simulated annealing can deal with arbitrary systems and cost functions. Simulated annealing is relatively easy to code even for complex problems, and generally gives a good solution. This makes annealing an attractive option for optimization problems where heuristic (specialized or problem specific) methods are not available. In this paper simulation are performed on 5- Bus System, IEEE 26 bus test system and IEEE 118 bus system. The obtained results are very encouraging and reveal the capability of the artificial intelligence methods to solve the economic dispatch problem.

II. FACTS IN ECONOMIC DISPATCH

The Optimum Power Flow [4]-[10] find the generation levels in various generating units with minimum cost of generation. In the system operation with any load condition, the contribution from each plant and each unit in the plant must be determined so that the cost of delivered power should be minimum. The main constraint in this is the demand of the system which must be met. Although the major portion of the generation costs are due to Fuel costs, there are other contributors such as maintenance costs and transmission loss. In general, only those costs that can be controlled by operating strategy enter into the economic dispatch. Those parameters which can be adjusted to achieve the required optimization are called controlled variables. The costs are a function of the control variables, power demand, generator setting, and the load flow of the system.

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A simplified formulation of the problem can be made by assuming that the cost of generation is just fuel cost. The only constraint is the total demand that is to be met. This is equal incremental cost rule, states that the optimum dispatch is achieved when the incremental cost at each unit is same. In other words, the objective is to find a generation level at which the cost of producing one watt is the same for all units involved in the dispatch.

The equal incremental cost rule does not consider losses in the transmission system. It will be more expensive to supply a load from a unit A which is 5 miles away from the load than supply the same load from a unit B which is 1 mile away. The incremental cost of each unit may be the same, but because unit A has to supply the load plus the losses in the 5-mile line, the actual cost is higher. Therefore, B-coefficients method states that the optimal dispatch of a system is reached when the penalized incremental costs of each unit are equal. This penalty factor accounts the distance between the unit and the load. Larger the distance, more the losses, more the penalty.

The constraints may be classified depending whether a specified value is to be met (equality constraints), or if a system quantity is to be bounded by a lower and/or upper limit value. Inequality constraints include upper/ lower bus voltages at generator and load buses, var limits at generator buses, maximum power rating of a unit, and maximum line loading limits. An example of an equality constraint is to meet out the load demand. The incorporation of constraints in the optimal dispatch method is required in order to obtain a realistic and reliable solution.

Economic optimal dispatch is used both in the planning and operation of a power system. In system planning studies, feasibility and project costs are the main concern. In system operation, minimizing the operating cost is the primary objective.

It was mentioned earlier that the economic optimal dispatch problem depends on the power flow in the system. If the power flows in the system without any control it creates control problems such as parallel and loop flows appear. Thus economic dispatch is therefore constrained, not just by the fuel costs, but by many operational limits imposed. The generation is usually limited to values below the established stability limits.

The effectiveness of power stability depends on the ability to control the impedance and phase angle. The devices discussed in the preceding sections have such ability. Furthermore, there is a device that controls both parameters. FACTS devices control the power flow [11]-[12] in a system without generation rescheduling or topological changes. This will improve the performance of the system because the economic optimal dispatch problem would be less constrained.

Without violating the economic optimal dispatch, power transfers may be controlled in such a way that thermal limits are not exceeded, losses are minimized, and contractual requirements are fulfilled. If the capacity of the lines is fully utilized, the constraint imposed by the line limits has now a broader range, which will result in a less constrained dispatch problem For example; a 250 kV line may have a loading limit for safe operation if there is no power flow control. But if FACTS devices are used, the loading limit of the line may be almost the same as its thermal limit.

The objective of power flow control is to regulate power flows through some predefined lines at specified levels. FACTS technology achieves this objective. These diminish the loops and parallel flows which were caused by the free flow of power in the transmission system. .

Relief of overloaded transmission lines is usually performed by rescheduling of the generation when fast power flow control is not available. This method has the drawback of shifting the generation away from the economical operation point. FACTS technology would avoid the overloading of the lines by series compensation or phase shifts. Thus to avoid line overloading FACTS devices may be used.

