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AN ANALYSIS METHOD OF TRACER TESTS BY USING GENETIC ALGORITHMS AND ITS APPLICATION

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ABSTRACT

In the case of a tracer test analysis using a nonlinear least squares method, we should notice that the final estimates are influenced by the initial values of the reservoir properties for the estimation. In this study, we apply the genetic algorithm and that of hybridized with a nonlinear least squares method as a local search to tracer test analysis. Genetic algorithms are stochastic optimization and search algorithms. Compared with a nonlinear least squares method, genetic algorithms have some remarkable features as follows: the initial guess for the values of the parameters is not required; they can search simultaneously many estimates in an identical search space. This paper shows that the hybrid genetic algorithm is effective to estimate the reservoir properties on the tracer test analysis resulting from the numerical simulations and the analysis of the field data. In general, the increase in the number of estimates at the same time can improve the convergence speed. It is more effective to use the local search algorithm for the rapid convergence and for the accuracy of the estimates.

1. INTRODUCTION

In the tracer test analysis, inversion methods may be classified into direct inversion method and optimization method. In direct inversion method, the characteristics of observed data that are tracer concentration changes with time at observation wells are used directly to estimate the reservoir properties. These methods are usually based on a certain mathematical model, which can be solved.

In the optimization method, a particular mathematical model of tracer concentration distribution is also assumed. However, tracer concentration changes with time are calculated and compared with the observed data. After the comparison, the reservoir model parameters are improved to minimize the sum of the square residuals of the observed data and the calculated values. This process is repeated until the sum of the residuals become sufficiently small. This optimization procedure is sometimes influenced by the choice of the initial values of the reservoir parameters. To find the objective estimate independent of the initial values, a new optimization method, which does not need initial values, is required.

Recently, many soft-computing techniques, which are genetic algorithms, neural network, fuzzy reasoning, and so on, are applied to various inverse problems. In reservoir evaluations, genetic algorithms are applied to reservoir modeling by Sen et al. (1995), to identifying reservoir properties using tracer breakthrough by Guerreiro et al. (1998), to interference test analysis by Tanaka et al. (1998), to geophysics by Stoffa and Sen (1991), and Mallick, S. (1995).

In this paper, we apply the genetic algorithm combined with the local search by using nonlinear least squares method, which called hybrid genetic algorithm, to estimation of reservoir properties on tracer tests analysis.

2. HYBRID GENETIC ALGORITHMS

Genetic algorithms are stochastic search algorithm based on the mechanics of natural selection and natural genetics (Goldberg, 1989). Genetic algorithms use the analogy of the principle of the survival the fittest. When genetic algorithms are used as a minimization or an optimization procedure, they have some remarkable features, which are different from other conventional mathematical optimization method. They do not require the objective function that is unimodal, continuous, and differentiable. They do not require appropriate initial guesses for the values of the parameters to estimate, and they can find the global optimum with the many local optima. Because of these advantages, genetic algorithms are applied to many inverse problems in engineering and science. However, DeJong (1993) pointed out that genetic algorithms are poor optimizers. Therefore, many hybrid algorithms combined with genetic algorithms are proposed to improve the disadvantages. When the problem-specific information or the explicit objective function exists, it may be advantageous to consider a hybridized genetic algorithm (Goldberg, 1989).

In this study, the hybrid genetic algorithms combined a simple genetic algorithm with a nonlinear least squares method for local search are applied to the estimation of the reservoir properties in the tracer tests analysis. In the initial stage of the hybrid genetic algorithms, a part of the genetic algorithm is used in order to search for the domain close to the global solution. The solution obtained can be expected to be good initial values and to be further improved by using the nonlinear least squares method.

2.1 Gene Operation

The simplest implementation of a genetic algorithm uses three gene operations, which are reproduction, crossover, and mutation. Figure 1 shows the flow chart of the simple genetic algorithm and the hybrid genetic algorithm.

At first, the system is initialized with the population of N individuals that contain the binary bit strings encoded reservoir properties. In genetic algorithms, the term “individual” is defined as the each estimate. Similarly, the “population” is defined as the total number of them in the search space.

Reproduction is a next process after initialization in which two individuals are selected according to their objective values called fitness or misfit values. The strings within an individual with a higher fitness or with a smaller misfit value have a higher probability of selection to reproduce a new population of offspring.

After reproduction, a crossover site is selected at random and bits are exchanged partially between two strings at the right side of the crossover site shown in Figure 2 (a). In this paper, however, we used a multi-point crossover in which each reservoir parameter is crossed over with the corresponding reservoir parameter between two strings.

