Kwon, S. I., Huh, D. G., Lee, W. S., Kim, H. T., Kim, S. J., Sung, W. M., Development and application of inverse model for reservoir heterogeneity characterization using parallel genetic algorithm.
International Symposium on the Fusion Technology of Geosystem Engineering, Rock Engineering and Geophysical Exploration
Seoul, Korea, Nov. 18-19, 2003

Development and application of inverse model for reservoir heterogeneity characterization using parallel genetic algorithm

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Abstract: This paper presents the development of reservoir characterization model equipped with parallelized genetic algorithm, and its application for a heterogeneous reservoir system with integration of the well data and multi-phase production data. A parallel processing method performed by PC-cluster was applied to the developed model in order to reduce time for an inverse calculation. By utilizing the developed model, we performed the inverse calculation with the production data obtained from three layered reservoir system to estimate porosity and permeability distribution. As a result, the pressures observed at well almost identical to those calculated by the developed model. Also, it was confirmed that parallel processing could be applied for reservoir characterization study efficiently.

1. Introduction

Since the early 1990's, geostatistical and stochastic methods have been applied to reservoir characterization studies. Namely, reservoir characterization studies have been achieved by integrating static data, such as cores, logs, seismic, experiment, etc, and dynamic data, such as production, 4D seismic data (Huang et al., 1997). In order to integrate dynamic data into reservoir characterization models, an optimization algorithm in inverse method must be used in order to minimize the difference between observed and calculated data. Therefore, several researchers compared and studied the efficiency of optimization algorithms for inverse calculations, such as simulated annealing, metropolis algorithm and genetic algorithm, etc (Sen et al., 1995).

Among these algorithms, a genetic algorithm has an advantage in being able to apply an optimization algorithm to various reservoir systems, by easily exchanging the forward simulator. Seo et al. (1998) applied the genetic algorithm to the phase equilibrium model. Romero et al. (2001) also developed a reservoir characterization model using a genetic algorithm, and applied it to the actual field. They performed the inverse calculation by using pilot points as well as observed points, and estimated the distributions of parameters by a geostatistical method for the whole reservoir.

2. Genetic Algorithm (GA)

The GA proposed by Holland, in 1975, is an optimization method that imitates natural evolution, and progressively improves the solutions caused by the simulated evolution in the population. Until the early 1990's, GAs were mainly coded by binary numbers, but the real-coded genetic algorithm (RCGA) has been proposed in order to handle larger constraints, or for the application to various constraint conditions in complex optimization problems.

In cases having a large constraint, due to the reservoir heterogeneity and less observation data, or in estimating the accurate solution, the application of the RCGA was useful. This algorithm is easily coded by a one-to-one correspondence between the variables (phenotype) and genes (genotype), and can improve the efficiency of search because of needless to the encoding and decoding processes (Eshelman, 1993). It is also possible to prescribe the large constraint, without loss of the accuracy, in cases with no previous information relating to a solution.

3. Reservoir Characterization-Inverse Model

The reservoir characterization model was developed using genetic algorithm with the integration of static data of cores and logs, and dynamic data of production. Applying the developed model to reservoir characterization, we generated upscale grid system and estimated spatial distributions of porosity and permeability by Kriging method from the well data, and then determined the constraints of each inverse grid. As the next step, initial individuals were generated in random from the constraints, and the fitness of each individual was calculated by differences between observed data at well and calculated ones with the forward simulator. After fitness calculation had been completed, the selection operation was performed according to the fitness of the individuals. And then the crossover and mutation operations were carried out. Once the mutation operation is finished, one cycle of the genetic algorithm is completed. These processes are repeated up to terminate conditions.

The forward simulator used in this study is 3-D, 3-phase FDM model and was modified and validated by Park et al. (1997). The fitness was defined by an inverse number of the objective function value as follows

$$\text{Objective Func.} = \sum_{i} \sum_{j} \left|P_{obs} - P_{cal}\right| + w_f \sum_{j} \left|WOR_{obs} - WOR_{cal}\right| = 1/\,\text{Fitness}$$

In the above equation, i is the number of production wells, and j is the number of observed data at well. Also P is the bottomhole pressure at production well and WOR is the field production water oil ratio.