Reactive power may be supplied when needed, not in a permanent way as in the case of static compensation. FACTS devices may reduce the var generation to zero when there is no need of reactive power in the system. The generators may not to be used to supply reactive power because FACTS devices can supply the reactive power demand.

III. OPTIMAL POWER FLOW FORMULATION

The objective of an Optimal Power Flow (OPF) algorithm is to find steady state operation point which minimizes generating cost, loss etc. or maximizes social welfare, loadability etc. while maintaining an acceptable system performance in terms of limits on generators' real and reactive powers, line flow limits, output of various compensating devices etc. Traditionally, classical optimization methods were used to effectively solve OPF. But more recently due to incorporation of FACTS devices and deregulation of a power sector, the traditional concepts and practices of power systems are superimposed by an economic market management, so OPF have become complex. In recent years, Artificial Intelligence (AI) methods have been emerged which can solve highly complex OPF problems.

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OPF is formulated mathematically as a general constrained optimization problem.

Minimize a function F(c,x) -------(1)

Subject to h(c,x) = 0 -------(2)

and g(c,x) ≥ 0 -------(3)

Where, c is the set of controllable quantities in the system and x is the set of dependent variables. F(c,x) is an objective function which is scalar. Equality constraints (2) are derived from conventional power balance equation. Inequality constraints (3) are the limits on control variables and the operating limit on the other variables of the system.

Equality and inequality constraints however, do not specify one unique network state. An enormous number of power system states can be computed when taking these constraints into account only.

There are mainly two objectives which are considered in this paper.

- Reduction of the total cost of the generated power.
- Minimize the deviations in voltage magnitudes at load.

Optimal power flow formulation

objective:

$$Min \sum_{i=1}^{n} F(P_i) \quad (4)$$

Where $F(P_i)$ is the fuel cost function of the i^{th} unit and Pi is the power generated by the i^{th} unit, subject to power balance constraints.

$$D = \sum_{i=1}^{n} P_i - P_L \quad (5)$$

Where D is the system load demand and P_L is the transmission loss, and generating capacity constraints:

$$P_i(\min) \leq P_i \leq P_i(\max) \quad \text{for } i = 1,2, \ldots n \quad (6)$$

Where $P_i(\min)$ and $P_i(\max)$ are the minimum and maximum power outputs of the i^{th} unit.

The fuel cost function of the generating units is given by

$$F(P_i) = a_i P_i^2 + b_i P_i + c_i \quad (7)$$

Where a_i, b_i , and c_i are the fuel cost coefficients of the i^{th} unit.

Economic problem with Valve _point Effect:

When the valve point effect [13] is considered in the input output curve, the possibility of non convex curves must be accounted for if extreme accuracy is desired. If non convex input output curve are to be used, equal incremental cost methodology cannot be used , since there are multiple outputs for any given value of incremental cost. Thereby the effects of valve point loading is modeled as a recurring rectified sinusoid contribution and added to the basic quadratic cost function

$$F_i(P_i) = (a_i + b_i P_i + c_i P_i^2)\left|e_i \sin\left(f_i(P_{imin} - P_i)\right)\right| \quad (8)$$

Where e_i and f_i are the fuel cost coefficients of unit i with valve point effect. Now, the modified objective function for the economic dispatch problem is to minimize subject to given constraints.

IV. GENETIC ALGORITHM

Genetic Algorithms (GAs) [14]-[17] are search methods based on principle of natural selection and genetics. GAs encodes the decision variables of a search problem into finite-length strings of alphabets of certain cardinality. The strings which are candidate solutions to the search problem are referred to as chromosomes, the alphabets are referred to as genes and the values of genes are called alleles. For example, in a problem such as the traveling salesman problem, a chromosome represents a route, and a gene may represent a city. In contrast to traditional optimization techniques, GAs work with coding of parameters, rather than the parameters themselves.

To evolve good solutions and to implement natural selection, we need a measure for distinguishing good solutions from bad solutions. The measure could be an objective function that is a mathematical model or a computer simulation, or it can be a subjective function where humans choose better solutions over worse ones. In essence, the fitness measure must determine a candidate solution's relative fitness, which will subsequently be used by the GA to guide the evolution of good solutions.

