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Multi-Objective Reactive Power Compensation Using Evolutionary Programming and Particle Swarm Optimization

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Abstract— The stress on the transmission lines are increasing day by day. So it is very difficult to install new transmission system. So it is better to enhance the performance of existing transmission system by Reactive Power Compensation. Reactive Power Compensation in Electric Power Systems is usually studied as constrained Single-Objective Optimization Problem where an objective function is a factor of transmission line losses only. This paper aims in Multi-Objective Optimization which includes the system voltage deviation, the active power loss in transmission lines and cost involved in reactive power compensation. This has been achieved by using optimization techniques namely Evolutionary Programming and Particle Swarm Optimization. The results of the two methods are compared with each other.

Keywords— Reactive Power Compensation, Multi-objective Optimization, Evolutionary Algorithms, Particle Swarm Optimization and Comparison result.

I. Introduction

The stress on the transmission lines are increasing day by day. Because of the high cost involved and the restrictions in obtaining the Right of Way, it is preferable to enhance the performance of existing transmission system by installing Reactive Power Compensation rather than introducing new transmission lines. Reactive Power Compensation (RPC) is commonly addressed as a constrained Single-objective Optimization Problem (SOP). With this approach, an adequate location and size of shunt capacitor banks are found.

Optimal size and locations of RPC in Electric Power Systems is usually studied as constrained SOP where an objective function is a factor of transmission line losses only, subject to operational constrains, such as reliability and voltage profile. SOP Algorithms usually provide a unique optimal solution.

In this paper, the optimisation problem is formulated as a Multi-Objective Optimization Problem (MOP) including the system voltage deviation, the active power loss in transmission lines and cost of introducing RPC. Multi-objective Optimization independently and simultaneously optimizes several parameters turning most traditional constraints into new objective functions. This seems more natural for real world problems where choosing a threshold may seem arbitrary. The MOP has been solved by using optimization techniques namely Evolutionary Programming (EP) and Particle Swarm Optimization (PSO). The results of the two methods have been compared.

II. MULTI-OBJECTIVE OPTIMIZATION PROBLEMS

A general MOP includes a set of n decision variables, a set of k objective functions, and a set of m restrictions. Objective functions and restrictions are functions of decision variables. This can be expressed as:

$$\text{Optimize } \; Y = F(X) = [F_1(X) \;\; F_2(X) \; \ldots \; F_k(X)] \qquad (1)$$
$$\text{s.t.} \qquad e(X) = [e_1(X) \;\; e_2(X) \; \ldots \; e_m(X)] \geq 0$$

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Vol. 2, Issue 1, January 2014

where $X = [x_1 \ x_2 \ ... \ x_m] \in X$
$Y = [y_1 \ y_2 \ ... \ y_k] \in Y$

X is known as decision vector and Y as objective vector. X denotes the decision space and the objective space are denoted by Y. Depending on the problem at hand "optimize" could mean minimize or maximize.

The set of restrictions $e(X) \geq 0$ determines the set of feasible solutions X_f, and its corresponding set of feasible objective vectors Y_f. From this definition, it follows that every solution consists of an n-tuple X, which yields an objective vector Y, where every X must satisfy the set of restrictions $e(X) \geq 0$. The optimization problem consists in finding the X that has the "best" F(X). In general, there is not one "best" solution, but a set of solutions, none of which can be considered better than the others if all objectives are considered at the same time. This derives from the fact that there could be (and mostly there are) conflicts between the different objectives that compose a problem. Thus, a new concept of optimality should be established for MOPS.

III. MATHEMATICAL FORMULATION

The following assumptions are made in the formulation of the problem:

- Shunt-capacitor/reactor bank cost per MVAr is the same for all bus-bars of the power system.
- Power system is considered only at peak load. Based on these considerations, three objective functions F_i (to be minimized) have been identified.

F_1 and F_2 are related to investment and transmission losses, while F_3 is related to quality of service. The objective functions are:

F_1: Investment in reactive compensation devices

$$F_1 = \sum_{i=1}^{n} \alpha |B_i| \qquad s.t. \begin{cases} 0 \leq F_1 \leq F_{1m} \\ 0 \leq B_i \leq B_m \end{cases} \tag{2}$$

Where,

F_1: The total required investment,
F_{1m}: The maximum amount available for investment,
B_i: The compensation at bus-bar i measured in MVAr,
B_m: The absolute value of the maximum amount of compensation in MVAr allowed at a single bus-bar of the system,
α: The cost per MVAr of a capacitor bank and
n: The number of bus-bars in the electric power system.

