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A Particle Swarm Optimization for Reactive Power Optimization

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***ABSTRACT**:*
This paper presents implementation of new algorithm Particle Swarm Optimization (PSO) for Energy Saving through minimizing power losses. The PSO Algorithm Solution is tested in standard IEEE 30 Bus system. The objective is to optimize the reactive power dispatch with optimal setting of control variables without violating inequality constraints and satisfying equality constraint. Control Variables are of both types: Continuous and Discrete. The continuous control variables are generator bus voltage magnitudes;whereas the discrete variables are transformer tap settings and reactive power of shunt compensators (Capacitor banks) .

***KEYWORDS**: Energy Saving by Particle Swarm Optimization, Optimal Reactive Power Dispatch.*

I. INTRODUCTION

Power system economics procedure includes of two aspects: active power regulation and reactive power dispatch. This forms a global optimization problem of a large-scale industrial system.The reactive power problem is less manageable to solve than the active power problem due to its more complicated relationship between variables. The reactive power problem is largelyassociated to voltage stability.Reactive power and voltage control is incredibly essential for the right operation and control of power system. Reactive power dispatch is one of the necessary tasks in the operation and control of power system.Voltage stability is a drawback in power systems that are heavily loaded, faulted or have a deficiency of reactive power. The character of voltage stability may be analysed by examining the generation, transmission and consumption of reactive power. Transfer of reactive Power is toughbecause of extremely high reactive power losses; that's why the reactive power needed for voltage control is generated and consumed at the control area.Optimization is a mathematical procedurewhich discusses the finding of maxima or minima of functions in some realistic region. There's no industry or businessthat is not involved in solving optimization problems.By Optimizing reactive power Dispatch in Power systems, the maximum active power transfer capability to the distribution systems can be improved. Stand-by reactive power sources (capacitor banks generally) are needed for loss minimization, in order to maintain the voltage stability in the Power systems [11-12].

For solving all optimization problems, there is no known single optimization method available. For solving the differentkinds of optimization problems, plenty of optimization techniques have been established in recent years. Linear programming (LP), non-linear programming and gradient based techniques were traditional optimization techniques [1], [4] for solving Reactive Power optimization problems. Since, Approximations are used in linearized models, thus LP results don't signify optimal result for objective function utilized in reactive power optimization problem. Traditional solution strategies have tendency to converge to a local optimal solution instead of the global one. Expert System methodologies [5] have been recommended for the reactive power based calculations. Expert System methodology is based mostly on 'if-then' based rules.Evolutionary computational techniques like Genetic algorithm (GA), Evolutionary programming (EP) and Evolutionary strategy have additionally been projected to solve the optimizations problems relating to the reactive power dispatch [6-8].The contemporary (non-traditional) optimization approaches are very powerful and popular approaches for solving complex engineering problems. These approaches are neural networks, genetic algorithm, ant colony optimization, fuzzy optimization and particle swarm optimization algorithm Particle Swarm Optimization (PSO) stands as acomparatively new, modern, and powerful technique of optimization that has been virtually shown to perform well on several of these optimization problems [13-14]. PSO exists as a population based stochastic optimization technique. PSO algorithm is applied while not violating inequality constraints and satisfying equality constraint.The aim of minimising reactive power losses is achieved by appropriate adjustment of reactive power variables like generator voltage magnitudes (V_{gi}), reactive power generation of capacitor banks (Q_{ci}) and transformer tap settings (t_k) [7-10]. In electrical power system, Reactive Power Loss Minimization problem is taken into account as a static, non-linear, single objective optimization problem. The suggested PSO algorithm solution has been experimented on the standard IEEE 30-Bus test system with both continuous and discrete control variables despite the fact that keeping the system under safe voltage stability limit. The recommended algorithm shows better results

II. PROBLEM FORMULATION

The customary optimization problem is often written in the following form,
Minimise *F(x)* (the objective function)
subject to:
$h_i(x) = 0, i = 1, 2, ..., n$ (equality constraints)
$g_j(x) = 0, j = 1, 2, ...,m$ (inequality constraints)

