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Optimal Power Flow using Genetic Algorithm andParticle Swarm Optimization

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ABSTRACT

In this work, Particle Swarm Optimizationand Genetic algorithm for the solution of the optimal power flow (OPF) is studied. Traditionally, classical optimization methods were used to effectively solve OPF. But more recently due to incorporation of Flexible A.C. Transmission System (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 methods (GA etc) have emerged which can solve highly complex OPF problems. 26-bus system has been studied to show the effectiveness of the algorithm.

Keywords: Particle Swarm Optimization (PSO), Genetic Algorithm (GA),Flexible A.C. Transmission System (FACTS), Optimal Power Flow (OPF)

INTRODUCTION

In OPF[2,3] the main objective is to minimize the cost of meeting the load demand for the power system while satisfying all the security constraints. Since OPF is a non-linear problem, decouple of the control parameter of the FACTS device[1]is a highly nonlinear problem so that Genetic algorithm and particle swarm optimization is used as a methodology to solve. In this context, more control facilities may complicate the system operation. As control facilities influence each other, a good coordination is required in order to bring all devices to work together, without interfering with each other. It has also been noted that theOPF problem with series compensation may be a non-convex and non-linear problem, which will lead the conventional optimization method stuck into local minimum.

Genetic algorithms and Particle Swarm Optimization[9] offer a new and powerful approach to these optimization problems made possible by the increasing availability of high performance computers. These algorithms have recently found extensive applications in solving global optimization searching problems when the closed-form optimization technique cannot be applied. Genetic algorithms are parallel and global search techniques that emulate natural genetic operators. The GA is more likely to converge toward the global solution because it, simultaneously, evaluates many points in the parameter space. The method is not sensitive to the starting points and capable to determining the global optimum solution to the OPF for range of constraints and objective functions. In this paper a simple genetic algorithm is applied to the problem of optimal power flow. To accelerate the processes of GAOPF, the controllable variables are decomposed to active constraints that effect directly the cost function are included in the Genetic algorithms process and passive constraints which are updating using a conventional load flow program.

PROBLEM FORMULATION

The economic dispatch problem [12] is to simultaneously minimize the overall cost rate and meet the load demand of a power system. The power system model consists of n generating units already connected to the system. The economic dispatch problem can be expressed as the most commonly used objective in the OPF problem[14,15] formulation is the minimization of the total cost of real power generation. The individual costs of each generating unit are assumed to be function, only of active power generation and are represented by quadratic curves of second order. The objective function for the entire power system can then be written as the sum of the quadratic cost model at each generator.

$$Min \sum_{i=1}^{n} F_i(P_i)$$
$$F_i(P_i) = (a_i + b_i P_i + c_i P_i^2) \quad (1)$$

where a_i, b_i and c_i are the cost coefficients of i-th generator and n is the number of generators committed to the operating system. P_i is the power output of the i-th generator. The economic dispatch problem subjects to the following constraints

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

$$\sum_{i=1}^{n} P_i - P_D - P_L = 0 \quad (3)$$

$$where P_L = [P_1, P_2, \ldots P_n] \begin{bmatrix} B_{11} & \cdots & B_{1n} \\ \vdots & \ddots & \vdots \\ B_{1n} & \cdots & B_{nn} \end{bmatrix} \begin{bmatrix} P_1 \\ \vdots \\ P_n \end{bmatrix} + [P_1, P_2, \ldots P_n] \begin{bmatrix} B_{01}/2 \\ \vdots \\ B_{0n}/2 \end{bmatrix} + B_{oo} \quad (4)$$

where $P_{i(min)}$ and $P_{i(max)}$ are the minimum and maximum generating limits respectively for the plant i. P_D is the load demand and P_L represents the transmission losses. B_{ii} and B_{oi} are the loss coefficients.

PARTICLE SWARM OPTIMIZATION

The Particle Swarm Optimization (PSO) algorithm[6,7], as one of the latest algorithms inspired from the nature, was introduced in the mid 1990s. Since then, it has been utilized as an optimization tool in various applications, ranging from biological and medical applications to computer graphics and music composition. Since conventional computing algorithms are not capable of solving real-world problems because of sometimes having an inflexible structure mainly due to incomplete or noisy data and some multi-dimensional problems, Natural computing paradigms seem to be a suitable replacement in solving such problems. These paradigms consist of simple elements that can solve complicated problems of the real world when working together.

