Hydraulic well testing inversion for modeling fluid flow in fractured rocks using simulated annealing: a case study at Raymond field site, California

Shinsuke Nakao a, *, Julie Najita b,1, Kenzi Karasaki b,1

a Geological Survey of Japan, 1-1-3 Higashi, Tsukuba, Ibaraki, 305-8567, Japan
b Lawrence Berkeley National Laboratory, Berkeley, CA 94720, USA

Received 2 August 1999; accepted 23 June 2000

Abstract

Cluster variable aperture (CVA) simulated annealing (SA) is an inversion technique to construct fluid flow models in fractured rocks based on the transient pressure data from hydraulic tests. A two-dimensional fracture network system is represented as a filled regular lattice of fracture elements. The algorithm iteratively changes element apertures for a cluster of fracture elements in order to improve the match to observed pressure transients. This inversion technique has been applied to hydraulic data collected at the Raymond field site, CA to examine the spatial characteristics of the flow properties in a fractured rock mass. Two major conductive zones have been detected by various geophysical logs, geophysical imaging techniques and hydraulic tests; one occurring near a depth of 30 m and the other near a depth of 60 m. Our inversion results show that the practical range of spatial correlation for transmissivity distribution is estimated to be approximately 5 m in the upper zone and less than 2.5 m in the lower zones. From the televiewer and other fracture imaging logs it was surmised that the lower conductive zone is associated with an anomalous single open fracture as compared to the upper zone, which is an extensive fracture zone. This would explain the difference in the estimated practical range of the spatial correlation for transmissivity.

Keywords: Hydraulic well test; Inversion; Fluid flow model; Fractured rocks; Simulated annealing

1. Introduction

For engineering concerns such as environmental remediation, it is quite important to characterize subsurface fractures that control groundwater flow and transport properties of fractured rocks. Pressure interference testing due to pumping or injection using multiple wells is a useful and direct method to collect information on transmissivities of the fracture system. Once pressure transient data is obtained, an inverse method can be applied to match the observed data and hence to construct a hydrological model (Carrera and Neuman, 1986; Finsterle, 1993; Doughty et al., 1994).
Hydrological characterization of fractured rocks is extremely difficult because fracture distributions are highly heterogeneous and discontinuous. If the rock is extensively fractured and all the fractures are hydrologically active, the medium would behave like an equivalent porous medium. However, cross-hole and tracer tests show that this is not usually the case (Billaux et al., 1989). In the case where the rock matrix can be considered impermeable, major hydraulic behavior is governed by the geometry of the fracture network. In order to overcome some of these problems, after extracting fracture zones by geological and geophysical methods, fracture network models with a partially filled lattice were used to characterize the heterogeneity of the zone (Long et al., 1991). Our study follows this approach.

Simulated annealing (SA), on the other hand, is a stochastic search method and has attracted attention as a scheme for optimizing the objective function, because the algorithm selects parameters outside the neighborhood of a local minimum. Although in practical applications obtaining the global minimum is not guaranteed, near-optimal solutions can be often found by representing SA as a Markov chain with adequate parameters (Geman and Geman, 1984; van Laarhoven and Aarts, 1987). SA has been used in a variety of optimization problems (Kirkpatrick et al., 1983), and also been applied to geophysical exploration (e.g. Sen and Stoffa, 1991; Vasudevan et al., 1991), and hydrology to develop a groundwater management strategy (Dougherty and Marryott, 1991) and stochastic reservoir modeling (Deutsch and Journel, 1994).

In hydrological applications, Lawrence Berkeley National Laboratory (LBNL) has been developing an inverse method for well test data using SA (Mauldon et al., 1993). A partially filled lattice represents a fracture network and an individual fracture element is changed randomly from conductive to nonconductive or vice versa. The effect of this change is examined by numerically simulating well tests and comparing simulations with field test data. Jacobsen (1993) and Najita and Karasaki (1995) developed a SA method called cluster variable aperture (CVA) SA that uses a distribution of fracture apertures. The algorithm changes element transmissivities by changing element apertures following the cubic law. In addition, the algorithm will change the property of a cluster of elements instead of a single element. Cluster size and shape, which represent simplified fracture sets, are the parameters specified in the inversion. Sensitivity studies, investigating optimal cluster size using synthetic models with spatially correlated transmissivity, showed that the optimal cluster size seems to be 20–40% of the practical range of spatial correlation for transmissivity distribution (Nakao et al., 1999).