F_2: Active power losses

$$F_2 = P_g - P_L \geq 0 \tag{3}$$

Where,

F_2: The total active losses of the power system in MW,
P_g: The total active power generated in MW and
P_L: The total load of the system in MW.

F_3: Maximum voltage deviation

$$F_3 = \max_i (V_i - V_i^*) = \|V - V^*\|_\infty \geq 0 \tag{4}$$

Where,

F_3: The maximum voltage deviation from the desired value in (pu),
$V \varepsilon \Re^n$: The voltage vector (unknown) and
$V^* \varepsilon \Re^n$: The desired voltage vector.

In summary, the optimization problem to be solved is the following:

$$\min F = [F_1 \quad F_2 \quad F_3] \tag{5}$$

Where,

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International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 2, Issue 1, January 2014

$$F = \left[\sum_{i=1}^{n} \alpha |B_i| \quad P_g - P_L \quad \|V - V^*\|_\infty \right]$$

Subject to $0 \le F_1 \le F_{1m}$, $0 \le B_i \le B_m$ and the load flow equations:

$$\begin{aligned} P_k &= V_k \sum_{i=1}^{n} Y_{ki} V_i \cos(\theta_{ki} + \delta_i - \delta_k) \\ Q_k &= -V_k \sum_{i=1}^{n} Y_{ki} V_i \sin(\theta_{ki} + \delta_i - \delta_k) \end{aligned} \tag{6}$$

Where,

V_k : The voltage magnitude at node k,
Y_{ki} : The admittance matrix entry corresponding to nodes k and i,
δ_k, δi : The voltage phase angle at node k and i respectively,
θ_{ki} : The phase admittance matrix entry corresponding to nodes k and i,
P_k : The active power injected at node k and
Q_k : The reactive power injected at node k.

To represent the amount of reactive compensation to be allocated at each bus-bar i, a decision vector B, is used to indicate the size of each reactive bank in the power system, i.e.,

$$B = [B_1 \;\; B_2 \;\; \dots \;\; B_n], B_i \in \Re, |B_i| \le B_m \tag{7}$$

IV. MULTI-OBJECTIVE REACTIVE POWER COMPENSATION USING EVOLUTIONARY PROGRAMMING

A. EVOLUTIONARY PROGRAMMING ALGORITHM

More than 45 years ago, several researchers from US and Europe independently came up with the idea of mimicking the mechanism of biological evolution in order to develop powerful algorithms for optimization and adaptation problems. This set of algorithms is known as Evolutionary Algorithms (EA). One of the most commonly used evolutionary algorithms is EP. This technique was originally conceived by Fogel in 1960. The schematic diagram of the EP algorithm is depicted in figure 1. The general scheme of the EP follows the sequence below:

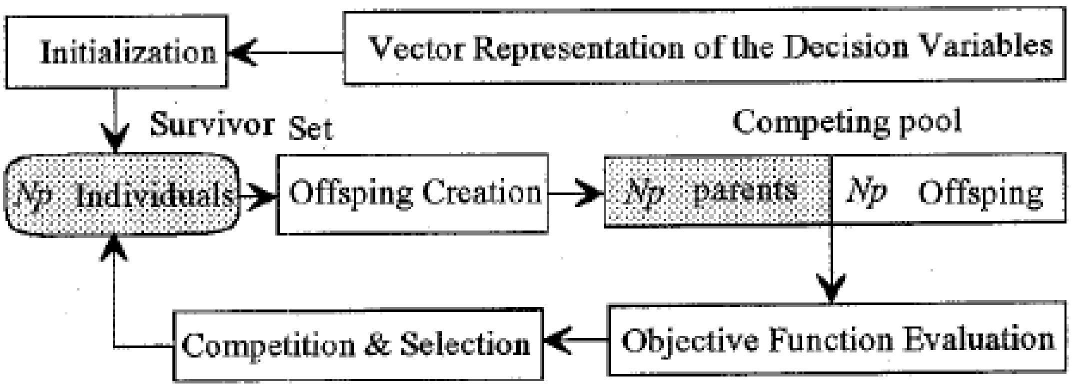

Figure 1: Schematic diagram of the evolutionary programming algorithm

Step 1. Initialization: An initial population of parent individuals P_i, i=1, …, N_P, is selected randomly from a feasible range in each dimension. Typically, the distribution of initial trials is uniform.