Ontogeny group is associated with the algorithms in which the adaptation of a special organism to its environment is happened. The algorithms like PSO and Genetic Algorithms (GA) are of this type and in fact, they have a cooperative nature in comparison with other types. The advantages of above-mentioned categories can be noted as their ability to be developed for various applications and not needing the previous knowledge of the problem space. Their drawbacks include no guarantee in finding an optimum solution and high computational costs in completing Fitness Function (F.F.) in intensive iterations. Among the aforementioned paradigms, the PSO algorithm seems to be an attractive one to study since it has a simple but efficient nature added to being novel. It can even be a substitution for other basic and important evolutionary algorithms.

The most important similarity between these paradigms and the GA is in having the seam interactive population. This algorithm, compared to GA, has a faster speed in finding the solutions close to the optimum and it is faster than GA in premature convergence.

DESCRIPTION OF PSO

In 1995, Kennedy and Eberhart[5,8] first introduced the PSO method, motivated with the social behavior of organisms such as fish schooling and bird flocking. PSO, as an optimization tool, provides a population based search procedure in which individuals called particles change their positions (states) with time. 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 neighboring particles, making use of the best position encountered by itself and its neighbors. The swarm direction of a particle is defined by the set of particles neighboring the particle and its history experience.

Let x and v denote a particle coordinates (position) and its corresponding flight speed (velocity) in a search space, respectively. Therefore, the i^{th}particle is represented as $x_i=(x_{i1}+x_{i2}\ldots\ldots x_{id})$ in the d dimentional space. The best previous position of the i^{th} particle is recorded and represented as $pbest_i= (pbest_{i1}, pbest_{i2}\ldots\ldots pbest_{id})$. The index of the best particle among all the particles in the group is represented by $gbest_d$. the rate of the velocity for particle i is represented as $v_i =(v_{i1}, v_{i2},\ldots,v_{id})$. The modified velocity and position of each particle can be calculated using the current velocity in distance from $pbest_{id}$ to $gbest_d$.

$$v_{id}^{(t+1)}=w.v_{id}^{(t)} + c_1*rand()*(pbest_{id}-x_{id}^{(t)}) + c_2* rand() *(gbest_d - x_{id}^{(t)})$$

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

Where:

n is the number of particles in a group.

m is the number of members in a particle.

t is the pointer of iterations.

w is the inertia weight factor.

c_1 and c_2 are two uniform random values in the range [0,1].

$v_i^{(t)}$ is the velocity of the particle i at iteration t

$v_d^{min} \leq v_{id}^{(t)} \leq v_d^{max}$

$x_i^{(t)}$ is the current position of particle i at iteration t.

in the above procedures, the parameter v^{max} determines the resolution, or fitness, with which regions are to be searched between the present position and the target position. If v^{max} is too high, particles might fly past good solutions. If v^{max} is too small, particles may not explore sufficiently beyond local solutions. In many experiences with PSO, v^{max} was often set at 10-20% of the dynamic range of the variable on each dimention.

The constants c_1 and c_2 represent the weighing of the stochastic acceleration terms that pull each particle toward the pbest and gbest positions. Low values allow particles to roam far from the target regions before being tugged back. On the other hand, high values result in abrupt movement towards, or past, target regions. Hence the acceleration constants $c_1$and c_2 were often set to be 2.0 according to past experiences.

Suitable selection of inertia weight w provides a balance between global and local explorations, thus requiring less iteration on average to find a sufficiently optimal solution. As originally developed, w often decreases linearly from about 0.9 to 0.4 during a run. In general, the inertia weight w is set according to the following equation:

$$w= w_{max}- \frac{(w\max - wmin)}{itermax} x \text{ iter}$$

where:

w_{max} is the initial weight, w_{min} is the final weight, iter is the current iteration number, and $iter_{max}$ is the maximum iteration number.