To develop multi-disciplinary field testing techniques and analysis methods for characterizing hydraulic properties of fractured rocks, a dedicated field site was established near the town of Raymond, CA (Karasaki et al., 1994). Questions that are being addressed at this site include: (1) the number of boreholes, the number and type of the hydrologic and geophysical well tests needed to characterize a given volume of rock, (2) the possibility of predicting fluid transport based on fracture geometry, (3) how to scale-up the observations made at a smaller scale, and (4) how to relate geometric fracture information from outcrops and boreholes to hydrology. Various geophysical and hydrologic tests have been conducted in a cluster of nine wells at this site to image the hydrologic connections of a fractured rock mass. The results from these tests indicate that flow is mainly confined in the two dominant upper and lower conductive zones (Cohen, 1993). The preliminary result of hydrologic modeling for the upper conductive zone using SA was presented in Nakao et al. (1999). In this article, comprehensive results of hydrologic modeling using SA will be presented to examine the spatial characteristics of the flow properties in both the upper and lower conductive zones at the Raymond field site. We will start with a brief description of the Raymond field site, then proceed to describe the hydraulic well testing inversion using SA and the application to the field test data.

2. Raymond field site

The Raymond field site is located in the foothills of the Sierra Nevada, approximately 3.2 km east of Raymond, CA. The site lies within the Knowles granodiorite which is light-gray, equigranular and non-foliated, and is widely used as a building mate-
Various geophysical logs, geophysical imaging techniques and hydraulic tests have been conducted to image the hydrologic connection of the fractured rock mass (Cohen, 1993; Karasaki et al., 1995; Cook, 1995; Cohen, 1995; Vasco et al., 1996). Regional characterization and site specific fracture measurements show that there are two sets of subvertical tectonic fractures: one set strikes at N30W and the other strikes at N60E (Cohen, 1995). The current...
conceptual model (Fig. 1b) consists of two dominant conductive zones: one occurring near a depth of 30 m and the other between 54 and 60 m. The presence of these zones are also imaged by ground penetrating radar reflection and a seismic tomography survey (Vasco et al., 1996). It should be noted that these surveys respond to different physical properties, i.e. the seismic method responds to a rock stiffness contrast, while the radar responds to the electro-magnetic properties of the media. Furthermore, the results from hydraulic tests indicate that there is a high degree of heterogeneity in transmissivity distributions within the two conductive zones (Cohen, 1993). The main purpose of the application of SA is to characterize the heterogeneity of transmissivity distributions within the zones.

3. Analysis method

3.1. SA in general

SA has its origins in thermodynamics and the manner in which liquid metals cool and anneal. In physical annealing, a metal is heated and allowed to cool very slowly in order to obtain a regular molecular configuration having the lowest possible energy state. If the temperature $T$ is held constant, the system approaches thermal equilibrium and the probability distribution for the configuration with energy $E$ approaches the Boltzmann probability $Pr(E) = \exp(-E/k_bT)$; where $k_b$ is the Boltzmann constant. Metropolis et al. (1953) first introduced a simple algorithm to incorporate these ideas into numerical calculations. The following criterion known as the Metropolis algorithm is applied in determining whether a transition to another configuration occurs at the current temperature. For the $n$ - 1st configuration $X_{n-1}$ and the $n$th configuration $X_n$ with energies $E_{n-1}$ and $E_n$, respectively, the transition probability at some system temperature $T$ is given by

$$Pr( X_{n-1} \rightarrow X_n ) = \begin{cases} 1 & \text{if } E_n - E_{n-1} < 0 \\ \exp[-(E_n - E_{n-1})/T] & \text{if } E_n - E_{n-1} > 0. \end{cases}$$

This criterion always allows a transition to a configuration if system energy is decreased and sometimes allows a transition to a configuration with higher energy. This stochastic relaxation step allows SA to search the space of possible configurations without always converging to the nearest local minimum. In SA, the objective function for an optimization problem is analogous to energy state and the set of free parameters (configuration) is analogous to the arrangement of molecules. “Temperature” is simply a control parameter in a given optimization problem. We will refer to the objective function as “objective function (energy)” and also refer to the temperature as “control parameter $T$” in the following sentences.

