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A Particle Swarm Optimization Algorithm for Reactive Power Compensation

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Abstract

This paper proposes an application of Particle Swarm Optimization (PSO) algorithm to Reactive Power Compensation (RPC). Several techniques have been developed to make Particle Swarm Optimization practicable to solve a real power system problem and other practical problems. The problem of locating and sizing of capacitors for reactive power compensation is modelled as a multi-objective programming problem. The proposed approach has been used in the IEEE 30 bus system. Two objective functions of technical and economical nature are explicitly considered in this system: minimization of system losses and minimization of capacitor installation costs. The performance of the proposed algorithm is evaluated by means of simulation in MATLAB. The proposed method results are compared with the Real Coded Genetic Algorithm.

Keywords: Reactive Power Compensation; Particle Swarm Optimization; Power Loss Minimization.

Introduction
Reactive power compensation is an important issue in electric power systems, involving operational, economical and quality of service aspects. Consumer loads (residential, industrial, service sector, etc.) impose active and reactive power demand, depending on their characteristics. Active power is converted into “useful” energy, such as light or heat. Reactive power must be compensated to guarantee an efficient delivery of active power to loads, thus releasing system capacity, reducing system losses and improving bus voltage profile. The achievement of these aims depends on the sizing and location of shunt capacitors (sources of reactive power).

This paper deals with the problem of optimal capacitor placement in IEEE 30 bus system considering two objective functions: minimizing capacitor installation cost and minimizing system losses. The problem of optimal capacitor placement in IEEE 30 bus system is considered as follows: identifying locations to install capacitors, the dimension of each capacitor to be installed, the utilisation of existing capacitors and the operation of the capacitors at different load levels.

Initially, the problem of capacitor location has been handled with analytical methods [1]-[7]. However, recently other methodologies such as mixed integer programming [8]-[10] and linear programming models [11]-[14] have been proposed. The methods based on heuristic search techniques such as tabu search [15]-[18] and real coded genetic algorithm [19]-[21] have also been proposed. The proposed approach has been used in the RPC problem for the IEEE 30-bus system.

Problem formulation

The problem of reactive power compensation involves determining the location and sizes for shunt capacitors (sources of reactive power) to be installed. The model described here assumes the multi-objective nature of the problem by considering the objective functions: minimizing losses and minimizing capacitor installation costs of new sources of reactive power. Quality of service requirements associated with an acceptable voltage profile in load buses are included as constraints resulting from legislation.

A set of recursive equations (1)-(5) describe the physical requirements associated with power flow through each branch in IEEE 30 bus system. Equations (1) and (3) establish that the active/reactive power that flows from bus i+1 is equal to the sum of the power that flows from the previous bus, minus the active power feeder(that connects bus i to bus i+1) losses, minus the active load demand on bus i+1.

The load flow calculation imposes a significant computational burden in the assessment of the merit of each solution. The procedure used for this purpose (recursive equations (1)-(5)) is adapted to IEEE 30 bus system.

$$P_{n0}^{k} = P_{0k}^{0},\ P_{n(i+1)}^{k} = P_{ni}^{k} - r_{ni}^{k}\frac{P_{ni}^{k^2}+Q_{ni}^{k^2}}{V_{ni}^{k^2}} - P_{Ln(i+1)}^{k},\ i=0,\dots,M_n^k-3\ \ \forall n\neq 0 \text{ and } k\neq 0 \tag{1}$$

$$P_{00}^{0} = P_{L00}^{0},\ P_{0(i+1)}^{0} = P_{0i}^{0} - r_{0i}^{0}\frac{P_{0i}^{0^2}+Q_{0i}^{0^2}}{V_{0i}^{0^2}} - P_{L0(i+1)}^{k} - \sum_{n=1}^{N^{i+1}} P_{n0}^{(i+1)},\ i=0,\dots K-3 \tag{2}$$

