A New Concept of Power Flow Analysis

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Abstract – The solution of the power flow is one of the most important problems in electrical power systems. These traditional methods such as Gauss-Seidel method and Newton-Raphson (NR) method have had drawbacks up to now such as initial values, abnormal operating solutions and divergences in heavy loads. In order to overcome theses problems, the power flow solution incorporating genetic algorithm (GA) is introduced in this paper. General operator of genetic algorithm, arithmetic crossover, and non-uniform mutation operator of GA are suggested to solve the power flow problem. While abnormal solution cannot be obtained by a NR method, multiple power flow solution can be obtained by a GA method. With a heavy load, both normal solution and abnormal solution can be obtained by a proposed method. In this paper, a floating number representation instead of the binary number representation is introduced for accuracy. Simulation results have been compared with traditional methods.

Keywords: Newton-Raphson method, Power Flow problem

1. Introduction

In a power system, power flows from generating centers to load centers. In this process, investigation is required in regards to bus voltages and amount of power flow through transmission lines. Power flow study aims at reaching to the steady state solution of complete power networks. Power flow study is performed during the planning of a new system or the extension of an existing system. It is also necessary to evaluate the effect of different loading conditions of an existing system [1]. Power flow equations represent a set of non-linear simultaneous algebraic equations, for which there has been no general solution until now. There are two famous methods, the Gauss-Sieidel method and the Newton-Raphson Method (NR). Genetic algorithms (GA) application to power systems is found in areas such as economic dispatch, power system planning, reactive power allocation, and power flow problem. In this paper the power flow problem will be described with its solution using the NR Method, which has been widely used in the last decade in the study of power flow in power systems. The NR method has rapid convergence characteristics. However, it has the following limitations

a) The performance is highly dependent on initial values in the power flow problem.

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b) It's difficult to determine abnormal operating solution. In general, the power flow equation has multiple solutions, one is the normal solution and the others are abnormal solutions. Since any extra loading imposed on the system beyond the limit can lead to voltage collapse, the estimation of steady-state operating limit is important.
c) The solution can be diverged when the power system is loaded extremely. When the power system is operating very close to its ceiling point, the Jacobian of the power flow equation set tends to be singular.

To overcome these limitations and difficulties of the conventional NR method, the proposed floating number GA representation is introduced. The reason is that

a) The GA optimization process is almost insensitive to initial settings of the solution variable.
b) It has the ability to determine the multiple power flow solutions.
c) When the power system is highly stressed, the GA algorithm is capable of finding the power flow solution because this process does not require the formation of Jacobian matrix.

The proposed method uses arithmetical crossover, non-uniform mutation, and top selection to produce offspring from parents. It is applied to a 5-bus system and 11-bus system. The output result has been compared with that of the NR method. From the compared result, it is observed that the proposed method shows its efficiency in solving the power flow problem.

2 Genetic Algorithm Approach

Over the last decade, a few research papers have been introduced to the GA as a tool for solving the power flow problem. Ref. [3] uses the simple GA to calculate multiple power flow solution. Binary number representations were used to represent the chromosome. To increase the speed of the problem a genetic algorithm with a sharing scheme has been introduced in [3].

In this paper, the technique represented in [3] will be modified to use the floating number chromosome representation instead of the binary number representation. It is more practical for large systems to use real number representation. It has been widely confirmed that real number encoding performs better than binary or Gray encoding for function optimizations and constrained optimizations [4].

2.1 Genetic Algorithm construction

A genetic algorithm is a simulation of evolution where the rule of survival is applied to a population of individuals.

The basic genetic algorithm is as follows:

1. Create an initial population.
   (Usually a randomly generated string)
2. Evaluate all individuals.
   (Apply some function or formula to the individuals)
3. Select a new population from the old population based on the fitness of the individuals as given by the evaluation function.
4. Apply some genetic operators (mutation & crossover) to members of the population to create new solutions.
5. Evaluate these newly created individuals.
6. Repeat steps 3-6 (one generation) until the termination criteria has been satisfied (usually performed for a certain fixed number of generations).

2.2 Chromosome Representation

Each element (variables values) in the population is called ***Chromosome***, which consists of Genes. Each group of Genes represents a variable. A chromosome is made up of a sequence of genes. An element could consist of binary digits, floating point numbers, integers, symbols (i.e. A, B, C,....) and matrices.