Another important concept of GAs is the notion of population. Unlike traditional search methods, genetic algorithms rely on a population of candidate solutions. The population size, which is usually a user-specified parameter, is one of the important factors affecting the scalability and performance of genetic algorithms. For example, small population sizes might lead to premature convergence and yield substandard solutions. On the other hand, large population sizes lead to unnecessary expenditure of valuable computational time.

Once the problem is encoded in a chromosomal manner and a fitness measure for discriminating good solutions from bad ones has been chosen, we can start to evolve solutions to the search problem using the following steps:

a) Initialization.

The initial population of candidate solutions is usually generated randomly across the search space. However, domain-specific knowledge or other information can be easily incorporated.

b) Evaluation.

Once the population is initialized or an offspring population is created, the fitness values of the candidate solutions are evaluated.

c) Selection.

Selection allocates more copies of those solutions with higher fitness values and thus imposes the survival-of-the-fittest mechanism on the candidate solutions. The main idea of selection is to prefer better solutions to worse ones, and many selection procedures have been proposed to accomplish this idea, including roulette-wheel selection, stochastic universal selection, ranking selection and tournament selection, some of which are described in the next section.

d) Recombination.

Recombination combines parts of two or more parental solutions to create new, possibly better solutions (i.e. offspring). There are many ways of accomplishing this (some of which are discussed in the next section), and competent performance depends on a properly designed recombination mechanism. The offspring under recombination will not be identical to any particular parent and will instead combine parental traits in a novel manner.

e) Mutation.

While recombination operates on two or more parental chromosomes, mutation locally but randomly modifies a solution. Again, there are many variations of mutation, but it usually involves one or more changes being made to an individual's trait or traits. In other words, mutation performs a random walk in the vicinity of a candidate solution.

f) Replacement.

The offspring population created by selection, recombination, and mutation replaces the original parental population. Many replacement techniques such as elitist replacement, generation-wise replacement and steady-state replacement methods are used in GAs.

g) Repeat steps a–f until a terminating condition is met.

V. PARTICLE SWARM OPTIMIZATION

Kennedy and Eberhart,[18] considering the behavior of swarms in the nature, such as birds, fish, etc. developed the Particle Swarm Optimization (PSO) algorithm. The PSO has particles driven from natural swarms with communications based on evolutionary computations. PSO combines self-experiences with social experiences. In this Algorithm,[19]-[21] a candidate solution is presented as a particle. It uses a collection of flying particles (changing solutions) in a search area (current and possible solutions) as well as the movement towards a promising area in order to get to a global optimum.

PSO is initialized with a group of random particles and the searches for optima by updating generations. In every iteration each particle is updated by following "two best" values. The first one is the best solution (fitness value) it has achieved so far. This value is called Pbest. Another best value that is tracked by the particle swarm optimizer is the best value obtained so far by any particle in the population. This best value is the global best called G_{best}. After finding the best values the particles update its velocity and position with the following equation:

$$V_i^{k+1} = W*V_i^k + C1*(P_{besti} - S_i^k) + C2*\text{rand2}*(G_{besti} - S_i^k)$$

$$S_i^{k+1} = S_i^{k+1} + V_i^{k+1}$$

$$W = W_{max} - \frac{W\max - W\min}{\text{iter max}}$$

Where

V_i^k = Velocity of agent i at kth iteration k +1

V_i^{k+1} = Velocity of agent i at (k +1)th iteration

W = The inertia weight

C1 = C2 = Weighting Factor (0 to 4)

S_i^k = Current position of agent i at kth iteration

S_i^{k+1} = Current Position of agent i at (k+1)th iteration

iter max = Maximum iteration number

iter = Current iteration number

P_{besti} = P of agent i best

G_{besti} = G of the group best

W_{max} = Initial value of inertia weight = 0.9

W_{min} = Final value of inertia weight = 0.2

Implementation of an optimization problem of GA is realized within the evolutionary process of a fitness function. The fitness function adopted is given as:

$$\text{Fitness function} = \frac{1}{\text{objective} + \text{penality}}$$

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Where objective function is the generation cost and the penalty is the bus voltage angle. Penalty cost has been added to discourage solutions which violate the binding constraints. Finally, the penalty factor is tended to zero. The PSO algorithm to solve the optimal power flow with FACTS devices can be summarized as follows:

Step 1. Initialize the population of individuals is created in normalized form so as to satisfy the generation constraints and FACTS devices constraints.
Step 2. for each individual in the population, the fitness function is evaluated in the normalized form.
Step 3. The velocity is updated and new population is created.
Step 4. If maximum iteration number is reached,
then go to next step else go to step 2.
Step 6. Print the best individual's settings.