$$\left.\begin{aligned} &Q_{n0}^{k} = Q_{0k}^{0},\ Q_{n(i+1)}^{k} = Q_{ni}^{k} - x_{ni}^{k}\frac{P_{ni}^{k^2}+Q_{ni}^{k^2}}{V_{ni}^{k^2}} - Q_{Ln(i+1)}^{k} + Q_{Cn(i+1)}^{k},\ i=0,\dots,M_n^k-3,\\ &\forall n\neq 0 \text{ and } k\neq 0 \end{aligned}\right\} \tag{3}$$

$$\left.\begin{aligned} &Q_{00}^{0} = Q_{L00}^{0},\ Q_{0(i+1)}^{0} = Q_{0i}^{0} - x_{0i}^{0}\frac{P_{0i}^{0^2}+Q_{0i}^{0^2}}{V_{0i}^{0^2}} - Q_{L0(i+1)}^{0} - \sum_{n=1}^{N^{i+1}} Q_{n0}^{(i+1)} + Q_{C0(i+1)}^{0}\\ &i=0,\dots K-3 \end{aligned}\right\} \tag{4}$$

$$V_{n(i+1)}^{k^2} = V_{ni}^{k^2} - 2 * \left(r_{ni}^{k} P_{ni}^{k} + x_{ni}^{k} Q_{ni}^{k}\right) + \left(r_{ni}^{k^2} + x_{ni}^{k^2}\right) * \left(\frac{P_{ni}^{k^2} + Q_{ni}^{k^2}}{V_{ni}^{k^2}}\right) \ \forall \text{n,k,i} \tag{5}$$

The main feeder has index n=0, i.e. it is considered the zeroth lateral and k=0. Besides power flow equations there are other conditions to be satisfied for each lateral (including the feeder). From the last bus of each branch, there is no power flowing to other branches:

$$P_{nm}^{k} = Q_{nm}^{k} = 0, m = M_{n}^{k} - 1 \tag{6}$$

Constraints Equations (1)-(6)-load flow equations-are of physical nature. New capacitors are characterized by their capacity and the installation cost equation (7). Standard units, generally used in IEEE 30 bus system, are considered.

$$Q_{Cnm}^{k} = b_{nm}^{k} \sum_{j=1}^{J} a_{nm}^{kj} Q_{Fj} \ \forall \text{ m,n,k} \tag{7}$$

Constraints equation (8) impose that, at most, one capacitor can be placed in each node B_{nm}^{k}.

$$\sum_{j=1}^{J} a_{nm}^{kj} \leq 1 \ \forall \text{m,n,k} \tag{8}$$

Constraint equation (9) is related with quality of service, regarding the upper and lower bounds of node B_{nm}^{k} voltage magnitude.

$$V_{nm_{min}}^{k} \leq V_{nm}^{k} \leq V_{nm_{max}}^{k} \ \forall \text{m,n,k} \tag{9}$$

Two objective functions are considered, dealing with minimization of the system losses equation (10) and the minimization of the cost associated with installing capacitors equation (11)

$$\text{Min} \sum_{k=0}^{K-1} \sum_{n=0}^{N^k-1} \sum_{m=0}^{M_n^k-1} \frac{P_{nm}^{k^2} + Q_{nm}^{k^2}}{V_{nm}^{k^2}} \tag{10}$$

$$\text{Min} \sum_{k=0}^{K-1} \sum_{n=0}^{N^k-1} \sum_{m=0}^{M_n^k-1} \sum_{j=1}^{J} a_{nm}^{kj} C_j \tag{11}$$

With

$$a_{nm}^{kj} \begin{cases} = 1 \textit{ if the capacitor } j \textit{ whose capacity is } Q_{F_j} \textit{ is installed in } B_{nm}^{k} \\ 0 \text{ otherwise} \end{cases} \tag{12}$$

The multi-objective problem herein formulated is of the combinatorial nature because of its structure and decisions to be made, involving both discrete and continuous variables, and it is nonlinear due to electric laws.