Mutation is simply the alteration of bit selected randomly in the parameter code shown in Figure 2 (b) and carried out based on the specified mutation probability.

In genetic algorithms, when the density of individuals is not sufficient in the search space of the objective function, the search efficiency tends to be worse. While the density of individuals is sufficient for the search efficiency, the calculation time becomes longer in proportion to the number of individuals.

Genetic algorithms are blind search procedures and exploit only the coding and the objective function value to improve the estimates. Therefore, a number of authors have suggested the hybrid techniques, which combines genetic algorithms with various search techniques as a local optimization. In this paper, a nonlinear least squares method is used for the local optimization method in the hybrid genetic algorithm. Because of the quadratic convergence in the convergence domain of a specific problem, a nonlinear least squares method is available for finding some local optima in the search space and for improving the search efficiency of a simple genetic algorithm

Figure 3 shows the distribution changes of individuals with optimization process in a search space of the nonlinear least squares method, the simple genetic algorithm and the hybrid genetic algorithms. In the nonlinear least squares method shown in Figure 3 (a), an appropriate initial guess is given and is improved to the global optimum. In the simple genetic algorithm shown in Figure 3 (b), the distribution of individuals around the global optimum and the local optima becomes denser with optimization process. In the hybrid genetic algorithm shown in Figure 3 (c), not only the distribution of individuals becomes denser but they can also be improved by the local search close to the global optimum and to the local optima on each generation.

3. NUMERICAL EXPERIMENT

3.1 Tracer Concentration Function

In this study, we apply the genetic algorithms to estimating the reservoir properties on the tracer test analysis. We assume that the one-dimensional multi flow paths are connected between a reinjection well and a production well in the homogeneous reservoir. The dimensionless tracer concentration C^*_S at a production well is given by the following expression,

$$C_S^* = \frac{G_I v_I}{G_w v_w} \sum_{i=1}^{n} f_i C_i^* (a_i, Pe_i) \qquad (1)$$

where G_I, G_w and v_I, v_w are the mass flow rate and the specific volume at the reinjection well and the production well respectively, n is the number of flow paths , C^*_i, is the dimensionless tracer concentration, f_i is the flow contribution coefficient, a_i is the mean traveling time, and Pe_i is the Peclet number at the i-th flow path. The dimensionless tracer concentration at the i-th flow path is given by

$$C_i^* = \frac{1}{2}\Big[\big\{E_{Ci}^-(t) + \exp(Pe_i)E_{Ci}^+(t)\big\} - \big\{E_{Ci}^-(t-t_1) + \exp(Pe_i)E_{Ci}^+(t-t_1)\big\}\Big] \qquad (2)$$

where t is the time, t_1 is the tracer release time, and the function $E^{\pm}_{Ci}(t)$ is as follows

$$E_{Ci}^{\pm}(t) = erfc\left(\frac{a \pm t}{2\sqrt{(a/Pe)t}}\right) \qquad (3)$$

where $erfc$ is the complementary error function and the dimensionless tracer concentration C^*_i is given by

$$C_i^* = \frac{C_i - C_0}{C_1 - C_0} \qquad (4)$$

where C_i is the measured tracer concentration at the production well, C_0 is the back ground natural tracer concentration in the reservoir, and C_1 is the inputting synthetic tracer concentration at the reinjection well.

3.2 Implementation of Hybrid Genetic Algorithms for Tracer Test Analysis

We use binary code to encode the value of each parameter with the discrete equal intervals between the maximum value and the minimum value in the logarithmic scale because of its wide variation. The value b_x which is the part of the binary bit strings in length l is decoded the value of parameter according to the following equation

$$x = 10^{\frac{\log x_{\min} - \log x_{\max}}{2^l - 1} b_x + \log x_{\min}} \qquad (5)$$

where x describes each parameter which is the flow contribution coefficient f, the mean traveling time a, and the Peclet number Pe respectively. The subscript max and min indicate the maximum and minimum value of each parameter.