In general, the SA algorithm consists of the following tasks: (1) generate or randomly change system configuration, (2) calculate values of the objective function (energy), (3) perform the Metropolis algorithm to determine whether a new configuration is accepted or not, and (4) adjust the current control parameter $T$ according to the annealing (cooling) schedule.

Several choices of annealing schedule are possible. A computationally practical schedule is the widely used decrement rule (Press et al., 1986). Given an initial control parameter $T_0$, assign

$$T_k = T_0 \alpha^k; \quad k = 0, 1, 2, 3, \ldots ,$$

where $\alpha$ is between 0 and 1. This general form has been implemented by others with values of $\alpha$ ranging from 0.5 to 0.99 (e.g. van Laarhoven and Aarts, 1987). In this schedule, the current control parameter $T$ is kept fixed until a finite number of transitions, $L_d$, have been accepted, then the parameter $T$ is lowered.

3.2. Implementation to well test inversion

In order to use SA for the inversion of well tests, we consider a two-dimensional fracture network model as shown in Fig. 2. Fractures at multiple depths are not considered. Each element represents a simplified fracture that controls the transmissivity. Transmissivity (m$^2$/s), specific storage (m$^{-1}$), aperture (m), unit thickness (1 m) and length are imposed on each element. Well locations are specified at node points and pressure transients (hydraulic head
changes) due to pumping or injection are calculated at each node using the finite element code TRINET (Karasaki, 1987). Note that neither the SA algorithm nor TRINET is limited to the two-dimensional model. We use a two-dimensional model because of the complexity and large computational requirements for a 3-D representation. Fluid flow along fractures is assumed to be laminar. It is also assumed that the transmissivity of any fracture element follows the cubic law ($T = \rho gb^3/12\mu$), where $\rho$: density of water, $g$: acceleration due to gravity, $\mu$: dynamic viscosity of water, $b$: aperture. Whether the cubic law is applicable here is not pertinent to the present study, although the subject itself is very important.

In CVA SA, the objective is to find a near-optimal fracture network geometry by modifying clusters of element apertures (hence transmissivities) and calculating pressure transient curves in order to simultaneously match observed head data at observation wells. At each step of the algorithm, a cluster of elements is randomly selected using the Wolff algorithm (Wolff, 1989) and their aperture is changed to an aperture chosen at random from a discretized distribution. In this study, we use a finite list of aperture choices. The number and the values of replacement apertures are user-specified parameters. In the case of Fig. 2, two discretized apertures, thick (high transmissivity) and thin (low transmissivity) lines, are specified. The transmissivity of the cluster of elements is also updated according to the cubic law. This step is analogous to the perturbation step in the general SA algorithm.

Cluster elements are dependent on the maximum cluster size and the location of the cluster origin. The cluster origin is an element chosen at random from the fracture network. In the first stage of cluster formation, all conductive elements that are connected to the cluster origin are determined. Each of these neighbors is added as a new cluster element. If the maximum cluster size is not reached, the algorithm proceeds to a second stage where conductive elements connected to new cluster elements are identified and accepted as new cluster elements as long as the element is not already in the cluster. This process continues until the maximum cluster size is reached or no new elements can be added. The maximum cluster size is a parameter specified by a user and is held constant throughout the iterations. In general, a cluster becomes random shape, because the regular lattice is used. We call it isotropic. As the maximum
cluster size increases, however, the cluster shape more likely becomes circular. Instead of the random cluster shape, as shown in Fig. 2, we also have an option in the cluster selection so that the cluster shape can be anisotropic (elliptical) to incorporate a priori information, namely, geological information about regional fractures such as strikes and scales. These two parameters, cluster size and shape, play a key role in the inversion, because these are a direct representation of simplified fracture sets. As mentioned before, the optimal cluster size approximately corresponds to the spatial correlation length of transmissivity distributions (Nakao et al., 1999).

Following the perturbation step, well tests are simulated on the fracture network and the calculated pressure transients are compared with observed data. The objective function (energy) to be minimized is the sum of the squared differences between the calculated and observed pressure transients due to pumping or injection. In this study, all wells included in the objective function (energy) are unweighted under the assumption that errors in field measurements due to noise or the accuracy of pressure transducers are approximately equal for all wells. At the $i$th iteration:

$$E_i = \sum_{j=1}^{\text{#wells}} \sum_{k=1}^{\text{times}[j]} (o_{jk} - p_{ijk})^2,$$

where $o_{jk}$ refers to the observed pressure transient at the $k$th time step for $j$th well. $p_{ijk}$ refers to the simulated pressure transient at the $i$th iteration for the $j$th well and $k$th observed time step.