2.3 Genetic operations

2.3.1 Crossover

• <u>one point crossover operator</u>

Generate a random number "pos" in the range [1..m-1]. The new chromosome will be:-

$x_i' = x_i$ if $i < pos$ and y_i otherwise
$y_i' = y_i$ if $i < pos$ and x_i otherwise

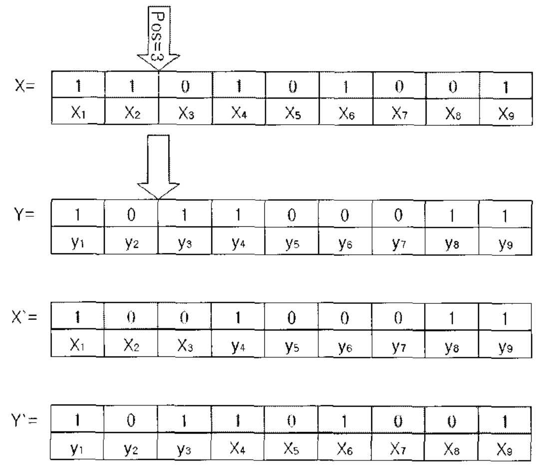

Fig. 1. Crossover of X and Y chromosomes.

• <u>Arithmetical crossover operator</u>

Arithmetical genetic operators will be used to produce children by applying them to parents. For each pair, chromosomes (X_1, X_2) in the population draw a random number between 0 and 1. If this number is less than or equal to crossover probability, this pair is eligible for crossover. The offspring for these two parents are:

$Y_1=\lambda_1.X_1 + \lambda_2.X_2,$ $\qquad Y_2=\lambda_1.X_2 + \lambda_2.X_1$

A convex crossover is used i.e. $\lambda_1 + \lambda_2 = 1, \lambda_1 > 0, \lambda_2 > 0$. Each time, crossover will be applied to pick a random number between 0 and 1 as a value for λ_1.

2.3.2 Mutation

• <u>Uniform mutation</u>

Assume a value for the probability of mutation Pm. Each bit each chromosome in the new population generates a number r from [0 ... 1]. If $r < p_m$ flips that bit from 1 to zero or zero to one in case of binary representation. In case of real number representation, choose a random number for the selected gene between variables of lower and upper bounds.

• <u>Non-uniform mutation</u>

Each gene in each chromosome picks a random number between 0 and 1. If this number is less than or equal to mutation probability, this gene is eligible for mutation. For a given parent X, the element X_k is selected for mutation. Produced offspring is

$X' = [x_1, x_2, \ldots\ldots, x'_k, \ldots\ldots, x_n]$,
where x'_k is randomly selected from two possibilities

$$X'_k = X_k + \Delta(t, X_k^u - X_k) \quad \text{or} \quad X'_k = X_k - \Delta(t, X_k - X_k^L)$$

Where X_K^U and X_K^L are the upper and lower bounds for X_k.

The function Δ(t,n) returns a value in the range [0 , n] such that the value of Δ(t,n) approaches to 0 as t increases.

$$\Delta(t,n) = n.r.\left(1-\frac{t}{T}\right)^b$$

where

t is the current generation number

T is the maximum generation number

r is a random number from [0,1]

b is a parameter determining the degree of non uniformity.

2.3.3 Selection

Selection is the process used to choose new generation population from the old population. There are many strategies for the selection process; among them the one used in the proposed algorithm is the Top Selection Method. Assume that population size equals to 'pop#' and the number of offspring produced after applying the previously mentioned crossover and mutation operators will be "child #". Top selection means that the new generation will be the highest fitness value chromosome. Hence, new generation consists of pop # chromosome chosen from the previous pop # parents and child # children. Evaluate each chromosome v_i (i= 1⇒pop_size) using the function f. So, for each chromosome, calculate the fitness value eval(v_i). Find the total fitness of the population. Calculate the probability of a selection p_i for each chromosome v_i. Calculate a cumulative probability q_i for each chromosome v_I. Save the best value of f in this population.

1. The selection process is based on spinning the roulette wheel pop_size times. Each time we select a single chromosome for the new population.
2. Generate a random number r from the range [0..1].
3. If $r < q_1$ then select v_1 otherwise select the i-th chromosome v_i such that:
   $q_{i-1} < r \le q_i$
4. Some chromosomes will be selected more than once. The best chromosome gets more copies, the average stays even, and the worst dies off.

3. Genetic Algorithm in Power Flow Problem

3.1 Formulation of Power Flow Problem

In this section the power flow problem will be introduced and its solution will be found using the NR method. The conventional power flow problem consists of the calculation of power flow parameters for a specified terminal or bus.