VI. SIMULATED ANNEALING

The Simulated Annealing Algorithm [22]-[23] is a way of finding optimum solutions to problems which have a large set of possible solutions. The process of heating the solid body to the high temperature and allowed to cool slowly is called Annealing. Annealing makes the particles of the solid material to reach the minimum energy state. This is due to the fact that when the solid body is heated to very high temperature, the particles of the solid body are allowed to move freely and when it is cooled slowly, the particles are able to arrange itself so that the energy of the particles are made minimum.

The energy of the particle in thermodynamic annealing process can be compared with the cost function to be minimized in optimization problem. The particles of the solid can be compared with the independent variables used in the minimization function.

Initially the values assigned to the variables are randomly selected from the wide range of values. The cost function corresponding to the selected values are treated as the energy of the current state. Searching the values from the wide range of the values can be compared with the particles flowing in the solid body when it is kept in high temperature.

The next energy state of the particles is obtained when the solid body is slowly cooled. This is equivalent to randomly selecting next set of the values.

When the solid body is slowly cooled, the particles of the body try to reach the lower energy state. But as the temperature is high, random flow of the particles still continuous and hence there may be chance for the particles to reach higher energy state during this transition. Probability of reaching the higher energy state is inversely proportional to the temperature of the solid body at that instant.

In the same fashion the values are randomly selected so that cost function of the currently selected random values is minimum compared with the previous cost function value. At the same time, the values corresponding to the higher cost function compared with the previous cost function are also selected with some probability. The probability depends upon the current simulated temperature 'T'. If the temperature is large, probability of selecting the values corresponding to higher energy levels are more. This process of selecting the values randomly is repeated for the finite number of iteration. The values obtained after the finite number of iteration can be assumed as the values with lowest energy state (i.e) lowest cost function Thus the simulated annealing algorithm is summarized as follow.

An annealing algorithm needs four basic components:

1. Configurations: a model of what a legal placement (configuration) is. These represent the possible problem solutions over which we will search for an answer.
2. Move set: a set of allowable moves that will permit us to reach all feasible configurations and one that is easy to compute. These moves are the computations we must perform to move from configuration to configuration as annealing proceeds.
3. Cost function: to measure how good any given placement configuration is.
4. Cooling schedule: to anneal the problem from a random solution to a good, frozen, placement. Specifically, we need a starting hot temperature (or a heuristic for determining a starting temperature for the current problem) and rules to determine when the current temperature should be lowered, by how much the temperature should be lowered, and when annealing should be terminated.

The optimization problem is to estimate the best values for P_i *(i= 1,…n, where n= number of generators)* such that the cost function $\sum_{i=1}^{n} F_i(P_i)$ is minimized. P_i Varies from $P_{i(min)}$ to $P_{i(max)}$

Step-1. Initialize the value of the temperature 'T'.
Step-2. Randomly select the current values for the variables P_i from the range as defined above. Let it be P_{ic}
Step-3. Compute the corresponding cost function value, $\sum_{i=1}^{n} F_i(P_{ic})$.
Step-4. Randomly select the next set of values for the variables P_i from the range as defined above. Let it be P_{in}.
Step-5. Compute the corresponding cost function value $\sum_{i=1}^{n} F_i(P_{in})$.

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Step-6. If $\sum_{i=1}^{n} F_i(P_{in})$<= $\sum_{i=1}^{n} F_i(P_{ic})$, then the current values for the random variables $P_{ic} = P_{in}$.
Step-7. $\sum_{i=1}^{n} F_i(P_{in}) > \sum_{i=1}^{n} F_i(P_{ic})$, then the current values for the random variables $P_{ic} = P_{in}$, are assigned only when exp $[(\sum_{i=1}^{n} F_i(P_{ic}))$- $(\sum_{i=1}^{n} F_i(P_{in}))/T]$ > rand
Note that when the temperature 'T' is less, the probability of selecting the new values as the current values is less.
Step-8. Reduce the temperature T=r*T. r' is scaling factor varies from 0 to 1.
Step-9. Repeat STEP 3 to STEP8 for n times until 'T' reduces to the particular percentage of initial value assigned to 'T'

VII. RESULTS

In the Paper, simplified methods are used to implement the SVC in Optimal Power Flow. Algorithms are tested on 5 Bus System[2], 26-Bus system[2] and 118 Bus System[24].