GENETIC ALGORITHM

Genetic algorithms[10] are search algorithms based on the process of biological evolution. In genetic algorithms, the mechanics of natural selection and genetics are emulated artificially. The search for a global optimum to an optimization problem is conducted by moving from an old population of individuals to a new population using genetics-like operators. Each individual represents a candidate to the optimization solution. An individual is modeled as a fixed length string of symbols, usually taken from the binary alphabet. An evaluation function, called fitness function, assigns a fitness value to each individual within the population. This fitness value is measure for the quality of an individual. The basic optimization procedure involves nothing more than processing highly fit individuals in order to produce better individuals as the search progresses. A typical genetic algorithm cycle involves four major processes of fitness evaluation, selection, recombination and creation of a new population.

Although the binary representation is usually applied to power optimization problems, in this paper, we use the real valued representation scheme for solution. The use of real valued representation in the GA is claimed by Wright to offer a number of advantages in numerical function optimization over binary encoding. Efficiency of the GA is increased as there is no need to convert chromosomes to the binary type; less memory is required as efficient floating-point internal computer representations can be used directly; there is no loss in precision by discretisation to binary or other values; and there is greater freedom to use different genetic operators. For the real valued representation, the *k*-th chromosome

C_k can be defined as follows:

$C_k = [\ P_{k1}, P_{k2}, \ldots, P_{k1}]\ k = 1, 2, \ldots, popsize$

Where*popsize*means population size and Pki is the generationpower of the *i*-th unit at *k*-th chromosome.

Reproduction involves creation of new offspring from themating of two selected parents or mating pairs. It is thoughtthat the crossover operator is mainly responsible for the globalsearch property of the GA. We used an arithmetic crossoveroperator that defines a linear combination of twochromosomes. Two chromosomes, selected randomly forcrossover, C_i^{gen} and C_j^{gen} may produce two offspring, C_i^{gen+1} and C_j^{gen+1} may produce two offspring, $C_i^{gen+1\ and}$ C_j^{gen+1}, which is a linear combination of theirparents i.e.,

$C_i^{gen+1} = a.C_i^{gen} + (1\text{-}a)C_j^{gen}$

$C_j^{gen+1} = (1\text{-}a).C_i^{gen} + a.C_j^{gen}$

where*a* is a random number in range of [0, 1].

The mutation operator is used to inject new genetic materialinto the population and it is applied to each new structureindividually. A given mutation involves randomly alteringeach gene with a small probability. We generate a random realvalue which makes a random change in the *m*-th elementselected randomly of the chromosome.

The objective function[11] is used to provide a measure of howindividuals have performed in the problem domain. In the caseof a minimization problem, the fitindividuals will havethe lowest value of the associated objective function. Thefitness function is normally used to transform the objectivefunction value into a measure of relative fitness. The fitnessfunction is defined as

Fit(x) = g (f (x))

where f(x) is the objective function, g transforms the value ofthe objective function to non-negative number.

An elitist which GA search is used guarantees that the bestsolution so far obtained in the search is retained and used in the following generation, n and thereby ensuring no good solution already found can be lost in search process.

APPLICATION STUDY

This paper proposes an application of genetic algorithm and Particle Swarm Optimization to solve the Economic Dispatch problems. In this paper transmission losses are included by calculating the B coefficients of transmission losses. The results are taken on 26 bus system (fig-2) to test the effectiveness of the proposed method. The system consists of 46 lines and 6 generators, bus one is taken as reference bus, others are taken as load buses. The initial angle at respective buses is assumed as zero degree.