4. PC-Cluster and Parallel Algorithm

In this study, we have made a PC-cluster by connecting PC in order to operate the inverse model with parallel genetic algorithm, efficiently. The cluster is homogeneous system equipped with a CPU of Pentinum 4 1.8 GHz and a main memory of 256 MB, respectively. Each node (PC) is connected with network cards of 100 Mbps and switching hub to transport the data as high speed. Also, MPICH package is installed in each node. A parallel genetic algorithm is generally used to reduce a calculating time of a fitness evaluation and to solve a problem of a memory lack caused by increasing of population size. In the case of applying a genetic algorithm to a reservoir characterization study as optimisation algorithm, most of the calculating time uses the fitness evaluation performed by a forward simulator. Therefore, we parallelized the fitness evaluation process only by applying the global parallelization strategy.

5. Application of the Developed Model

The reservoir system to characterize the heterogeneity of porosity and permeability using the developed model consists of 3 layers, 4 producers and 7 injectors, as illustrated in Fig. 1 (a). The first layer has strongest heterogeneity among 3 layers. Production was performed for two years at 4 production wells and water was injected by 7 injection wells from one year later of production, as shown in Fig. 1 (b). The reservoir was divided into 20×15 grid in each layer to forward simulation.

In order to perform the inverse calculation, we divided blocks of 31, 16, 13 in each layer as illustrated in Fig. 1 (c). Firstly, we drew spatial distributions for the porosity and permeability using Kriging method with the well data of 11 wells, and then determined the constraint of each block (Table 1). The inverse calculation was performed with the population generated by the constraint. The population size was set as 300, and tournament selection and modified simple crossover operator were used.

Table 1. Constraint of each block for inverse calculation.

layer1									
Block	Porosity		Permeability		Block	Porosity		Permeability	
	min	max	min	max		min	max	min	max
1	0.081	0.096	102.0	121.0	17	0.054	0.102	67.0	129.0
2	0.077	0.096	99.0	121.0	18	0.058	0.090	71.0	114.0
3	0.078	0.107	98.0	135.0	19	0.052	0.098	63.0	123.0
4	0.091	0.117	116.0	148.0	20	0.094	0.207	120.0	268.0
5	0.064	0.102	87.0	131.0	21	0.072	0.214	92.0	278.0
6	0.075	0.087	94.0	109.0	22	0.078	0.241	99.0	313.0
7	0.073	0.132	92.0	169.0	23	0.083	0.270	104.0	348.0
8	0.103	0.137	133.0	175.0	24	0.088	0.266	110.0	344.0
9	0.062	0.124	85.0	160.0	25	0.202	0.286	261.0	374.0
10	0.086	0.113	109.0	144.0	26	0.219	0.300	285.0	391.0
11	0.090	0.180	113.0	230.0	27	0.246	0.300	320.0	391.0
12	0.094	0.170	119.0	217.0	28	0.229	0.294	296.0	382.0
13	0.072	0.141	91.0	181.0	29	0.280	0.304	366.0	396.0
14	0.069	0.092	87.0	119.0	30	0.294	0.304	383.0	396.0
15	0.082	0.124	104.0	159.0	31	0.276	0.301	359.0	392.0
16	0.047	0.102	59.0	129.0					