Step 2. Creation of Offspring: Equal number of offspring P_i^*, i=1, …, N_P, is generated by adding a Gaussian random variable with zero mean and preselected standard deviation to each component of P_i. Therefore, individuals including parents and offspring exist in the competing pool (Figure 1).

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Step 3. Competition & Selection: Each individual in the competing pool must stochastically strive against other members of the pool based on the functions f (P_i) and f (P_i^*). The Np individuals with the best function values (minimum for the minimization problem) are selected to form a survivor set according to a decision rule. The individuals in the survivor set are new parents for the next generation.

Where,

P_i : Initial Population,
P_i^* : Offspring Population,
N_P : Number of Population,
f (P_i) : Fitness value of initial population and
f (P_i^*) : Fitness value of offspring population.

Step 4. Stopping Rule: The process of generating new trials and selecting those with best function values are continued until the function values are not obviously improved or the given count of total generations is reached.

B. EP IMPLEMENTATION

i). Initialization

Generate and initial population size 'n', as $V_i = \left[V_1, V_2 \ldots V_j\right]$ and $Q_i = \left[Q_{inj1}, Q_{inj2} \ldots Q_{inj\,j}\right]$. The initial parent trial vectors V_i and Q_i, i = 1, 2…N_P is determined by setting its j^{th} components. Where j=1, 2... N and j is not of a combined cycle unit. Evaluate the fitness for each individual as,

$F = K_1 \sum_{i=1}^{n} \alpha |B_i| + K_2 (P_g - P_L) + K_3 \|V - V^*\|_\infty$ and store the maximum fitness value as f_{max}.

Where, K_1, K_2 and K_3 are penalty factors

ii). Creation of offspring

The initial parent population produces 'n' number of offspring vectors V_i^1 and Q_i^1 is created from each parents V_i and Q_i by adding to each components of V_i and Q_i, a Gaussian random variable with zero mean and a standard deviation proportional to the scaled values of the parent trial solution, i.e.,

$$V_i^1 = \left[V_1^1, V_2^1 \ldots V_j^1\right] \tag{8}$$

$$Q_i^1 = \left[Q_{inj1}^1, Q_{inj2}^1 \ldots Q_{inj\,j}^1\right] \tag{9}$$

$$V_j^1 = V_i + N(0, \sigma_i^2) \tag{10}$$

$$Q_j^1 = Q_i + N(0, \sigma_i^2) \tag{11}$$

For j=1, 2... N, *j* is not a combined-cycle unit. Where $N(\mu, \sigma^2{}_i)$ represents a Gaussian random variable with mean μ and standard deviation σ_i. The standard deviation σ_i indicates the range the offspring is created around the parent trial solution. σ_i is given according to the following equation:

$$\sigma_i = \beta \times \frac{f_{p_i}}{f_{min}} \left(Q_{inj\,max} - Q_{inj\,min}\right) \tag{12}$$

Where β is a scaling factor, which can be tuned during the process of search for optimum. f_{p_i} is a fitness value of the i^{th} individual and f_{max} is the maximum fitness among the parents. After adding a Gaussian random number to parents, the element of offspring may violate real power constraints.

iii). Competition & Selection

The Np parent trial vectors V_i and Q_i, i = 1... Np and their corresponding offspring V_i^1 and Q_i^1, i = 1**...** Np contend for survive with each other within the competing pool. The score for each trial vector after a stochastic competition is given by,

$$w_{p_i} = \sum_{t=1}^{N_P} w_t \tag{13}$$

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Vol. 2, Issue 1, January 2014

$$w_t = 1 \text{ if } u_1 > \frac{f_{p_i}}{f_{p_r} + f_{p_i}}$$
$$= 0, \text{ otherwise}$$

Where the competitor P_r selected at random from among the 2Np trial solutions based on ***r*** = [2Np u_2+ 1]. [X] denotes the greatest integer less than or equal to x, and u_1, u_2 are uniform random number ranging over [0, 1]. After competing, the 2Np trial solutions, including the parents and the offspring, are ranked in descending order of the score obtained in (13). The first Np trial solutions survive and are transcribed along with their objective functions fp_i into the survivor set as the basis of the next generation. A maximum number of generations (i.e., iterations) N_m, is given.

iv). Next generation

Steps (ii) and (iii) are repeated until the maximum generation or iteration count is reached N_m. The best solution at the end of the process gives the optimal solution.

v). Calculation of optimum fitness value

After reaching the minimum fitness value the cost of reactive power compensation, total active power loss and maximum voltage deviation can be calculated.