In the reproduction process, the most basic selection method uses the ratio of each fitness value to the sum of all fitness values. The fitness and misfit value of each individual are reciprocal each other defined by following equation

$$misfit = \frac{1}{fitness} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{C_{mi}^* - C_{ci}^*}{\sigma}\right)^2 \qquad (6)$$

where n is the number of concentration data, σ is the standard deviation of the measurement error of the tracer concentrations, C^*_{mi} and C^*_{ci} are the i-th measured tracer concentration at the production well and the calculated it by the formula (1) respectively. To reproduce a new population of offspring, two individuals are selected according to the probability P_s:

$$P_S = \frac{fitness_i}{\sum_{j=1}^{n} fitness_j} = \frac{\frac{1}{misfit_i}}{\sum_{j=1}^{n}\frac{1}{misfit_j}} \qquad (7)$$

The crossover probability is 0.9 and the mutation probability is 0.1 in this numerical experiment. The mutation probability should be kept low but nonzero to maintain the diversity of the population. We used a synthetic inverse problem shown in Figure 4 for this numerical experiment to investigate the potential to estimate the reservoir properties by this hybrid genetic algorithm.

3.3 Effects of Population and Local Search Probability for Convergence

A rapid convergence can be expected by the increase in population and the local search probability. Figure 5 shows that the misfit changes of the simple genetic algorithm with generation on both logarithmic scale for the three types of population 10, 30 and 100. In order to investigate the effects of the increase in population on convergence process and to avoid the effect of the local search, the local search probability P_{LS} is fixed to be 0% in hybrid genetic algorithm. Under this condition, the hybrid genetic algorithm can be identified with the genetic algorithm. The misfit changes with generation decrease according to the increase in population of the individuals. Nevertheless, they cannot reach the minimum value of this problem shown in Figure 5. Because the decreasing rates of them decline asymptotically after 50th generation and they are nearly equal to 0 after 200th or 300th generation in every population.

The results of the effects of the local search for the rapid convergence are presented in Figure 6. The local search probabilities are changed from 20% to 100% with 20% interval when the population is fixed to be 30. The misfit values decline rapidly to the minimum value in the early stage of the generation earlier than the 10th generation with the increase in local search probability. The comparison of the results shown in Figure 5 and Figure 6 leads to the conclusion that the local search in the hybrid genetic algorithm is more effective to converge rapidly than the increase in population of the individuals in the genetic algorithm.

In this study, to evaluate the effect of the local search quantitatively, the local search power is defined as the product of the local search probability by the maximum iteration number of the nonlinear least squares estimation at each generation. However, the strong local search power is necessary to estimate the parameters for a difficult problem. The calculation time tends to increase with the population and with the local search power. It is necessary to select an appropriate local search power to analyze the problem according to it. The choice of the appropriate local search power according to the problem is important to analyze it certainly and to reduce the calculation time.

Figure 7 shows the distributions of the convergence probabilities for 10 and 30 population with various local search powers in the hybrid genetic algorithm. For 10 population of individuals, the convergence probabilities increase from 94% to 100% according to the local search power increases. For 30 population, the convergence probabilities are 100% in the whole range of the local search power. While in genetic algorithm, the convergence probabilities for 10 and 30 population are less than 10% and 82% respectively.

Figure 8 shows the convergence times versus local search power in the simple and the hybrid genetic algorithm. Since the increase of the amount of the calculation, the convergence time increases in proportion to the local search power for 10 and 30 populations. When the population is 3 times from 10 to 30, the convergence times for 30 population are about 1.5 times as long as those of 10 population at the same local search power. The reason for the reduction in the increasing ratio of the calculation time is that the search space is dense with the individuals according to the increase in population, so that the search efficiency can be improved.

3.4 Analysis of Field Data

To verify the utilization of the hybrid genetic algorithm for the estimation of the reservoir properties, we analyze the field data reported in Fukuda et al. (1992) and compare the results using this method with that of conventional one.

Considering the above result of the numerical experiments, the population and the local search power are fixed to be 30 and 50 respectively for the analysis of the field data.

The estimated results of reservoir properties are listed in Table 1 and the fittings between the measured concentrations and the calculated values from them are shown in Figure 9. Very good fit between the measured and the calculated tracer concentrations is obtained from this analysis. Resulting from this analysis, the flow contribution coefficient at each flow path is 0.35%, 1.55% and 0.12% respectively. The total flow contribution coefficient is 2.02%, so that the result agrees well with the results using the conventional analysis method described in Fukuda et al (1992). Comparing with the conventional method for tracer test analysis, the objectivity of the results obtained from the new analysis method can be improved.

4. CONCLUSION

We have developed the new analysis method for the tracer test analysis using the hybrid genetic algorithm which combines the simple genetic algorithm with the nonlinear least squares method for the local search.
As the result from above numerical experiments and analysis of the field data, we make sure of the effectiveness of this new method for tracer test analysis and can conclude as follows:

(1) The increase in population of individuals can improve the convergence speed for the estimation of the reservoir properties on the tracer test analysis.