The reactive power optimization problem targets to minimize the power losses in the transmission network and improve voltage profile while satisfying the unit and system constraints. The aim is achieved by appropriate setting of reactive power variables like generator voltage magnitudes (V_{gi}), reactive power generation of capacitor banks (Q_{ci}) and transformer tap settings (t_k) [7-8].The equality constraints are power/reactive power equalities, the inequality constraints consist of bus voltage constraints, generator reactive power constraints, reactive power capacity constraints and the transformer tap position constraints, etc.At this juncture the reactive power dispatch problem is treated as a single objective optimization problem by linear combination of two objective functions i.e. P_{Loss}

$$F = min. P_{loss} \ldots \text{...............[1]}$$

A. Energy Saving through Minimization of power system losses (P_{loss})

The RPD problem targets at saving of energy by minimizing the real power loss in a power system while satisfying the unit and system constraints. This objective is accomplished by appropriate adjustment of reactive power variables like generator voltage magnitudes (V_{Gi}), reactive power generation of capacitor banks (Q_{Ci}) and transformer tap settings (T_k).
The minimization of system real power losses (MW) is calculated as follows:

$$\text{Min } F = P_{Loss} = \sum_{K=1}^{nl} g_k \left[V_i^2 + V_j^2 - 2V_iV_j \cos(\delta_i - \delta_j)\right]$$

The real power loss given by (P_{Loss}) is a non-linear function of bus voltages and phase angles that are a function of control variables and n_l is the number of transmission lines; g_k is the conductance of the k^{th} line; V_i and $V_j$are the voltage magnitude at the end buses i and j of the k^{th} line, respectively, and δ_i and δ_j are the voltage phase angles at the end buses i and j.

III. CONSTRAINTS

The real power loss (given by equation) is treated as a non-linear function of bus voltages and phase angles that are functions of control variables. The minimization problem is subjected to the following equality and inequality constraints:

Equality constraints

These constraints are typical load flow equations which can be represented as follows
1. Real Power Constraints:

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{N_B} V_j \left(G_{ij} Cos(\delta_i - \delta_j) + B_{ij} Sin(\delta_i - \delta_j)\right) = 0 \ldots[2]$$
$$i = 1,2 \ldots \ldots .. N_B$$

2. Reactive Power Constraints:

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{N_B} V_j \left(G_{ij} Sin(\delta_i - \delta_j) - B_{ij} Cos(\delta_i - \delta_j)\right) = 0, \ldots[3]$$
$$i = 1,2 \ldots \ldots .. N_{PQ}$$

Where,
V_i= Voltage magnitude at bus I
V_j = Voltage magnitude at bus j
P_i, Q_i = Real and reactive powers injected into network at bus i
G_{ij}, B_{ij} = Mutual conductance and susceptance between bus i and bus j
Q_{gi} = Reactive power generation at bus i
$N_B - 1$ = Total number of buses excluding slack bus

N_{PQ} =Number of PQ buses

δ_{ij} = Voltage angle difference between bus i and bus j

Inequality constraints :

3. Bus Voltage magnitude constraints:

$V_i^{min} \leq V_i \leq V_i^{max}$; $i\varepsilon N_B$… [4]

4. Transformer Tap position constraints:

$t_k^{min} \leq t_k \leq t_k^{max}$; $i\varepsilon N_T$… [5]

5. Generator bus reactive power constraint:

$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max}$; $i\,\varepsilon N_g$..[6]

6. Reactive power source capacity constraints:

$$Q_{ci}^{min} \leq Q_{ci} \leq Q_{ci}^{max} \;;\; i\varepsilon N_c\text{… [7]}$$

7. Transmission line flow constraints:

$|s_1| \leq |s_1^{max}|$….[8]

$|s_1| \leq |s_1^{max}|$…[9]

8. Generation capacity constraint:

$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max}$; $i \in N_B$[10]

The total power generation should cover the overall demand $P_D$and the real power loss in transmission lines P_L. This relation is often expressed by Power Balance Constraint:

9. Power balance constraint:

$\sum_{i=1}^{NB} P_{Gi} = P_D + P_L$….[11]

The symbols used are as follows:

t_k= Tap setting of transformer at branch k

Q_{Ci}= Reactive power generated by i^{th} capacitor bank

Q_{gi} = Reactive power generation at bus i

S_l = Apparent power flow through the i^{th} branch

N_B = Total number of buses

g_k= Conductance of buses

N_T= Number of tap-setting transformer branches

N_c= Number of capacitor banks

N_g= Number of generator buses

The control variables for voltage-control problem, which will be modified by the Particle Swarm optimization process, are:

a. Voltages magnitude at voltage-controlled buses (PV-buses) including the slack bus.
b. Transformers tap settings.
c. Adjustable shunt capacitor banks.