Particle swarm optimization

Particle Swarm Optimization (PSO) is a population-based stochastic optimization algorithm modelled after the simulation of the social behaviour of bird flocks. It is a relatively new evolutionary algorithm that may be used to find the optimal (or near optimal) solutions to numerical and qualitative problems. Particle Swarm Optimization was originally developed by a social psychologist (James Kennedy) and an electrical engineer (Russell Eberhart) in 1995 [22]-[31]. Although there were a number of such algorithms getting quite a bit of attention at the time, Kennedy and Eberhart became particularly interested in the models developed by biologist Frank Heppner. Heppner studied birds in flocking behaviours mainly attracted to a roosting area. In simulations, birds would begin by flying around with no particular destination and spontaneously formed flocks until one of the birds flew over the roosting area.

Due to the simple rules the birds used to set their directions and velocities, a bird pulling away from the flock in order to land at the roost would result in nearby birds moving towards the roost. Once these birds discovered the roost, they would land there, pulling more birds towards it, and so on until the entire flock had landed. Finding a roost is like finding a solution in the field of possible solutions in a solution space. The manner in which a bird who has found the roost, leads its neighbour to move towards it, increase the chances that they will also find it. This is known as the “socio-cognitive view of mind”. The “socio-cognitive view of mind” means that a particle learns primarily from the success of its neighbours. Eberhart and Kennedy revised Heppner’s methodology so that particles could fly over a solution space and land on the best solution simulating the bird’s behaviour.

Each particle should compare themselves to others and imitate the behaviour of others who have achieved a particular objective successfully. Eberhart and Kennedy developed a model that balances the cooperation between particles in the swarm. An appropriate balance between exploration (individuals looking around for a good solution) and exploitation (individuals taking advantage of someone else’s success), is a main concern in the Eberhart and Kennedy model. Too little exploration and the particles will all converge to the first good solution found (typically a local solution). Too little exploitation and the particle will take longer to converge. In summary, the Eberhart and Kennedy model attempts to find the best compromise between its two main components, individually and sociality.

Particle Swarm Model for Continuous Variables

In Particle Swarm Optimization the particle are “flown” through the problem space by following the current optimum particles. Each particle keeps track of its coordinates in the problem space which are associated with the best solution (fitness) that it has achieved so far. This implies that each particle has a memory, which allows it to remember the best position on the feasible search space that it has ever visited. This value is commonly called previous best (p-best). Another best value that is tracked by the particle swarm optimizer is the best value obtained so far by any particle in the neighbourhood of the particle. This location is commonly called global best (g-best).

The basic concept behind the Particle Swarm Optimization technique consists of changing the velocity (or accelerating) of each particle toward its p-best and the g-best positions at each time step. This means that each particle tries to modify its current position and velocity according to the distance between its current position and p-best, and the distance between its current position and g-best. In its canonical form, Particle Swarm Optimization is modeled as follows:

$$v_i^{k+1} = wv_i^k + c_1\, rand_1(\ldots) \text{ x } (pbest_i - s_i^k) + c_2\, rand_2(\ldots) \text{x} (gbest - s_i^k) \tag{13}$$

$$s_i^{k+1} = s_i^k + v_i^{k+1} \tag{14}$$

where,

v_i^{k+1}: Velocity of particle i at iteration k+1

v_i^k: Velocity of particle i at iteration k

w: Inertia weight

c_1, c_2 : Acceleration coefficients

$rand(\ldots)_1$: Random number between 0 and 1

$rand(\ldots)_2$: Random number between 0 and 1

s_i^{k+1} : Position of particle i at iteration k+1

s_i^k : Position of particle i at iteration k

$pbest_i$: Pbest position of particle i

gbest: Gbest position of the group

Expressions in equations (13) and (14) describe the velocity and position update, respectively. Expression in equation (13) calculates a new velocity for each particle based on particle's previous velocity, the particle's location at which the best fitness has been achieved so far. In addition c_1 and c_2 are positive constants called the cognitive parameter and the social parameter, respectively. These constants provide the correct balance between exploration and exploitation. Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward p-best and g-best locations. The random numbers provide a stochastic characteristic for the particles velocities in order to simulate the real behaviour of the birds in a flock. In general, the inertia weight w is set according to the following equation (15)

$$w = w_{max} - \left(\frac{w_{max} - w_{min}}{Iter_{max}}\right) \times Iter \tag{15}$$