(2) Using the local search algorithm with the genetic algorithm, which is the hybrid genetic algorithm, is more effective to converge rapidly than the increase in population of individuals.

(3) It is necessary to select the appropriate local search power and the population of individuals to analyze the problem certainly and to reduce the calculation time according to it.
The choice of the appropriate local search power is important.

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(a)	(b)
1. Initialize 2.1 Reproduction 2.2 Crossover 2.3 Mutation	1. Initialize 2.1 Reproduction 2.2 Crossover 2.3 Mutation **2.4 Local Search**

Figure 1 Flow chart showing the order of the gene operations of (a) the simple genetic algorithm and (b) the hybrid genetic algorithm.

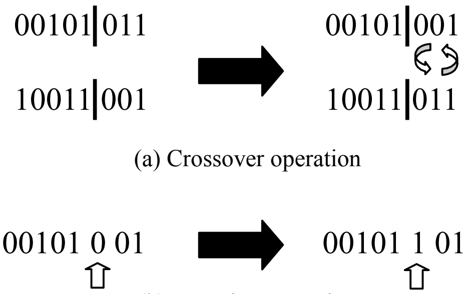

Figure 2 Schematic illustration of (a) the crossover and (b) the mutation operation.

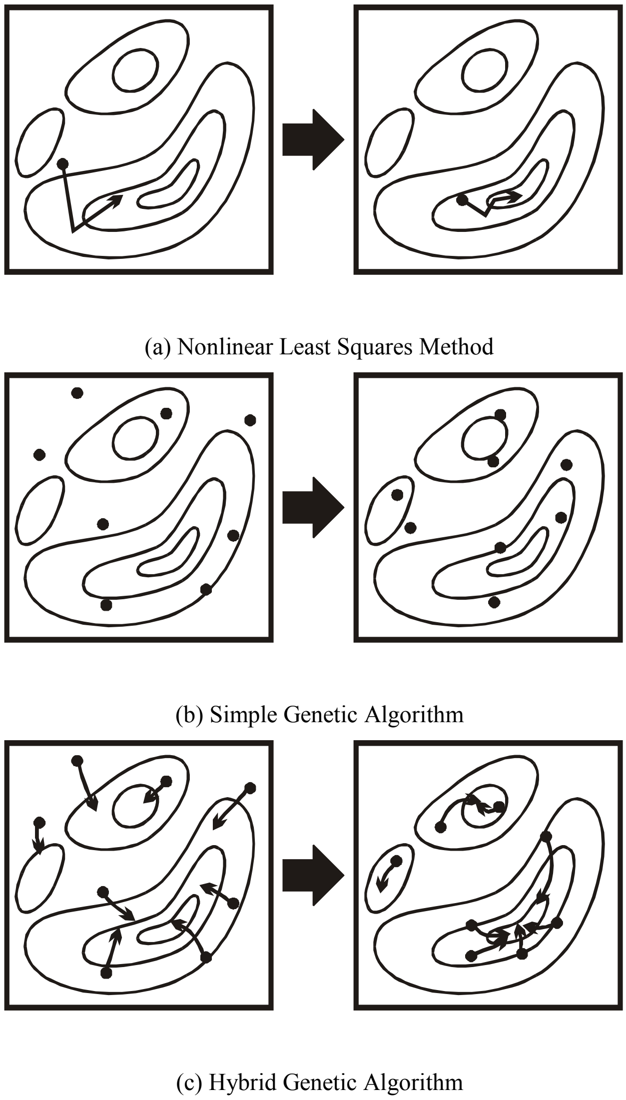

Figure 3 Distribution changes of individuals with the optimization process in a search space of (a) the nonlinear least squares method, (b) the simple genetic algorithm, and (c) the hybrid genetic algorithm.

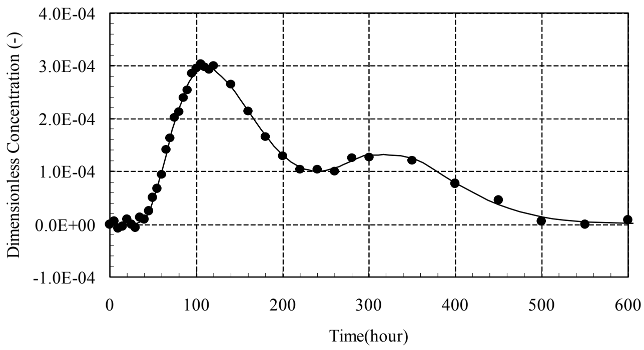

Figure 4 Synthetic dimensionless concentration changes with time which assume two flow path model and include 3% random noise for the numerical experiments.

