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유전자 알고리즘을 이용한 전력조류계산의 새로운 접근

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A New Approach for the Power Flow Solution Using Genetic-based Optimization

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Abstract

This paper presents a methodology of improving a conventional numerical model in power systems using GAs and a new GAs-based model which can directly solve the real-valued optimum in the optimization procedure. The power flow which is well known to the power engineer is solved using the proposed GAs as an alternative way of the traditional optimization method. In applying GAs to the power flow, both the notions on a way of the genetic representations and a realization of the genetic operators are fully discussed to evaluate the GAs' effectiveness.

I. Introduction

Genetic Algorithms(GAs) based on the mechanisms of evolution and natural genetics have strong points in not using the derivative information in an optimization procedure and, they provide robust search in complex spaces and an alternative to traditional optimization techniques by using directed random searches to locate optimal solutions[1][2]. The main operations of GAs are made by reproduction or selection, crossover, mutation process and, their carrying major factors are population size, chromosome length, crossover rate, mutation rate, and so on. According to the objective function how to construct, we need to prescribe its adequate fitness function. And, a variety of encoding, crossover and, mutation methodologies enable us to have diverse approaches to the problems.

Most of the power system analysis takes on highly nonlinear and computationally difficult charateristics in an optimization procedure. To solve these problems, many methodologies have been devised and modified so far. In recent years, there has been a growing concern for the above-mentioned GAs applications to the power system problems. Many papers have established the validity of GAs applicability to the power system control and operation such as *economic dispatches*[3], *reactive power optimization*[4], *thermal unit commitment*[5], *distribution network planning*[6] and, etc. But, most of these works take GAs as a presearching tool and stick to use a hybrid-type model.

In this study, we intend to enhance the numerical models in a power system with the aid of the resurgent GAs. To proceed with the study, we have decomposed the study into two topics. Frist, the propriety of the study has examined through determining the optimal points in a trigonometric objective function which contains multiple solution within a specified range. Second, the study on a large system optimization with GAs has carried out with solving the power flow. In genetic operation, each chromosome's fitness is scaled in many ways to prevent the premature convergence. And, we propose the methodology of prescribing the fitness function with an assumption that all the payoff values in the population pool depend upon the Q function defined by the Gaussian cumulative distribution function.

II. Review of GAs & Their Simple Application

Genetic Algorithms

GAs manipulate a population of potential solution to an optimization or search problem. Specifically, they operate on encoded representations of the solutions, equivalent to the genetic material of individuals in nature, and not directly on the solutions themselves. Each solution is associated with a fitness value that reflects how good it is, compared with other solutions in the population. The higher the fitness value of an individual, the higher the chances of survival and reproduction and the larger its representation in the subsequent epoch. Recombination of genetic material in GAs is simulated through a crossover mechanism that exchanges portions between strings. Another operation, called mutation, causes sporadic and random alteration of the bits of strings. Mutation also has a direct analogy from nature and plays the role of regenerating lost genetic materials. *Figure* 2.1 depicts the reproduction, crossover and mutation operations.

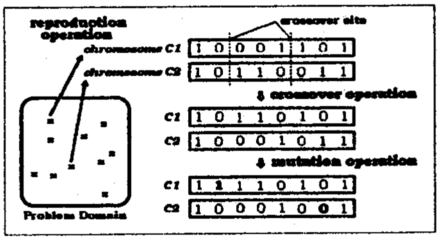

Figure 2.1 the three operations in GAs

Approaches to Trigonometric Function

For the purpose of taking prior steps to resolve the multiple solutions occurred in large systems, we have made a study of determining the optimal points in a trigonometric objective function. The objective function to be used for GAs optimization is

minimize

$$\frac{\sqrt{(1-x_1x_2\sin(500x_2))^2+(1-x_1x_2\cos(500x_1))^2}}{2} \quad (2.1)$$

subject to $-1 \le x_1 \le 1, \quad -1 \le x_2 \le 1.$

Since the described problem is kind of multi-variable optimization, the whole chromosome can be constructed by concatenating each. And then, each chromosome's representation of the variable must be converted to real numbers in an appropriate range. The decoding method used in this paper is as represented in equation (2.2).

$$r = \frac{r_{max}-r_{min}}{i_{max}-i_{min}}\, i + r_{min} \quad (2.2)$$

where, $i_{min}=0, \quad i_{max}=2^l-1$

The reproduction and crossover method used in this example are remainder stochastic sampling with replacement and two-point crossover, respectively. And, for a fitness scaling the linearization method is used[1]. As a process exit criterion, some finite number of epochs are generally used and then, the results of the fittest chromosome through the entire epoch are designated as an optimum. *Figure* 2.2 shows one of the simulation results.