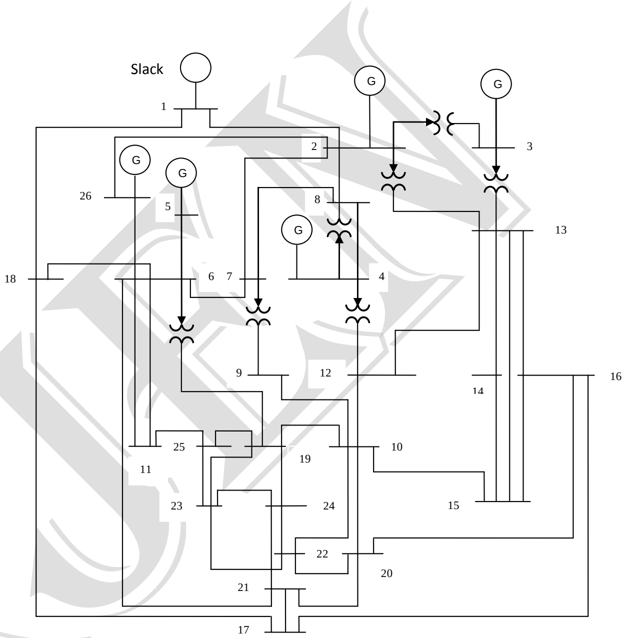

Fig-2: 26-bus power system network

Generator Operating Costs in \$/h, with P_i MW are as follows

$C_1 = 240 + 7.0P_1 + 0.0070P_1^2$
$C_2 = 200 + 10.0P_2 + 0.0095P_2^2$
$C_3 = 220 + 8.5P_3 + 0.0090P_3^2$
$C_4 = 200 + 11.0P_4 + 0.0970P_4^2$
$C_5 = 220 + 10.5P_5 + 0.0080P_5^2$
$C_{26} = 190 + 12.0P_{26} + 0.0075P_{26}^2$

Generator	Minimum (MW)	Maximum (MW)
1	100	500
2	50	200
3	80	300
4	50	150
5	50	200
26	50	120

ECONOMIC DISPATCH USING GENETIC ALGORITHM INCLUDING TRANSMISSION LOSSES

TO FIND THE LOSS COEFFICIENTS

- First a power solution is obtained for the initial operating state. This provides the voltage magnitude and phase angles at all buses.
- From these results load currents are obtained.
- Bus matrix is found.
- Transformation matrices are found.
- Finally B coefficients are evaluated.

The B coefficients are the functions of the system operating state. If a new scheduling of generation is not drastically different from the initial operating condition, the loss coefficients may be assumed constant.
B =

0.0014	0.0015	0.0009	-0.0001	-0.0004	-0.0002
0.0015	0.0043	0.0050	0.0001	-0.0008	-0.0003
0.0009	0.0050	0.0315	-0.0000	-0.0020	-0.0016
-0.0001	0.0001	-0.0000	0.0029	-0.0006	-0.0009
-0.0004	-0.0008	-0.0020	-0.0006	0.0085	-0.0001
-0.0002	-0.0003	-0.0016	-0.0009	-0.0001	0.0176

B0 = -0.0002 -0.0008 0.0067 0.0001 0.0000 -0.0012

B00 =0.0056

Total system loss = 15.53 MW

Total generation cost = 16760.73 $/h

Optimal Dispatch using Genetic algorithm

Genetic algorithm is used to calculate optimum value of generation taking the condition $P=P_D + P_L$

P1 = 444.8835
P2 = 172.5925
P3 = 268.7010
P4 = 123.8442
P5 = 173.4232
P6 = 95.0846
Total generating cost = 15483 $/h

Thus it can also be seen that the total generation cost per hour comes down by 16760.73 - 15483 = 277.73 $/h as a result of optimal dispatch using genetic algorithm.

Optimal Dispatch using Particle Swarm Optimization.

Particle Swarm Optimization is used to calculate optimum value of generation taking the condition $P=P_D + P_L$

P1 = 472.10
P2 = 171.96
P3 = 193.77
P4 = 150.00
P5 = 196.38
P6 = 103.73
Total generating cost = 15599 $/h

Thus it can also be seen that the total generation cost per hour comes down by 16760.73 - 15599 = 161.73 $/h as a result of optimal dispatch using Particle Swarm Optimization.

V. CONCLUSION

In this paper anew method with genetic algorithm and Particle Swarm Optimization is presented to solve the optimal power flow problem of power system. Application of these techniques to Optimal Power Flow has been explored and tested. The simulation results show that this simple algorithm can give a good result using only simple modifications. A case study on IEEE test system shows the potential for application of GA& PSO to determine optimal dispatch of generation with FACTS devices.

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