The Metropolis algorithm is applied to determine whether the current fracture configuration is acceptable based on the Eq. (1). When $L_k$ acceptances at control parameter $T_k$ have been achieved, the parameter is reduced to $T_{k+1}$ via Eq. (2) with $\alpha = 0.9$. $T_{k+1}$ stays constant until $L_{k+1}$ transitions have been accepted at $T_{k+1}$. This process continues until the annealing schedule is exhausted or the number of iterations has reached a user-specified maximum. At this point, the best model found thus far is expected to be close to the global minimum. In the following, we refer to “minimum objective function (energy)”; however, this is used to describe the smallest objective function (energy) found at the end of the inversion.

4. Hydraulic well test data

Hydraulic well testing was conducted at the Raymond field site on several occasions (e.g. Cohen, 1993; Karasaki et al., 1995; Cook, 1995; Cohen, 1995). The data used in this study was taken in 1995. Each of the nine wells was injected systematically with fresh water using a straddle packer system. The distance between the straddle packers was roughly 6 m. A typical injection test was conducted for 10 min. The pressure in the water tank was held constant using compressed air. Neither the flow rate nor the downhole pressure was actively controlled; they spontaneously adjusted themselves accordingly to the transmissivity of the injection interval. The advantages of this method are the simplicity of the set-up and the ease of test execution. After each test, the packer string was lowered by approximately 6 m. Depth intervals sealed by packers during a particular injection were kept unobstructed during the next, so that the entire length of the well was tested. There were approximately 15 injection tests per well in all nine wells. While these injections were conducted, the pressures in the remaining 31 intervals were simultaneously monitored. As a result, a total of 4200 interference pressure transients were recorded.

A schematic of the packer set up in the site is shown in Fig. 3. To analyze connections between wells using a large number of interference data, a binary inversion method was developed (Cook, 1995; Karasaki et al., 1995). In their method, each set of...
pressure transient data was reduced to a binary set: 1 (yes) if an observation zone responds to an injection, and 0 (no) otherwise, and they successfully visualized connections between wells. The result strongly supports the existence of two separated conductive zones, one at a depth of approximately 30 m and other at 60 m.

From the large number of interference data described above, three sets of injection data in series were selected for each zone: injection into wells 0-0, SE-1 and SE-3 for the upper zone, and injection into wells 0-0, SW-1 and SW-3 for the lower zone. These injection intervals are located approximately between depths of 20 to 30 m and between depths of 50 to 60 m. Intervals with interference response are also located in these depths. We believe these intervals are selected by trial and error. It is generally necessary to use a higher-than-usual specific storage in discrete fracture network models where the conductivity of an element is coupled to its volume through the cubic law. Because it is impossible to model all the fractures and pore spaces in the rock enumeratively due to the computational limitations, the specific storage value in the model is an effective one that represents the storage of the volume of rock that surrounds the fracture element. Mauldon et al. (1993) used a similar approach for their simulation of the fracture flow experiments conducted at Stripa Mine in Sweden. Our focus, too, is to estimate the distribution of the transmissivity contrast. Therefore, we feel it is justified to use the effective value for the specific storage.

In our forward simulation, we set the boundary condition at the well as the constant rate using the average flow rate over the injection period. Except for the very early time, when the compliance of the injection plumbing affected the apparent flow rate, the flow did not change greatly. Replacement apertures specified in the inversion are $1.07 \times 10^{-3}$, $4.96 \times 10^{-4}$, $2.30 \times 10^{-4}$ and $1.07 \times 10^{-4}$ m, which correspond to transmissivities of $10^{-3}$, $10^{-4}$, $10^{-5}$ and $10^{-6}$ (m$^2$/s), respectively. The upper and lower zones were modeled separately.