V. MULTI-OBJECTIVE REACTIVE POWER COMPENSATION USING PARTICLE SWARM OPTIMIZATION

A. PARTICLE SWARM OPTIMIZATION

PSO is an evolutionary computation technique developed by Kennedy and Eberhart. It is an exciting new methodology in evolutionary computation that is similar to Genetic Algorithm (GA) and EP in that the system is initialized with a population of random solutions. In addition, it searches for the optimum by updating generations, and population evolution is based on the previous generations. In PSO, the potential solutions, called particles, are "flown" through the problem space by following the current optimal particles. Each particle adjusts its flying according to its own flying experience and its companion's flying experience.

The update of the particles is accomplished by the following (14) which calculates a new velocity for each particle (potential solution) based on its previous velocity (v_{id}), the particle's location at which the best fitness so far has been achieved ($pbest_{id}$), and the population global location ($gbest_d$) at which the best fitness so far has been achieved. Equation (15) updates each particle's position in the solution hyperspace. The modified velocity and position of each particle can be calculated using the current velocity and distance from $pbest_{id}$ to $gbest_d$ as shown in the following equations:

$$v_{id}^{(t+1)} = \left[w * v_{id}^{t} + C_1 * rand_1() * (pbest_{id} - x_{id}^{(t)}) + C_2 * rand_2() * (gbest_d - x_{id}^{(t)}) \right] \quad (14)$$

$$x_{id}^{(t+1)} = x_{id}^{(t)} + v_{id}^{(t+1)}$$
$$i = 1, 2, ..., n, \quad d = 1, 2, ..., m \quad (15)$$

Where,

$v_{id}^{(t)}$: Velocity of particle i at iteration t; in d at dimensional space, $V_{d,min} \le V_{id}^{(t)} \le V_{d,max}$

$x_{id}^{(t)}$: Current position of particle i at iteration t,

w : inertia weight factor,

t : number of iterations,

n : number of particles in a group,

m : number of members in a particle,

k : constriction factor ,

C_1, C_2 : acceleration constant,

rand ( ) : random number between 0 and 1.

Appropriate selection of inertia weight in (15) provides a balance between global and local explorations. As originally developed, often decreases linearly during a run. In general, the inertia weight factor (w) is set to the following equation:

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International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 2, Issue 1, January 2014

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times iter \quad (16)$$

Where, $iter_{max}$ is the maximum number of iterations, and iter is the current number of iterations.

The velocity value of each dimension is clamped to the range $\left[-v_{id\,max}, v_{id\,max}\right]$. Here, $v_{id\,max}$ is usually chosen to be $k\,x_{id\,max}$, with $0.1 < k < 1$, where $x_{id\,max}$ denotes the domain of search space.

B. PARTICLE SWARM OPTIMIZATION IMPLEMENTATION

Step 1: Set the particle number n of the population, acceleration coefficients c_1 and c_2, inertia weight w, maximum iteration. After number of trial runs the best value is found to be:

$n = 200$, $c_1 = c_2 = 1.49618$,

$w = 0.7298$, Maxi. Iteration=25.

Step 2: Set particles maximum and minimum velocity and position range. Positions of all particles are generated randomly.

Step 3: According to the position of each particle, calculate the power flow equation. If for any particle, load bus voltage output is over its limit, a new particle should be yielded randomly to replace this one and the power flow equation should be calculated again until the particle position satisfies the load bus voltage limit.

Step 4: Based on the result of power flow equation, calculate the fitness of each particle. According to the fitness of particles update the global best position of the population and personal best position of each particle.

Step 5: Update the velocity and position of all particles using eqn. 14 and eqn. 15.

Step 6: Evaluate whether maximum iteration has reached. If not, go to Step 3.

Step 7: Acquire the global optimization solution. All saved best position values are compared and the best one is exported as the optimum. Calculate the power flow equation corresponding to this best particle position.

VI. SIMULATION RESULTS

The single line diagram of 9 bus system is shown in figure 2.