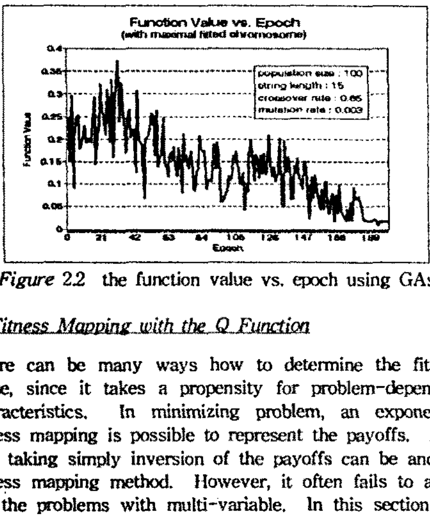

Figure 2.2 the function value vs. epoch using GAs

A Fitness Mapping with the Q Function

There can be many ways how to determine the fitness value, since it takes a propensity for problem-dependent characteristics. In minimizing problem, an exponential fitness mapping is possible to represent the payoffs. And, just taking simply inversion of the payoffs can be another fitness mapping method. However, it often fails to apply for the problems with multi-variable. In this section, we propose the methodology of prescribing the fitness function with an assumption that all the payoff values in the population pool depend upon the error function defined from Gaussian cumulative distribution function(*cdf*).

$\Phi(x)$ is the cdf of a Gaussian random variable with m=0 and σ=1 :

$$\Phi(x) = \frac{1}{\sqrt{2\pi}}\int_{-\infty}^{x} e^{-t^2/2}dt . \quad (2.3)$$

Therefore, any probability involving an arbitrary Gaussian random variable can be expressed in terms of $\Phi(x)$. Q function is defined by

$$\begin{aligned} Q(x) &= 1-\Phi(x) \quad (2.4) \\ &= \frac{1}{\sqrt{2\pi}}\int_{x}^{\infty} e^{-t^2/2}dt . \end{aligned}$$

According to the Börjesson's work[7], it has been found to give good accuracy for Q(x) over the range 0<x<∞.

As depicted in *Figure* 2.3 (b), the region is the errors or costs of the objective function and the domain is the

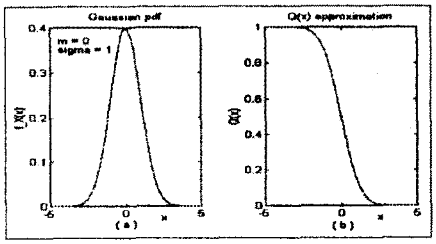

Figure 2.3 the Q(x) approximation for a fitness mapping

related fitness values. The chromosomes which has minimum errors in the population is assigned to fitness one and, the chromosome with maximum errors is mapped into fitness zero.

III. The Power Flow Using Genetic-based Optimization

In the power flow, the voltage magnitude and phase angle of the slack bus are dependent variables and, voltage magnitude of the generator bus is specified in advance. Therefore, in a n-bus system, the total number of independent variable is $2n-(2s+g)$ where, s is the number of slack bus and, g is the number of generator bus. Hence, the objective function can be formulated as follows.

minimize

$$\frac{\sqrt{\sum_{i\neq slack}(\Delta P_i)^2+\sum_{i=load}(\Delta Q_i)^2}}{N} \qquad i = 1, 2, \cdots, n \quad (3.1)$$

subject to $\Delta P_i = P_i^{specified} - P_{Ti}$

$\Delta Q_i = Q_i^{specified} - Q_{Ti}$

where, $P_{Ti} = f(V, \delta)$

$Q_{Ti} = g(V, \delta)$

N : number of independent variables

The chromosome structure can be organized, as follows. First, every independent variable is represented in one chromosome, and it is operated within one population pool. Secondly, changing the position of the independent variable is another kind of chromosome structure. In a third, taking up two population pool, the V_i (voltage magnitude) chromosome and the δ_i (phase angle) chromosome can be operated separately. Finally, with multi-population pool about the independent variable, each chromosome is operated respectively.

To quantify the effectiveness of GAs and inspect the convergence, the performance measure M is given by

$$M = \frac{\sum_{t=1}^{T} F_{max}^{t}(V, \delta)}{T} \quad (3.2)$$

where,

$F_{max}^{t}(V, \delta)$: payoff with max fitness in epoch t

T : predefined number of epoch

In words, this performance is an average evaluation of the objective function up to the current epoch. In this paper, this measure is used to determine the optimal genetic control parameter sets.