5. Results

5.1. The upper zone

Four cluster sizes, 1, 10, 20 and 40 were used for the inversion to investigate spatial characteristics of
the transmissivity distribution within the upper conductive zone. For each cluster size, inversions were run seven times starting from seven different random seeds. Inversions using cluster size of 10 with anisotropic clusters, with strikes at N30W and N60E, were also conducted. These major fracture sets were identified from the measurements of outcrops and the acoustic televiewer logs. Annealing (cooling) schedules for four cluster sizes are shown in Fig. 4. In these schedules, the total number of the element change in an inversion is set to be same for all cluster size cases. Namely, in the case of cluster size 40, the control parameter $T$ is lowered after 20 configuration changes are accepted, whereas the control parameter $T$ is lowered after 800 changes are accepted in the case of cluster size 1. We set all inversions will be stopped when the annealing schedule is exhausted. This means that the inversions using larger cluster sizes need less number of iteration. For example, the inversions using cluster sizes 1 and 40 requires approximately 22,460 and 980 total iterations, respectively.

Fig. 5 summarizes the inversion results. The lowest minimum objective function (energy), 4.7, is reached in the seed 4 of the cluster size 10, starting from the initial objective function (energy) of $3.33 \times 10^3$. The minimum objective function (energy) varies to some extent depending on a random seed for a given cluster size. The averaged minimum objective function (energy) is smallest for a cluster size of 1. As the cluster size decreases, the averaged minimum objective function (energy) also decreases. Comparison of pressure transients between observed and calculated data for the minimizing configuration obtained using the cluster size 10 (seed 4) is illustrated in Fig. 6. A relatively good match is achieved.

In order to represent average properties of the annealing solutions obtained using the same cluster size, seven annealing solutions are combined to produce one configuration by means of median filters, which are commonly used as velocity filters in data processing of vertical seismic profiling (e.g., Hardage, 1985). That is, the median transmissivity value (transmissivity value itself, not its logarithm) among seven values is selected for each fracture element so as to produce one median configuration. Five median-filtered configurations are shown in Figs. 7–9. The first result is found using a cluster size of 1. The
second, third and fourth results are found using cluster sizes of 10, 20 and 40 with isotropic clusters. The fifth result is found using a cluster size of 10 with anisotropic clusters, with strikes at N30W and
Fig. 7. Median-filtered inversion result with cluster size 1 (U1) and cluster size 10 (U2) for the upper zone. The injection test data into well 0-0, SE-1 and SE-3 in series (filled circles) was used in the inversion.
Fig. 8. Median-filtered inversion result with cluster size 20 (U3) and cluster size 40 (U4) for the upper zone.
Fig. 9. Median-filtered inversion result with cluster size 10 and anisotropic shapes for the upper zone (U5).

N60E. We refer to these as cases U1 through U5. It is difficult to observe the major feature common to all the results from these figures. However, the annealing results consistently show high transmissivities around well 0-0. SW-3 is relatively isolated in U3 and U5 results. This is because SW-3 had a very low interference response from all of three well injections (see Fig. 6). Aside from these two features, U1–U4 (isotropic clusters) do not seem to show a particular spatial pattern.

Since the inversion result is based on limited information and the hydraulic inversion is inherently non-unique, it is difficult to say how "real" such results are. Rather, we believe that assessing the validity of the result can best be done by testing how the result (model) predicts hydraulic behavior of the data, which is not used to build the model. Thus, to evaluate the inversion results, a cross validation test was conducted. We modeled the SW-2 injection test, which was not included in the inversion as injection data. TRINET (Karasaki, 1987) was again used to simulate injection into SW-2. Fig. 10 shows prediction errors for injecting at SW-2 for each cluster size results (U1–U5). The prediction error, which is the sum of the squared difference between the calculated and observed data given by Eq. (3), is approximately 4 for cases U1 and U2, while it is more than 15 for U3, U4 and U5. This result indicates that cases U1 and U2 are the good models among the results of five cluster types. From these results, we observe that cluster sizes of 1 and 10 are suitable to obtain good results.

The omnidirectional semi-variogram for U2 (cluster size of 10) is given in Fig. 11. The directional semi-variograms were also calculated to check the existence of geometric anisotropies. However, no significant anisotropies are observed in Fig. 11. A practical range of the spatial correlation is approximately 4.0 m (since both the element length and spacing are 2.5 m, we refer to this value as 5.0 m). This practical range is a little smaller than that obtained from each annealing solution because of the smoothing effect of the median filters. However, it is nearly consistent with the range (5–7.5 m) estimated from the optimal cluster size, in that the optimal cluster size corresponds to 20–40% of the number of fractures within the practical range of spatial correlation (Nakao et al., 1999).