Where w_{max} and w_{min} are the upper and lower limits of inertia weighting factor, $Iter_{max}$ is the maximum number of iterations and Iter is the current iteration number. An inertia weight parameter w was introduced in order to improve the performance of the original Particle Swarm Optimization model.

PSO implementation

The Particle Swarm Optimization algorithm is applied to the IEEE 30 bus system.
Algorithm:

Step 1: Initial positions and velocities are randomly generated for each of the particles.

Step 2: System losses and capacitor installation costs for each set of particles is evaluated based on the fitness function.

Step 3: Assign the particle's position to p-best position and fitness to p-best fitness. Identify the best among the p-best as the g-best.

Step 4: New velocities and new positions are formulated using the equations (13) and (14) respectively.

Step 5: System losses and capacitor installation costs corresponding to the new positions and velocities are evaluated.

Step 6: Compare the best current fitness evaluation with the population's g-best. If the current value is better than the g-best, reset g-best to the current best position and fitness value.

Step 7: If iteration reaches maximum number, then exit, otherwise go to step 4

Results and Discussions

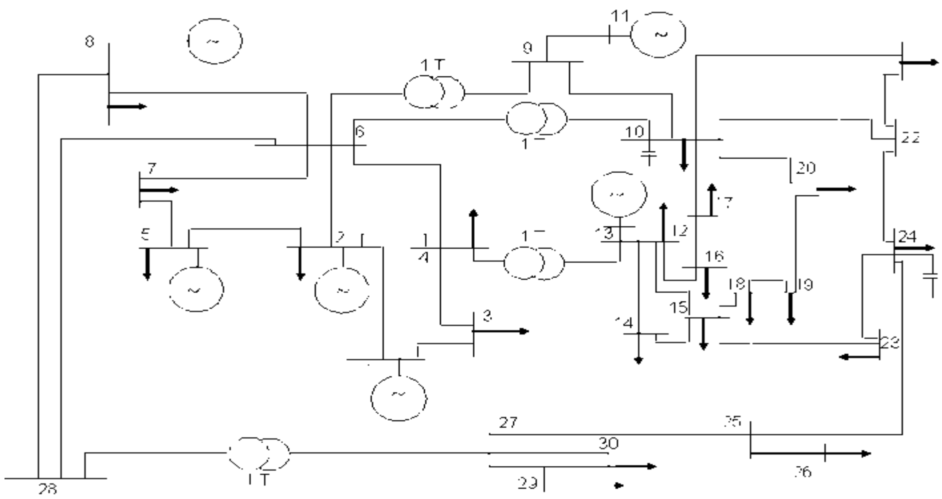

Figure 1: IEEE 30 Bus Test System

Fig 1 shows the IEEE 30 bus test system. This system consists of six generator buses, 24 load buses and 41 branches of which four branches, (6, 9), (6,10), (4,12) and (27,28) are under load tap-setting transformer branches. There are totally 19 control variables. The results obtained by PSO algorithm are compared with Real Coded Genetic Algorithm. Table I shows the comparison of results between PSO and RCGA. Here control variables are bus voltage magnitudes, transformer tap settings and the capacitor values. Fig 2 shows the convergence characteristics of RCGA. Fig 3 shows the convergence characteristics of PSO. In both characteristics, generations versus fitness are plotted. By using the real coded genetic algorithm for IEEE 30 bus system, the transmission line losses are obtained as 4.9 MW and the capacitor installation costs as 915 $. By using the particle swarm optimization algorithm for IEEE 30 bus system, the transmission line losses are obtained as 4.7 MW and the capacitor installation costs as 870 $. This shows that PSO gives better results, compared to RCGA. Moreover time taken for execution is less for PSO, compared to RCGA.