IV. PARTICLE SWARM OPTIMIZATION

PSO is an acronym for Particle Swarm Optimization. Particle Swarm Algorithm was introduced by Kennedy and Eberhart in 1995 [14]. PSO is a swarm intelligence method for global optimization.Particle Swarm Optimization is a concept introduced for the optimization of nonlinear functions using particle swarm methodology. Basically Particle Swarm Optimization is a method for optimization of continuous nonlinear functions. The method was discovered through simulation of a simplified social model. Particle Swarm Optimization comprises a very simple concept, and paradigms can be implemented in a few lines of computer code. It requires only primitive mathematical operators, and is computationally inexpensive in terms of both memory requirements and speed. Early testing has found the implementation to be effective with several kinds of problems.

PSO is based on the natural process of group communication to share individual knowledge when a group of birds or insects search food or migrate and so forth in a searching space, although all birds or insects do not know where the best position is. But from the nature of the social behaviour, if any member can find out a desirable path to go, the rest of the members will follow quickly.PSO traces its evolution to the emergent motion of a flock of birds searching for food. PSO uses a number of particles that constitute a swarm. Each particle traverses the search space looking for the global minimum (or maximum). In a PSO system, particles fly around in a multidimensional search space. During flight, each particle adjusts its position according to its own experience, and the experience of neighbouring particles, making use of the best position encountered by itself and its neighbours. The swarm direction of a particle is defined by the set of particles neighbouring to the particle and its history experience.

The basic elements of the PSO techniques are defined as:
1. **Particle X (t):**It is a candidate solution described by a k- dimensional real-valued vector, where k is the number of optimized parameters. At iteration i, the jth particle X (i,j) can be expressed as:

$X_i(t)=[x_{i,1}(t); x_{i,2}(t); \ldots\ldots;x_{i,k}(t)]$.

Where: x's are the optimized parameters and d signifies number of control variables

2. **Population**: It is basically a set of n particles at iteration i.

Pop (i) = [$X_1(i)$, X_2 (i), …….. X_n (i)] T

Where n signifies the number of candidate solutions
3. **Swarm**: Swarm is defined as an apparently unsystematic population of moving particles that tend to bunch together while each particle appears to be moving in a random direction.
4. **Particle velocity V (t):**Particle velocity is the velocity of the moving particles signified by a d-dimensional real valued vector. Particle Velocity is the step size of the swarm. It is the velocity of the moving particles represented by a k-dimensional real-valued vector. At time t, the i_{th} particle $V_i(t)$ can be described as

V_i $(t)=[v_{i,1}(t); v_{i,2}(t); \ldots\ldots;v_{i,k}(t)]$.

5. **Inertia weight ω(t)**: It is a regulation parameter, which is used to regulate the impact of the past (previous) velocity on the present velocity. Hence, it effects the trade-off between the global and local exploration capacities of the particles. For the initial stages of the search method, large inertia weight to reinforce the global exploration is usually recommended while it must be reduced at the last stages for higher local exploration. Therefore, the inertia factor drops linearly from about 0.9 to 0.4 throughout a run. In general, the inertia weight factor is set according to the equation given below:

$$W = \frac{(W_{max} - W_{min})}{iter_{max}} \times iter$$

All the control variables transformer tap positions and switch-able shunt capacitor banks are integer variables and not continuousvariables. Therefore, the value of the inertia weight is considered to be 1 in this study.
6. **Individual best X* (t)**: When particles are moving through the search space , it matches its fitness value at the existing position to the best fitness value it has ever grasped at any iteration up to the current iteration. The best position that is related with the best fitness faced so far is called the individual best X* (i). For every particle in the swarm, X* (i) may be determined and updated throughout the search.
7. **Global best X** (t):** It is the best position among all of the individual best positions achieved so far.
Various steps concerned with the implementation of PSO to the RPO problem are:
Step 1: Firstly scan the Input parameters of the system (bus, line and generator data) and alsoidentify the lower and upper boundaries of every variable. For N generators, optimization is applied out for N-1 generators and generator of maximum capacity is considered at slack bus.
Step 2: Then the particles of the population are randomly initialized i.e. are randomly selected between the respective minimum and maximum values. Also assign the velocity V initially between [-1 and 1].
Step 3: Obtain power flow solution and compute losses by Newton-Raphson method.

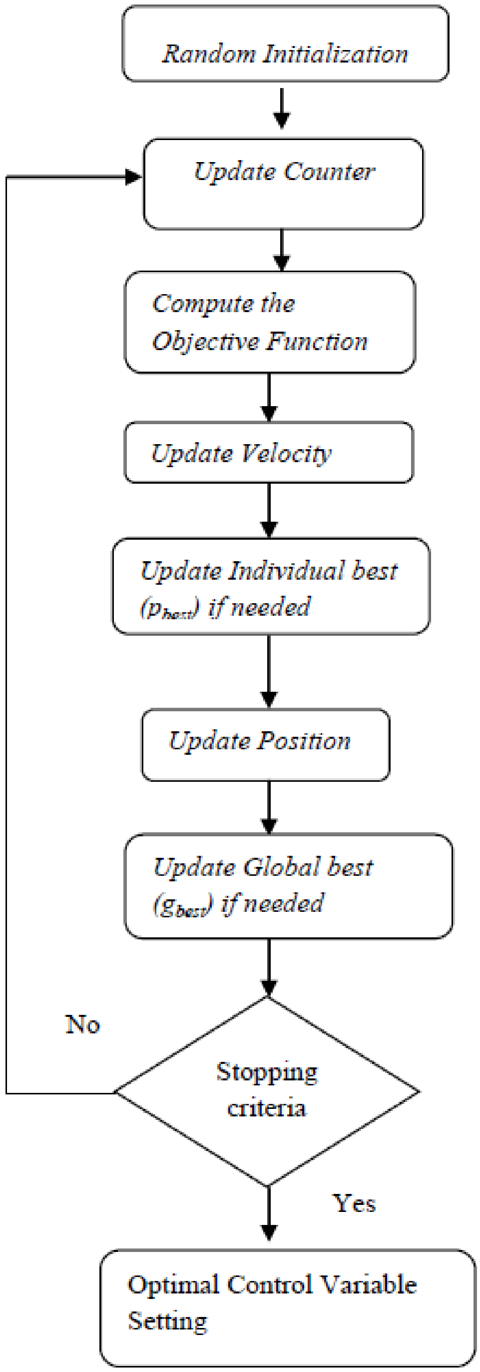

Fig.: **Flowchart for Basic PSO Algorithm**

Step 4: The best fitness is assigned as p_{Best}. At this stage the p_{Best} is also the g_{Best}.
Step 5: Iteration i= i+1 is updated.
Step 6: Modify the inertia weight *w* given by $W = \frac{(W_{max} - W_{min})}{iter_{max}} \times iter$

Step 7: Update the velocity *v* of each particle according to the stated equation
$V\ (k,j,i+1) = W^{*}V\ (k,j,i) +\ C1^{*}rand^{*}\left(p_{bestx}\,(j,k) - X\ (k,j,i)\right) +\ C2^{*}rand^{*}\left(g_{bestx}\,(k) - X\ (k,j,i)\right)$
Step 8: Position of each particle is also modified as per the mentioned equation. If a particle violates the position limits in any dimension, its position is set at the right limit.
$x(k,j,i\ 1)\ \ x(k,j,1\ i)\ \ v(k,j,i)$

Table: optimal parameter setting for PSO

Parameters	
Number of iterations	300
Cognitive constant, c_1	2.0
Social constant, c_2	2.0
Max. and Min. inertia weights W	0.4 and 0.95
Population size	30

Step 9: Evaluation of each particle is done according to its updated position by runningpower flow and calculate the fitness function. If the evaluation value of each particle is better than the previous p_{Best} then the current value is set to be p_{Best} . If the best p_{Best} is better than g_{Best} , the value is set to be g_{Best}.