5.2. The lower zone

We repeated the same procedure for the lower conductive zone. Fig. 12 summarizes inversion re-
results. The lowest minimum objective function (energy), 140.0, is reached in the seed 7 of the cluster size 1, starting from the initial objective function (energy) of $4.82 \times 10^3$. The averaged minimum objective function (energy) is smallest for a cluster size of 1. As the cluster size decreases, the minimum objective function (energy) also decreases. For cluster size of 10, the anisotropic-shapes case reaches smaller energy than that of isotropic-shapes case. Comparison of pressure transients between observed

Fig. 10. Predicted errors of injection into well SW-2 for five annealing solutions for the upper zone.

Fig. 11. Omnidirectional and directional semi-variograms of transmissivity for the inversion results with cluster size $= 10$ (U2) for the upper zone.
Fig. 12. Inversion results for the lower zone: minimum objective function (energy) vs. cluster sizes.

and calculated data for the minimizing configuration obtained using the cluster size 1 (seed 7) is illustrated in Fig. 13. Although a good match between observed and calculated data was obtained in the

Fig. 13. Pressure match for minimizing configuration obtained using cluster size of 1 (seed 7) for the lower zone. Symbols and lines represent the observed and calculated data, respectively.
Fig. 14. Median-filtered inversion result with cluster size 1 (L1) and cluster size 10 (L2) for the lower zone. The injection test data into well 0-0, SW-1 and SW-3 in series (filled circles) was used in the inversion.
Fig. 15. Median-filtered inversion result with cluster size 20 (L3) and cluster size 40 (L4) for the lower zone.
lower zone, the absolute head value of the injection into SW-3 is quite large. This causes the relatively high minimum objective functions (energies) rather than those of the upper zone cases.

Five median-filtered configurations are shown in Figs. 14–16. The first result is found using a cluster size of 1. The second, third and fourth inversion solutions are found using cluster sizes of 10, 20 and

Fig. 16. Median-filtered inversion result with cluster size 10 and anisotropic shapes for the lower zone (L5).

Fig. 17. Predicted errors of injection into well SW-2 and SE-1 for five annealing solutions for the lower zone.
Fig. 18. Omnidirectional and directional semi-variograms of transmissivity for the inversion results with cluster size = 1 (L1) for the lower zone.

40 with isotropic clusters. The fifth result is found using a cluster size of 10 with anisotropic clusters, with strikes at N30W and N60E. We refer to these as cases L1 through L5. A major feature common to all the results is that well SW-3 is clearly isolated. This is because SW-3 had a very high head change while injection (see Fig. 13). Annealing results also show a relatively high transmissivity area between wells SW-2 and SE-2.

In order to evaluate the inversion results, a cross validation test was again conducted. We modeled the SW-2 and the SE-1 injection tests, which were not included in the inversion as injection data. Fig. 17 shows predicted errors for injecting at SW-2 and SE-1 for each cluster size results (L1–L5). For cluster size of 10, the anisotropic-shapes case (L5) obtains smaller error than that of isotropic-shapes case (L2). This finding will be discussed in the next section. The prediction errors are smallest for L1 in both injections. This result indicates that L1 (cluster size of 1) is the most suitable among the results of five cluster types.

The directional and omnidirectional semi-variograms for L1 (cluster size of 1) are given in Fig. 18. A practical range of the spatial correlation is less than 2.5 m (since both of the element length and spacing are 2.5 m, we refer to this value as 2.5 m). This practical range is consistent with the range (around 2.5 m) estimated from the optimal cluster size (Nakao et al., 1999). It is impossible to observe whether geometric anisotropies of the correlation structure exist within the range of 2.5 m, because of the resolvable scale used in the configuration. Note that this is the first attempt to estimate the horizontal correlation length of transmissivity for both the upper and lower conductive zones at Raymond field site.

6. Discussion

In the preliminary analysis of the upper zone (Nakao et al., 1999), we conducted the SA inversion just once for each cluster size, resulting in a little overestimation of the practical range of the spatial correlation for transmissivity (5–10 m). In this study, seven realizations (annealing solutions) starting from seven different random seeds were obtained and
stacked to produce one average configuration by means of the median filters. This is because we really want to extract the average properties of the transmissivity distribution, which may be specific for the results obtained using each cluster size.