A single-phase representation is adequate since power systems are usually balanced. Associated with each bus, there are four quantities: active and reactive powers, and the voltage magnitude and phase angles (voltage angles). Buses in the power system can be classified into three categories:

1. Slack bus: Its voltage magnitude V and voltage angle δ are known. Its active power P and reactive power Q are unknown.
2. Generator buses: P, V are known and Q, δ are unknown.
3. Load buses: P, Q known and V, δ are unknown.

Generator buses are also known as PV bus and load buses as PQ bus. The bus admittance matrix Y_{bus} is in order of (n x n) where n is the number of buses. The diagonal entries of the Y_{bus} (Y_{jj}) are founded by summing the primitive admittance of lines and ties connected to bus # j. The off diagonal entries Y_{ij} are the negative of admittance of lines between buses i and j. If there is no line between i and j, this term is zero.

The basic power flow problem can be solved by NR method using a set of non-linear equations to express specified active and reactive power in terms of bus voltages [2]. These equations in their polar form can be introduced as follows:

The complex power at bus *i* is given by:

$$P_i - jQ_i = E_i^* I_i \tag{1}$$

Since

$$I_i = \sum_{j=1}^{n_b} (Y_{ij} * E_j) \tag{2}$$

where n_p: total number of buses then

$$P_i - jQ_i = E_i^* \sum_{j=1}^{n_b} (Y_{ij} * E_j) \tag{3}$$

In polar co-ordinates:

$$E_P = |E_P| e^{j\delta_P} \tag{4}$$

$$Y_{pq} = |Y_{pq}| e^{j\theta_{pq}} \tag{5}$$

Substituting in equation (3)

$$P_P - jQ_P = \sum_{q=1}^{n_P} |E_P E_q Y_{pq}| e^{-j(\delta_P - \delta_q - \theta_{pq})} \tag{6}$$

Then

$$p_p = \sum_{q=1}^{nb} \left| E_p E_q Y_{pq} \right| \cos(\delta_p - \delta_q - \theta_{pq}) \qquad (7)$$

$$Q_p = \sum_{q=1}^{nb} \left| E_p E_q Y_{pq} \right| \sin(\delta_p - \delta_q - \theta_{pq}) \qquad (8)$$

In rectangular co-ordinates, the power flow problem can be represented as a nonlinear optimization problem

$$P_i = E_i \sum_{j=1}^{N} (G_{ij} E_j - B_{ij} F_j) + F_i \sum_{j=1}^{N} (G_{ij} F_j + B_{ij} E_j)$$

Where
$i = 1,2,3,---,N$

$$Q_i = F_i \sum_{j=1}^{N} (G_{ij} E_j - B_{ij} F_j) - E_i \sum_{j=1}^{N} (G_{ij} F_j + B_{ij} E_j)$$

Where $i = 1,2,3,---,N$ (9)

Where G_{ij} and B_{ij} are the (i, j)th element of the admittance matrix. E_i and F_i are real and imaginary parts of the voltage at node i.

When node i is a PQ node, the mismatches in real and reactive powers are given by

$$\Delta P_i = P_{i(schadule)} - P_i \qquad (10)$$

$$\Delta Q_i = Q_{i(schadule)} - Q_i \qquad (11)$$

in which $P_{i(schduled)}$ and $Q_{i(scheduled)}$ are specified active and reactive power.

When node i is a PV node, the mismatches in voltage magnitude are given by

$$\Delta P_i = P_{i(schadule)} - P_i \qquad (12)$$

$$\Delta V_i = V_{i(schadule)} - V_i \qquad (13)$$

in which $V_{i(schduled)}$ is specified voltage magnitude. V_i is calculated nodal voltage at PV node i and given

$$V_i = \sqrt{E_i^2 + F_i^2} \qquad (14)$$

When solving the power flow problem, we can treat the power flow problem as an optimization problem. The squared mismatches of active and reactive powers at network nodes and squared mismatches of nodal voltages are to be minimized by two conditions. The one is the power balance requirements at the buses and the other is the voltage magnitudes at generator buses. The problem can be solved as an optimization problem, in which an objective function H is to be minimized.

Objective function can be defined as the sum of square of the power mismatches and the voltage mismatches as in

$$H = \sum_{i=2}^{nb} \Delta P_i^2 + \sum_{i=2}^{nb-ng} \Delta Q_i^2 + \sum_{i=2}^{ng} \Delta V_i^2 \qquad (15)$$

where
nb represents the total number of system buses
ng represents the number of voltage controlled buses

The objective function results from the summation of squares of active and reactive power mismatch. It is obvious that the optimal value for this function is 0. The unknown variables are:

E_P for all buses except the slack bus and voltage controlled buses in which E_p is known.