Step 10: If one of the stopping criteria is fulfilled then we go to Step 11. Else, we go to Step 5.
Step11: g_{Best} is the optimal/best value that is newest generated by the particle.

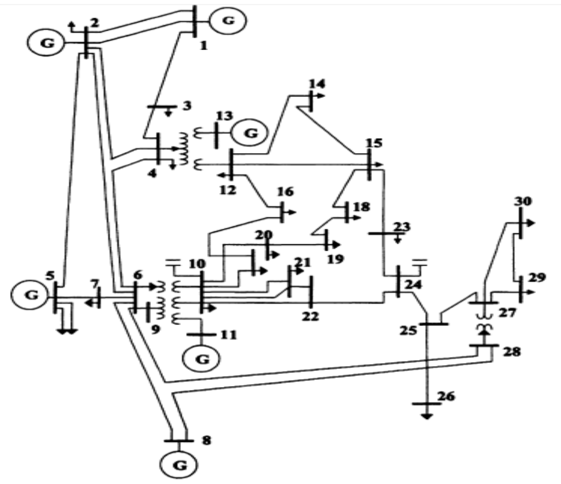

Fig.: IEEE 30 Bus System

V. RESULTS

Energy Saving through Minimization of systempower losses (P_{loss})

The proposed algorithm is run with minimization of real power losses as the objective function. As mentioned above, the real power settings of the generators are taken from [15-16]. The algorithm reaches a minimum loss of 5.3191MW. IEEE30 bus system is shown. The optimal values of the control variables are given in table shown above..

Table1: Test results of proposed approach.

Proposed Method	**Power Loss (MW)**
Particle Swarm Optimization	5.3191

	Min.	Max.	Initial(Base case)	Proposed PSO algorithm
V1	1.0	1.1	1.05	1.0824
V2	1.0	1.1	1.04	1.0470
V5	1.0	1.1	1.01	1.0347
V8	1.0	1.1	1.01	1.0209

V11	1.0	1.1	1.05	1.0376
V13	1.0	1.1	1.05	1.0402
T11	1.0	1.1	1.078	1.0196
T12	1.0	1.1	1.069	1.0783
T15	1.0	1.1	1.032	1.0573
T36	1.0	1.1	1.068	1.0963
Qc10	0.0	5.0	0.0	1.2677
Qc12	0.0	5.0	0.0	1.0610
Qc15	0.0	5.0	0.0	0.8607
Qc17	0.0	5.0	0.0	0
Qc20	0.0	5.0	0.0	2.5792
Qc21	0.0	5.0	0.0	1.7678
Qc23	0.0	5.0	0.0	1.6902
Qc24	0.0	5.0	0.0	0.5076
Qc29	0.0	5.0	0.0	0.6881
Power loss(MW)			5.8708	**5.3191**

Table 2:- Best results of individually run of p_{loss} as main function (IEEE-30 Bus)

Total Energy Saving :

From the table (shown below),
Reduction in losses – (5.8708 – 5.3191) = 0.5517 MW = 551.7 KW
Converting these reduced active power losses in form of energy we find:
Saved Energy in One Hour => 551.7 KWh
Saved Energy in One Day => 551.7 *24 = 13240.8 KWh
Saved Energy in One Week => 551.7 *24*7 = 92685.6 KWh
Saved Energy in One Year – 551.7 *24*365 = 4832892 KWh
So for an IEEE 30 bus system, estimation of energy saving is shown.For a standard IEEE 30 Bus system, 4832892 KWh (Units) is saved in a year by using PSO.

VI. CONCLUSION

A new improved integer coding Particle Swarm Algorithm is presented to solve this problem. The main objective is to minimize the active power loss in the network, while satisfying all the power system operation constraints. The particle swarm algorithm has been coded as well as the power flow fast-decoupled method using MATLAB. The simulation results show that PSO algorithm always leads to a better result.

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