The 5-Bus Power System has generators at buses 1, 2 and 3. Bus 1 with its voltage set at 1.06 pu is taken as slack bus. Voltage magnitude and real power generation at buses 2 and 3 and 1.045 pu, 40 MW, and 1.030 pu, 30 MW, respectively.

The 26-bus system consists of 26 lines, 6 generators, 7 Tap-changing transformers. Bus numbers 1, 2, 3, 4, 5 and 26 are generator buses and bus one is taken as reference bus, others are taken as load buses. The initial angle at respective buses is assumed as zero degree.

The 118 Bus System consists 54 Generators, 186 lines and tap changing transformers.

Power flow solution by Newton-Raphson Method is applied. The voltage profile at various buses and the total generating cost is obtained. Shunt FACTS devices can be directly incorporated in load flow without modification of Jacobian. Slight modifications are required in Load flow to include Static Voltage Compensator (SVC). The bus at which the SVC is connected has to be declared as generator bus with minimum and maximum reactive power limits. After the load flow converges to a solution the reactive power to be generated at SVC bus will be known. This reactive power corresponds to the rating of SVC.

Genetic Algorithm Parameters

Population Size= 50,
Generation= 500,
Time limit = 200,
Stall time limit= 100

PSO Parameters

Iterations between updating display = 100.
Maximum number of iterations to train, default = 2000.
Population size = 24
Acceleration const (local best influence), = 2
Acceleration const (global best influence), = 2
Initial inertia weight = 0.9
Final inertia weight = 0.4

SA Parameters

Initial Temperature =5000
Maximum Consecutive Rejection =10000
Maximum Success = 50
Maximum Tries = 10000
Stop Temperature 1e-10

A. Results with 5 bus system:

Value of SVC (11 Mvar) is calculated by declaring fifth bus as generator bus. After calculating the value of SVC , SVC is connected at fifth bus. Fig1. Shows Voltage profile of 5 Bus systems with or without SVC.

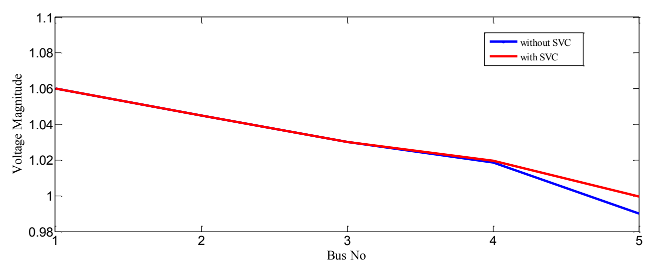

Fig1. Voltage profile of 5 Bus systems with or without SVC

Generating Cost without SVC = 1633.24 Rs/h
Generating Cost with SVC = 1631.28 Rs/h
Generating Cost after Optimal Power Flow using GA incorporating SVC = 1604.04 Rs/h
Generating Cost after Optimal Power Flow using PSO incorporating SVC = 1603.90Rs/h
Generating Cost after Optimal Power Flow using SA incorporating SVC = 1603.91Rs/h

B. Results with 26 bus system

To calculate the value of SVC, we declare the 24th bus as a generator bus and apply Newton-Raphson method to get the optimal value of SVC at the 24th bus. After load flow solution converges we get the reactive power to be generated at the 24th bus that is the optimal rating of the SVC is to be connected at the same bus. After getting the optimal value of SVC at 24th bus we again declare 24th bus as load bus and connect the SVC at 24th bus of the same rating 56.22 Mvar.