IV. The Case Study

For the case study, 5-bus and 14-bus systems are selected. *Figure* 4.1 summarizes the working of the power flow computation using GAs represented in pseudo-C code.

```
void main(void)
{
    int    epoch;

    randomize_module(independent_variables);
    for (epoch=1; epoch < MAX_EPOCH; epoch++)    {
        GAs_process_module(objective_function);
        if (acceptable_errors)
            power_flow_module(independent_variables);
    }
}
```

Figure 4.1 power flow procedure in pseudo-C code

Through the experiments, the states when the population size 300, crossover rate 1.0 or 0.8 and, mutation rate 0.001 or 0.0005 turn out to be proper. The remainder stochastic sampling without replacement where added on the elite population at the rate of 0.01 and two-point crossover occurred on the unit chromosome are used.

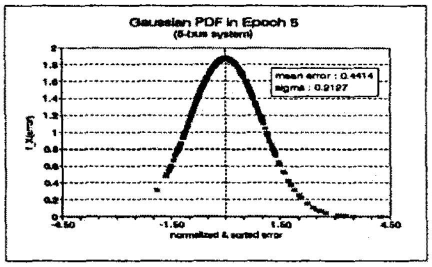

Figure 4.2 the 5th epochal population state represented in the Gaussian *pdf* (5-bus system)

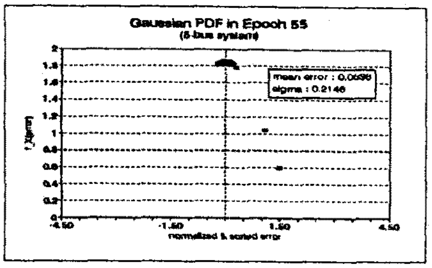

Figure 4.3 the 55th epochal population state represented in the Gaussian *pdf* (5-bus system)

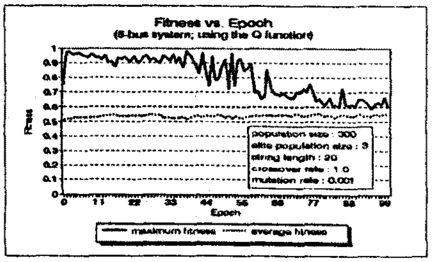

Figure 4.4 the fitness value in the 5-bus system

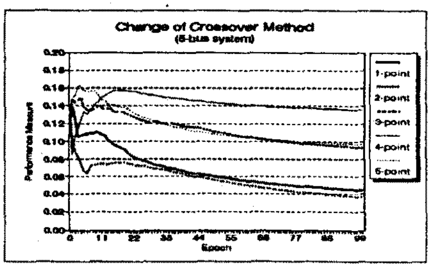

Figure 4.5 on-line performance with changing the crossover method (5-bus system)

Figure 4.2 and 4.3 show all the errors in the population pool where the randomly selected epoch have the Gaussian *pdf* characteristics. These characteristics validate the propriety of the proposed fitness mapping. In *Figure* 4.2, the negative side of the normalized and sorted errors is to be higher fitness than the average. *Figure* 4.3 implies that all the chromosomes have an identical payoff value as the GAs converge. This phenomenon seems to conform to the building blocks hypothesis.

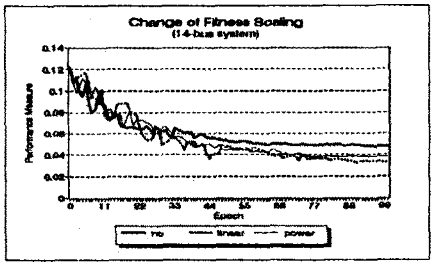

Figure 4.6 on-line performance with the fitness scaling (14-bus system)

Major concerns on GAs mechanics in this study can be enumerated, as follows. First, the effects as the modification of the chromosome structure are presented and their major results are compared. Secondly, the optimal choice of the genetic control parameter sets such as population size, chromosome length, crossover rate and, mutation rate in our problem is determined by the contemplated experiments. In a third, the effect of adding elite population is considered. Finally, the various reproduction and crossover mechanisms are compared and analyzed in order to get the best performance from the GAs.

V. Conclusions

The key issues in this paper can be summarized in two ways. First, the methodology of prescribing the fitness function using the Q function defined by the Gaussian *cdf* is presented. Secondly, the proposed method is applied to calculate the power flow in sample systems and, the results of computational experiments suggest an applicability of the GAs to the more complex power system problems.

VI. References

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