For the upper zone, we showed that the configuration achieved using cluster size of 1 or 10 with isotropic cluster shapes (cases U1 or U2) are the most suitable among five cluster types for obtaining good fluid flow models. Furthermore, the inversion using cluster size of 10 requires approximately one tenth of the iteration number for the cluster size of 1, which means that the cluster size of 10 is optimal to enhance convergence of the inversion from the viewpoint of computational effectiveness. From the semi-variogram analysis of U2, the practical range of the correlation structure is estimated to be 5.0 m, and no obvious geometric anisotropies are observed.

For the lower zone, we showed that the configuration achieved using cluster size of 1 (case L1) is the most suitable among five cluster types for obtaining good fluid flow models. On the other hand, both of the minimum objective function (energy) and prediction errors are smaller for the anisotropic cluster shape case (L5) than those for the isotropic cluster shapes case (L2). This suggests the possibility of the lower zone being anisotropic with possible strikes at N30W and N60E, and that the geometric fracture information from outcrops and boreholes may be correlated to hydrology. Even though this is the case, the practical range of the correlation structure is estimated to be less than 2.5 m from the semi-variogram analysis of the best result (L1).

From the televiewer, television and optical scanner logs it was determined that the lower zone is associated with an anomalous single open fracture as compared to the upper zone, which is an extensive fracture zone. This would explain the difference in the estimated practical range of the spatial correlation for transmissivity. Vasco et al. (1996) analyzed seismic velocity structures and Q attenuation structures at this site and reported that the velocity and attenuation anomalies appeared to coincide with the extensively fractured upper zone, although some discrepancies between the velocity and attenuation anomalies existed in the lower zone. They suggest that velocity and attenuation anomalies indicate fracture zones rather than individual fractures. This also supports the difference in fracture types between the upper and lower conductive zones.

We showed that the process of selecting a reasonable cluster size and shape using this algorithm by trial and error may lead to an estimated range of spatial correlation. With a possible range of spatial correlation parameters, we have much more valuable information, such as how to extrapolate model results to a larger region. Note that a cluster size of, say, five can be used to fine-tune the optimal cluster size. However, because we chose to use an orthogonal lattice, the resolvable length scale is nonetheless limited to the multiple of 2.5 m when we estimate the practical range of spatial correlation for transmissivity.

It is important to conduct cross validation tests to determine the variability in solutions, because the models we build use very limited data. This differs from building models based on a complete knowledge of the “real” fracture system. For future study, in order to reduce the uncertainty in the hydrological model, inversion of both hydraulic and tracer test data is planned, because the tracer test data analysis is more effective to estimate fluid flow paths within the fracture network. It is also important to conduct sensitivity studies to develop a field test design, such as the relative number of injection or pumping wells and observation wells, and the location of the wells. These factors are clearly related to the ability to detect heterogeneity of the hydraulic conductivity structure.

7. Conclusions

The inversion of hydraulic well tests using CVA SA is applied as an inverse technique to construct fluid flow models at the Raymond field site. We model two fracture zones, which are extracted from various geophysical and geological methods. Inversions are run seven times starting from seven different random seeds for four cluster sizes of 1, 10, 20 and 40 to investigate spatial characteristics of the transmissivity distribution within the fracture zones. In order to represent average properties of the annealing solutions obtained for a same cluster size,
seven annealing solutions are combined to produce one configuration by means of median filters.

Since a cluster size of 1 and 10 gives the minimum objective function (energy), the practical range of the spatial correlation of transmissivity is estimated to be 5 m in the upper extensive fracture zone. On the other hand, the practical range of the spatial correlation of transmissivity is estimated to be less than 2.5 m in the lower fracture zone, because the cluster size of 1 gives minimum objective function (energy). These results are confirmed by the cross validation of the injection test data, which is not used in the inversion.

Acknowledgements

This work was supported by Science and Technology Agency of Japan (STA). It was also partially supported by the Japan Nuclear Cycle Development Institute (JNC), through the U.S. Department of Energy Contract Number DE-AC03-76SF00098. We would like to thank two anonymous reviewers for their helpful comments.

References