Table 1: Comparison of Results between PSO and RCGA

Control variables	RCGA	PSO
V_1	1.0437 p.u	1.0500 p.u
V_2	1.0366 p.u	1.0409 p.u
V_5	1.0142 p.u	1.0258 p.u
V_8	1.0163 p.u	1.0234 p.u
V_{11}	1.0428 p.u	1.0796 p.u
V_{13}	0.9884 p.u	1.0023 p.u
t_{11}	1.0250 p.u	1.0323 p.u
t_{12}	1.0250 p.u	1.0036 p.u
t_{15}	1.0250 p.u	1.0086p.u
t_{36}	0.9500 p.u	0.9250 p.u
Q_{C10}	0.5266 MVAR	4.8516 MVAR
Q_{C12}	1.6563 MVAR	3.8004 MVAR
Q_{C15}	1.2953 MVAR	2.7015 MVAR
Q_{C17}	2.2731 MVAR	4.1661 MVAR
Q_{C20}	1.9439 MVAR	3.2033 MVAR
Q_{C21}	2.6051 MVAR	2.4375 MVAR
Q_{C23}	2.3100 MVAR	3.0383 MVAR
Q_{C24}	3.4029 MVAR	1.9391 MVAR
Q_{C29}	2.3230 MVAR	4.7521MVAR
Transmission line losses	4.9 MW	4.7 MW
Capacitor installation costs	915 $	870 $

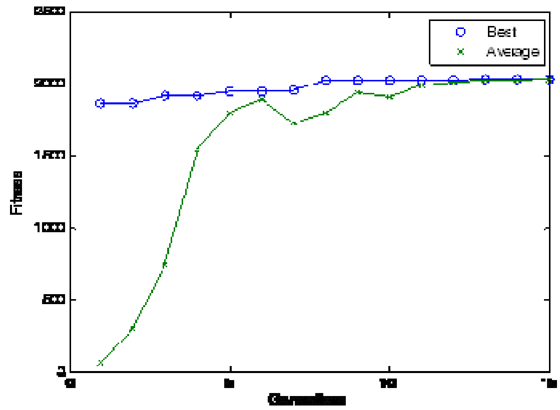

Figure 2: RCGA Convergence Characteristics

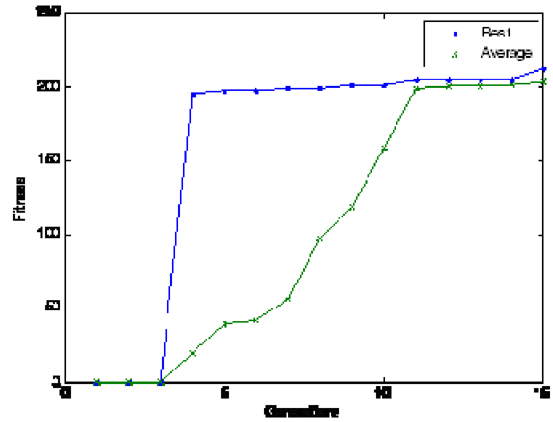

Figure 3: PSO Convergence Characteristics

Conclusions

In this paper, a multi-objective model and a PSO approach to provide decision support in the capacitor location and sizing have been presented. This formulation takes into account two objective functions: minimizing transmission line losses and minimizing capacitor installation costs. The results obtained by particle swarm optimization algorithm are compared with the real coded genetic algorithm. By comparing both the results, PSO gives better optimal solutions than RCGA. In future, any hybrid optimization algorithm will be used for reactive power compensation.

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