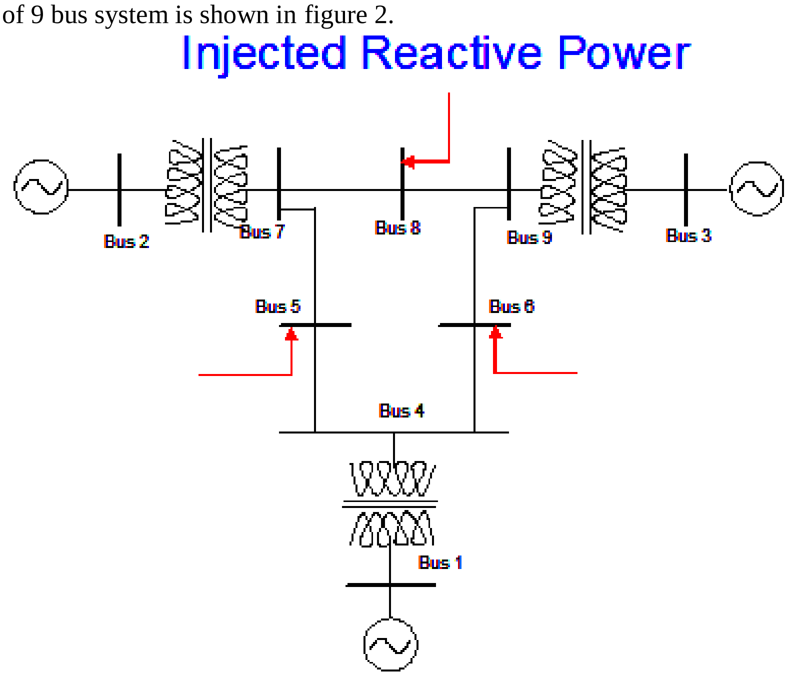

Figure 2: 9 Bus System

A. EP RESULT

Power system operating has to satisfy two constraints, i.e., load bus voltage limit and injected reactive power limit ($V_{min} = 0.95$, $V_{max} = 1.05$, $Q_{inj\ min} = 0$ $Q_{inj\ max} = 200$). In RPC problem, different constraints considered makeup of the different

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(An ISO 3297: 2007 Certified Organization)

Vol. 2, Issue 1, January 2014

calculation mathematical model. RPC is calculated for 9 bus system using EP Technique and the results are shown in Table I and Table II.

Table I – Optimization Result

Number of Iteration = 25; Number of Population = 200

Optimization Technique	Control Variables					F_1 MVAr	F_2 MW	F_3 p.u.	Fitness Value (F)	Operating Time (sec)
	V_2 p.u.	V_3 p.u.	Q_5 MVAr	Q_6 MVAr						
EP	1.033	1.012	139.785	117.228	8.731	361.892	8.340	0.0	8.731	27.33

Table II – Bus output

Bus No.	Voltage Magnitude (p.u.)	Angle degree	Load		Generation		Injected MVAr
			MW	MVAr	MW	MVAr	
1	1.040	0.000	0.0	0.0	75.375	6.375	0.000
2	1.033	8.780	0.0	0.0	163.000	21.236	0.000
3	1.012	4.325	0.0	0.0	85.000	16.987	0.000
4	1.044	-2.293	0.0	0.0	0.000	0.000	0.000
5	1.032	-4.083	125.0	150.0	0.000	0.000	139.786
6	1.032	-3.955	90.0	130.0	0.000	0.000	117.228
7	1.050	3.393	0.0	0.0	0.000	0.000	0.000
8	0.995	0.086	100.0	135.0	0.000	0.000	104.878
9	1.022	1.564	0.0	0.0	0.000	0.000	0.000

For EP Technique, the variation of minimum fitness values with the number of iterations for population size of n = 200 is shown in figure 3.

Figure 3: Convergence Characteristics by using EP

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ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 2, Issue 1, January 2014

B. PSO RESULT

RPC is calculated for 9 bus system using PSO Technique and the results are shown in Table III and Table IV.