After executing OPF, we get the improved voltage profile, improved voltage angle profile and reduced total generating cost as shown in Figure 2 and Figure.3

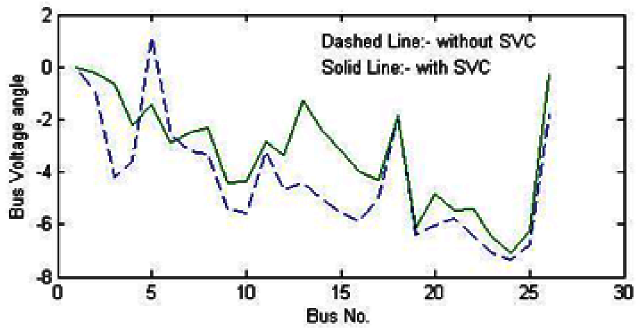

Figure-2. voltage profile of 26 bus system with and without SVC.

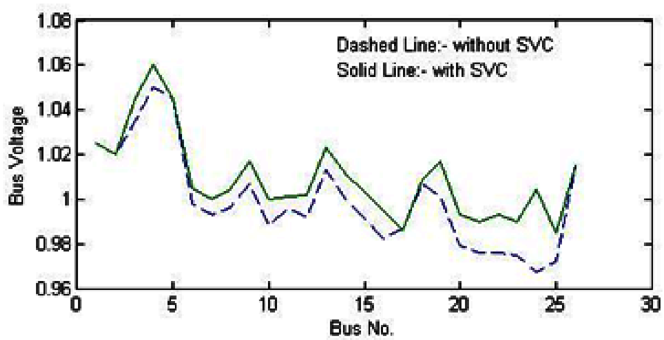

Figure-3. Bus voltage angle variation with and without SVC.

Generating Cost without SVC = 16762.44 Rs/h
Generating Cost with SVC = 16754.41 Rs/h
Generating Cost after Optimal Power Flow using GA incorporating SVC = 15430.38 Rs/h
Generating Cost after Optimal Power Flow using PSO incorporating SVC = 15429.83Rs/h
Generating Cost after Optimal Power Flow using SA incorporating SVC = 15429.83 Rs/h

C. Results with 118 bus system

Required value of SVC are calculated on 19th ,17th ,23rd ,30th ,37th ,39th ,45th 67th , 75th and 118th . values SVC are -200, -100, -70,-76, -185, 56, 24, -30, 17 and 41 Mvars.
After executing OPF, we get the improved voltage profile, improved voltage angle profile and reduced total generating cost as shown in Figure 4.
Genetic Algorithm Parameters
Population Size= 5000, Generation= 50000, Time limit = 200, Stall time limit= 100

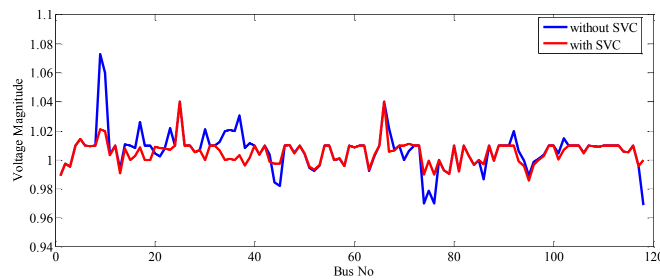

Fig 4 voltage profile of 118 bus system with or without SVC

Generating Cost without SVC = 60502 Rs/h
Generating Cost with SVC = 60469.63 Rs/h
Generating Cost after Optimal Power Flow using GA incorporating SVC = 58014 Rs/h
Time taken 165 seconds
Generating Cost after Optimal Power Flow using PSO incorporating SVC = 56358 Rs/h
Time Taken 07 seconds
Generating Cost after Optimal Power Flow using SA incorporating SVC = 59792 Rs/h
Time Taken 55 seconds

VIII. CONCLUSION

In this paper results shows that bus voltages and bus angles can be regulated as per requirement by incorporating FACTS devices. Optimal Power Flow using Genetic Algorithms, Particle Swarm Optimization and Simulated gives the accurate and same results when these algorithms are applied to small bus systems. But when we apply these algorithms to the larger bus systems, results varies. Genetic Algorithms slows when it applies to the larger system and also does not give the minimal optimal solution. Each time when GA executes results varies up to some value. Simulated Annealing is faster and accurate than Genetic Algorithms. Particle Swarm Optimization gives very accurate and fast results when it applies to the small bus systems or as well as applies to larger bus systems.

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