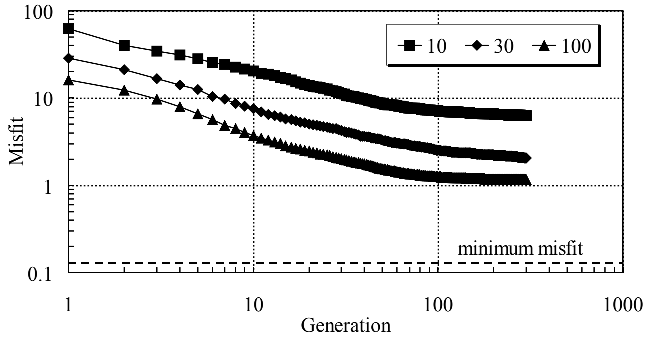

Figure 5 Effects of the increase in population for the convergence process by the simple genetic algorithm.

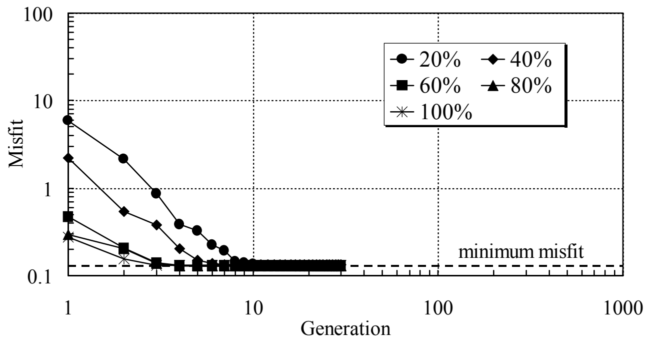

Figure 6 Effects of the local search with various probabilities for the convergence process by the hybrid genetic algorithm.

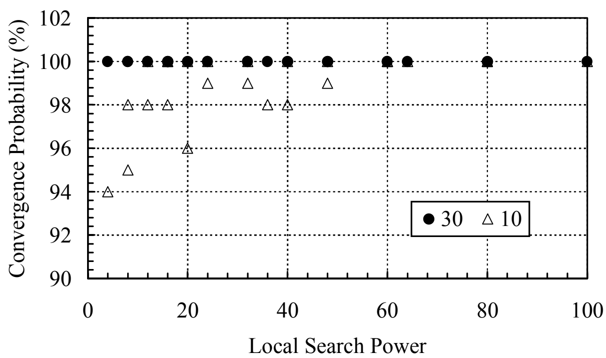

Figure 7 Convergence probabilities for 10 and 30 populations with the local search power.

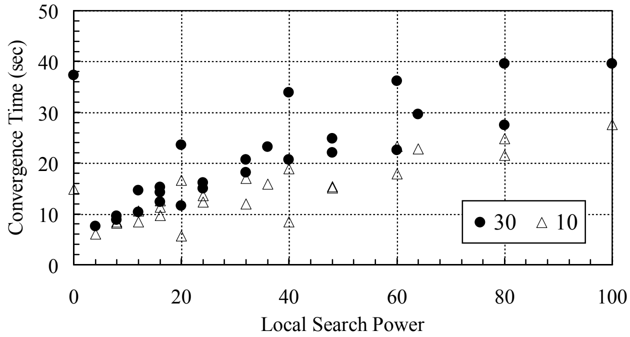

Figure 8 Convergence times for 10 and 30 populations with the local search power.

Table 1 Estimated results of the reservoir properties using three flow path model.

	f (%)	a (hour)	Pe (-)
Path1	0.35	278	6.53
Path2	1.55	1209	3.04
Path3	0.12	1789	77.0
Total	2.02		

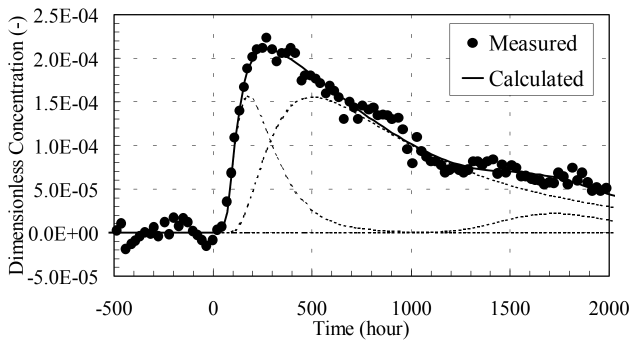

Figure 9 Fitting results to the field data reported in Fukuda et al. (1992) by the hybrid genetic algorithm.