δ_p for all buses except the slack bus.

These variables are allowed to lie within certain lower and upper bounds.

$E_p \in [E_{pmax}, E_{pmin}]$
$\delta_p \in [\delta_{pmax}, \delta_{pmin}]$

3.2 Disadvantage of Newton-Raphson (NR) method though simple example

The examples of Fig. 2 and Fig. 3 are shown in that the solution of the N-R method can be diverged when the power system is loaded extremely. The reason is that the Jacobian of the power flow equation tends to be singular. Table 1 presents the result and determinant of normal case.

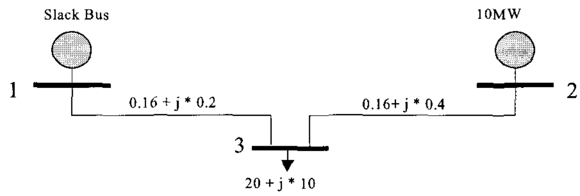

Fig. 2. Simple system

However, the next example shows the change of determinant of the Jacobian matrix. When load is stressed, the Jacobian of the power flow equation tends to be singular.

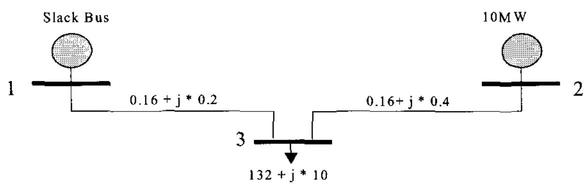

Fig. 3. The change of determinant of Jacobian matrix

Table 1. The result and determinant of normal case.

Bus	Voltage		Generation		Load	
#	Mae [pu]	Ang [deg]	P [MW]	Q [MVAR]	P [MW	Q [MVAR]
1	1.000	0.000	11.67	-14.47	-	-
2	1.1249	-2.871	10.00	27.94	-	-
3	1.0113	-2.634	-	-	20.00	10.00

Bus	Voltage		Generation		Load	
#	Mae [pu]	Ang [deg]	P [MW]	Q [MVAR]	P [MW]	Q [MVAR]
1	3	11.39	-14.81	0.553	0.69	-
2	3	9.44	26.55	1.114	2.78	-

• Determinant of Jacobian = 0.0084

When the load was over 133MW, the solution of N-R power flow did not converge. In the next section, GA will be introduced to solve the power flow problem.

3.3 Genetic Algorithm representation in power flow problem

Real numbers will be used to represent genes of the chromosome. Each chromosome consists of 2*nb-2-ng genes. The first np-1 gene represents the voltage angle of buses from bus #2 to bus # np. The remaining genes represent voltage magnitude from bus #2 to bus # np excluding ng voltage controlled buses. So a single chromosome will be as shown in Table 2. It is assumed that voltage controlled buses will be located at the last ng numbers from the nb numbers of the system buses.

Table 2. Chromosome representation

Voltage angles genes							Voltages magnitudes genes					
δ_1	δ_2		δ_i			δ_{nb}	E_2	E_3		E_i		E_{nb-ng}

3.3.1 Initialization

The algorithm initial steps can be summarized as follows:

1. Read all power system data from a text file describing system topology and data.
2. Choose the values of population size, crossover probability, mutation probability, and maximum generation numbers.
3. For each chromosome in the initial population, a random real number will be chosen for each chromosome gene. For genes representing voltage angles choose a random value for $\delta_p \in [\delta_{pmax}, \delta_{pmin}]$. For each gene representing voltage magnitude choose a random value for $E_p \in [E_{pmax}, E_{pmin}]$.
4. Evaluate each chromosome by calculating its fitness value as described in the next section.

3.3.2 GA Evaluation Function

The power flow objective function to be minimized, F is transformed and normalized to a fitness function to be maximized [3]:

$$F = \frac{M}{M+H}$$

where M is a small constant for amplifying the fitness value.

Thus, when the objective function decreases to nearly zero, the fitness approaches one.

4. Numerical Example

4.1 Case 1

A PASCAL program has been developed based on the proposed GA. The proposed method has been tested by applying it to the 5 bus system [3] shown in Fig. 4. Bus # 1 is the slack bus with E_1 =1.06, δ_1=0 with a voltage controlled bus 5, V_5= 1, and P_5=0.4. Buses 2, 3, and 4 are load buses as presented in Table 3.