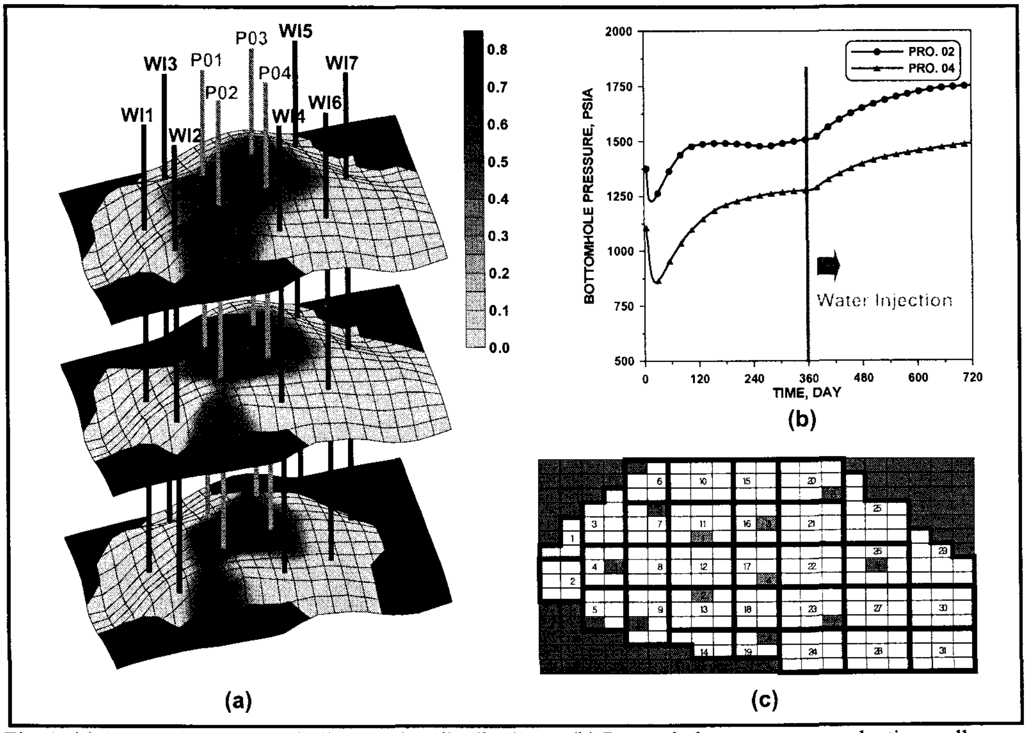

Fig. 1. (a) Reservoir system and oil saturation distribution. (b) Bottomhole pressure at production well.
(c) Grid system of inverse calculation for layer 1.

As a result of inverse calculation, number of generations for the convergence was 96 and the fitness was 0.00082 The permeability distribution of 1 layer calculated by the developed model was shown in Fig. 2. From the pressure matching result illustrated in Fig. 3, it was found that the pressures observed at the producer 2, 4 were almost identical to those calculated by the developed model. From the result, it was confirmed that the permeability distribution of 1 layer calculated by the developed model was valid.

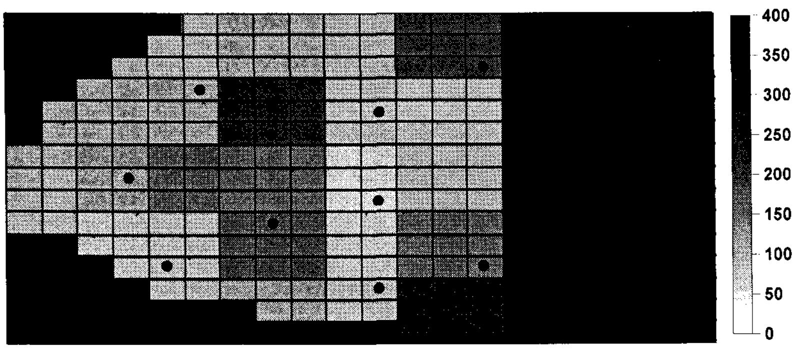

Fig. 2. Permeability distribution calculated by the developed model of layer 1.

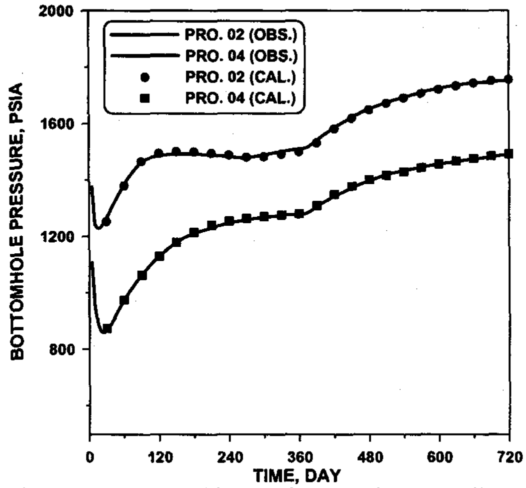

Fig. 3. Pressure matching results at production well.

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