Table III – Optimization Result

Number of Iteration = 25; Number of Population = 200

Optimization Technique	Control Variables					F_1 MVAr	F_2 MW	F_3 p.u.	Fitness Value (F)	Operating Time (sec)
	V_2 p.u.	V_3 p.u.	Q_5 MVAr	Q_6 MVAr						
PSO	1.034	1.012	131.061	101.905	8.731	344.561	8.308	0.0	8.655	23.77

Table IV – Bus output

Bus No.	Voltage Magnitude (p.u.)	Angle degree	Load		Generation		Injected MVAr
			MW	MVAr	MW	MVAr	
1	1.040	0.000	0.0	0.0	75.308	5.605	0.000
2	1.034	8.766	0.0	0.0	163.000	18.634	0.000
3	1.012	4.231	0.0	0.0	85.000	13.102	0.000
4	1.038	-2.301	0.0	0.0	0.000	0.000	0.000
5	1.030	-4.092	125.0	150.0	0.000	0.000	131.061
6	1.018	-3.940	90.0	130.0	0.000	0.000	101.905
7	1.050	3.384	0.0	0.0	0.000	0.000	0.000
8	0.998	-0.051	100.0	135.0	0.000	0.000	111.595
9	1.021	1.469	0.0	0.0	0.000	0.000	0.000

For PSO Technique, the variation of minimum fitness values with the number of iterations for population size of n = 200 is shown in figure 4.

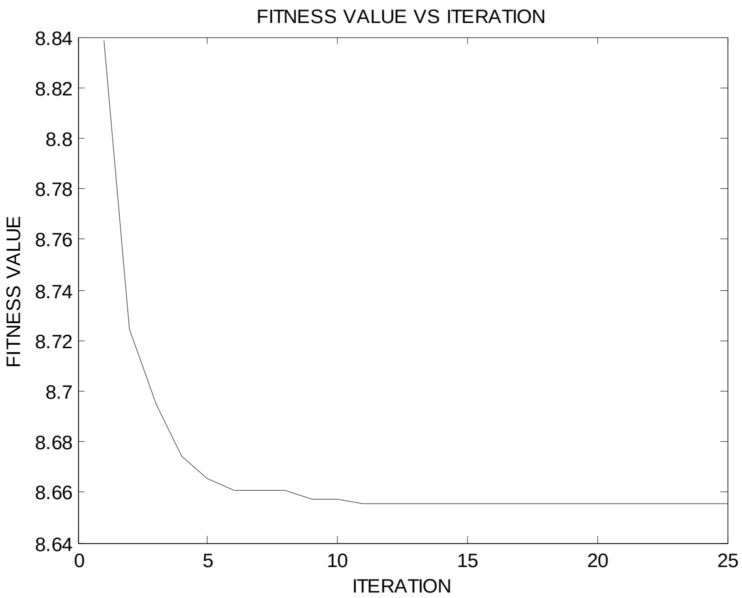

Figure 4: Convergence Characteristics by using PSO

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International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 2, Issue 1, January 2014

C. COMPARISON RESULT

The results are compared in Table V.

Table V– Comparison of Results
Number of Iteration = 25; Number of Population = 200

Optimization Technique	Control Variables					F_1 MVAr	F_2 MW	F_3 p.u.	Fitness Value (F)	Operating Time (sec)
	V_2 p.u.	V_3 p.u.	Q_5 MVAr	Q_6 MVAr	Q_8 MVAr					
EP	1.033	1.012	139.785	117.228	104.878	361.892	8.340	0.0	8.731	27.33
PSO	1.034	1.012	131.061	101.905	111.595	344.561	8.308	0.0	8.655	23.77

When the solutions obtained by the two optimization techniques are compared it can be clearly seen that the PSO algorithm reaches a solution very much closer to the best feasible solution as compared to EP algorithm. In case of PSO it can be observed that the losses are brought down to the minimum level. Thus, PSO technique has been successfully applied for solving the Reactive Power Compensation problem using Multi Objective function approach.

VII. CONCLUSION

In this paper, Reactive Compensation Problem is treated as a Multi-objective Optimization Problem with 3 conflicting objective functions: (i) investment in reactive compensation devices, (ii) active power losses and (iii) maximum voltage deviation. For the 9 bus system considered the test results suggests that the line losses has reduced effectively, the voltage deviation is found to be almost zero for the corresponding injected MVAr, this concludes that by injecting reactive power, the line losses are minimized and the bus voltages are controlled. When the two optimization techniques are compared, PSO technique yields better results as compared to EP.

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ISSN(Online): 2320-9801
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Vol. 2, Issue 1, January 2014

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BIOGRAPHY

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