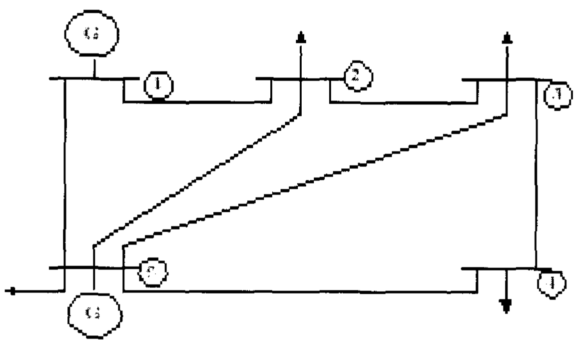

Fig.4. The simple 5 bus power system

Table 3. The data of case 1

(a) The real and reactive power

P_2	Q_2	P_3	Q_3	P_4	Q_4
0.45	0.15	0.4	0.05	0.6	0.1

(b) Impedance

Bus p-q	Impedance(pu)
1-2	0.08+j0.24
1-5	0.02+j0.06
2-3	0.01+j0.03
2-5	0.06+j0.18
3-4	0.08+j0.24
3-5	0.06+j0.18
4-5	0.04+j0.12

With attached load PL_5 = 0.2, QL_5= 0.1, the scheduled active power for bus 5 is P_5=0.4-0.2=0.2.

Table 4. The GA parameter of case 1

Pop	Pc	Pm	Max generation
30	0.7	0.5	1000
E_{max}	E_{min}	δ_{max}(radian)	δ_{min}(radian)
1.1	0.9	0.17453	- 0.17453

The best chromosomes in generations # 1, 100, 500, and 999 are shown in Table 5.

Table 5. The best chromosomes in generations

Iter.	1	…	100	…	500	…	999
δ_2	-0.0255		-0.0878		-0.0797		-0.0792
δ_3	-0.0447		-0.0926		-0.0852		-0.0847
δ_3	-0.0322		-0.1137		-0.0365		0.0994
δ_4	0.0015		-0.0440		-0.0365		0.0361
E_2	1.1144		0.9706		0.9801		0.9805
E_3	1.1061		0.9683		0.9767		0.9771
E_4	1.1052		0.9589		0.9658		0.9661
Fit.	0.0179		0.7885		0.9997		0.9999

- Mismatch in case of NR: $1.5*10^{-8}$
- Mismatch in case of GA: $1.5*10^{-9}$ and $3.1*10^{-12}$

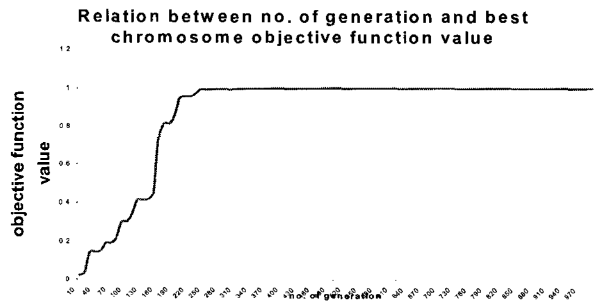

Fig. 5. Objective function convergence according to number of generation

Relation between generation No. and the best chromosome fitness value at this generation is given in Fig. 5. The solution after the number of 1000 competition is shown in Table 6, which is the GA and NR method. It can be seen that genetic algorithms have reached an accurate solution for the problem. The CPU time for GA (15.7 sec) was higher than that of NR method (3 sec).

Table 6. Results comparison using GA and using NR

Variable	GA solution	NR Method
δ_2	-0.079172	-0.079164
δ_3	-0.084717	-0.084709
δ_3	-0.099362	-0.09935
δ_4	-0.036090	-0.036085
E_2	0.980541	0.9805
E_3	0.9771	0.9771
E_4	0.96616	0.96617

4.2 Case 2

GA will be superior to the NR method when it cannot converge. Also there is an advantage of GA over NR in that the NR method must begin by initial solution near the exact solution. This is not the case in GA where the initial solution is generated randomly within variable limits. By using GA it is also possible to format the problem as a non-linear constrained optimization problem to include system restrictions on transmission capacity and reactive power production. The 11-bus test system [10] is applied. Bus 1 is slack bus at voltage level of 1.05 p.u. and bus 5 and bus 9 are PV buses with target voltage of 1.05 p.u. 1.0375 p.u., respectively.

The normal solution of light load is the same as the NR method. The mismatch is 0.007487. The GA parameters have been used as pop=50, pc=0.50000, and pm=0.60000.

Table 7. The normal solution in light-load case

bus #2 voltag mag	1.10769	Angle	-0.53176
bus #3 voltag mag	1.12754	Angle	-0.66628
bus #4 voltag mag	1.12285	Angle	-0.56919
bus #5 voltag mag	1.05000	Angle	0.04873
bus #6 voltag mag	1.14893	angle	-0.71141
bus #7 voltag mag	1.09894	angle	-0.32858
bus #8 voltag mag	1.07628	angle	-0.12755
bus #9 voltag mag	1.03750	angle	0.26762
bus #10 voltag mag	1.06808	angle	-0.09614
bus #11 voltag mag	1.12035	angle	-0.48442
for slack bus real power = 0.12650 reactive power = -4.80083 reactive power for voltag control bus #10 =-0.10005 reactive power for voltag control bus #11 =0.05596			

Table 8. The abnormal solution in light-load case

Bus #2 voltag mag	0.74495	angle	-0.15913
bus #3 voltag mag	0.67148	angle	-0.77645
bus #4 voltag mag	0.45346	angle	-2.06356
bus #5 voltag mag	1.05000	angle	-4.42400
bus #6 voltag mag	0.66909	angle	-1.71755
bus #7 voltag mag	0.97426	angle	-4.88679
bus #8 voltag mag	1.00089	angle	-5.27063
bus #9 voltag mag	1.03750	angle	-5.57574
bus #10 voltag mag	0.83584	angle	-4.40738
bus #11 voltag mag	0.02944	angle	-0.24095
for slack bus real power = 4.90154 reactive power = 21.39225 reactive power for voltag control bus #10 =2.63950 reactive power for voltag control bus #11 =-2.08802 reactive power for voltag control bus #11 =0.05596			
object function:=0.005887			

Table 9. The output results for power flow calculations

bus #2 voltag mag.	1.01953	angle	-6.40029
bus #3 voltag mag.	1.01260	angle	-9.43931
bus #4 voltag mag.	1.03106	angle	-7.23310
bus #5 voltag mag.	1.05000	angle	7.14732
bus #6 voltag mag.	1.03827	angle	-4.15312
bus #7 voltag mag.	1.00704	angle	-6.69516
bus #8 voltag mag.	1.00615	angle	-2.16692
bus #9 voltag mag.	1.03750	angle	9.24755
bus #10 voltag mag.	1.03684	angle	1.87048
bus #11 voltag mag.	1.09203	angle	-0.37757
for slack bus real power =5.62525 reactive power =0.63476 reactive power for voltag control bus # 10 =-2.02710 reactive power for voltag control bus #11 =5.82759			
object function:=0.000577			

5. Conclusion and Further Research

This paper represents the application of genetic algorithms to solve the power flow problem. The genetic operators for this paper are arithmetical crossover, non-uniform mutation, and top selection. To test the algorithm accuracy it has been applied to 2 cases to find its power flow solution. In the 5-bus system of case 1, obtained results have been compared to those of the conventional NR method. It has been shown that the proposed GA method has reached an accurate solution. It is believed that this method will be superior over other conventional methods in the case of very large systems. In the 11-bus system of Case 2, it is shown that the GA method can solve both normal solution and abnormal solution while the NR method can't solve abnormal solution. Moreover, it is shown that the GA method can be obtained with heavy loads. However, convergence of the GA method is slower than that of the NR method. We need to develop methods to accelerate the convergence of the GA method further so that a computation speed close to that of the NR method can be achieved and to develop methods for GA to deal with the violation of generator reactive power limits.

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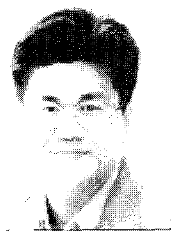

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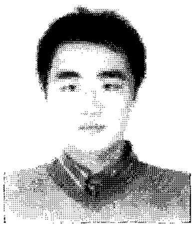

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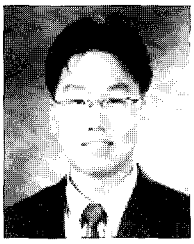

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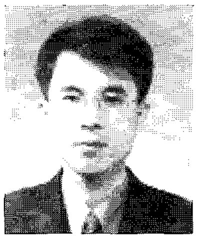

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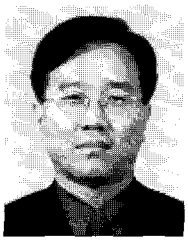

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