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Characterization of fracture network with geometrical properties

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Abstract

In order to delineate the flow system of fractured hard rock aquifer, numerical experiments are conducted and the results are analyzed with Mote Carlo simulation. The results show that the percolation threshold and the effective conductivity of a fracture network can be estimated with power law exponent (a) and fracture intensity. But the dependability of the estimated value relies on the percolation threshold, the system scale, and the characterization level.

key word : fracture network, dependability, effective conductivity, percolation threshold, system scale, characterization level

1. Introduction

For the simulation of flow and transport in fractured rocks, the equivalent medium approaches and the discrete fracture network approaches have been typically used. Which models, then, are appropriate for a given fractured rock of specific domain? Ji (2001) suggested that the percolation threshold and the correlation length of a fracture network can be used as criteria to evaluate which model is appropriate to describe the flow system for a given 2-D fracture network. But how about for 3-D fracture network?

The characterization level of a fracture network is important to conceptualize the flow system. In a highly dense fracture system where the geometry and the hydraulics are dominated by a number of statistically identical fractures, only the statistical information is available on the fractures in the system. On the contrary, in a sparse fracture system, flow phenomena are dominated by small number of conducting fractures and thus deterministic information for each contributing fracture is indispensable for analyzing flow and transport. Thus the characterization level for fractured rocks can be a criterion for the model selection.

In this study, we introduce the networks with power law size distribution, define the effective conductivity, and describe the Monte Carlo simulation. From the results, we evaluate and complement the suggestion of Ji (2001) in 3-D random fracture networks.

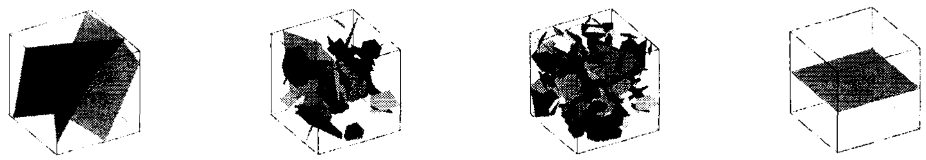
2. Fracture networks and flow simulation

There is increasing field evidence that fracture trace lengths (and thus fracture sizes) are distributed according to a power law (Segall and Pollard, 1983; Davy, 1993; Nicol et al., 1996; Odling, 1997), defined as

$$n(l) = \alpha l^{-a} \quad \text{for} \quad l \in [l_{min}, l_{max}] \tag{1}$$

where $n(l)dl$ is the probability of a fracture having a size in the range $[l, l+dl]$, α is a normalization factor, a is a characteristic power law exponent, and l_{min} and l_{max} are lower and upper cutoffs of the fracture size. In this study, fracture size (l) is defined as a diameter of the smallest circle, which can include the fracture. In power law 3-D fracture networks, when the characteristic exponent $a<1.5$, the conductivity of fracture networks are dominated by fractures which is larger than domain size, while when $a>4$, fractures of lower cutoff size rule the network properties. In the intermediate case, whole ranges of fracture size contribute to network properties (Bour and Davy, 1998).

Fracture networks with power law exponents 1.0, 2.5, 3.5, and 4.5 are considered for the simulations of various network structures. Fractures with hexagonal shape with unit aspect ratios are generated in three-dimensional domain of size $L \times L \times L$ (Fig. 1). Fracture locations are assumed to be independent each other. For each power law network structure, different fracture densities are applied to estimate the hydraulic conductivity of the network. For the purpose of analysis, the hydraulic conductivity of a generated fracture network is normalized to the conductivity of a network where single horizontal fracture composes the network in Fig. 1(d). In order to quantify the system variability for given network structures, we analyze the results with Monte Carlo simulation.



(a) (b) (c) (d)

Fig. 1. An ensemble of generated fracture networks with power law exponent: (a) 1.0; (b) 2.5; (c) 3.5. (d) is a fracture network for reference.

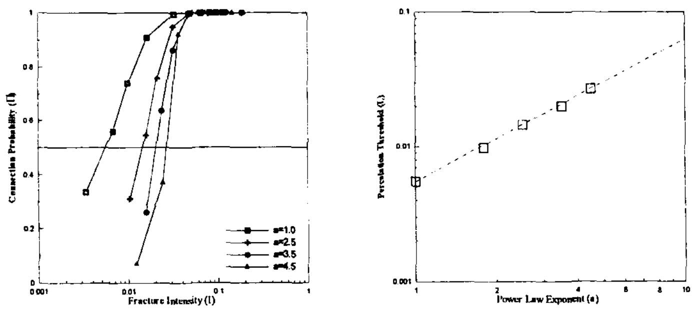
3. Results and discussion

The percolation thresholds (I_c) are calculated from the relation between connection probability (Π) and fracture intensity (I) at various power law exponent, a by Monte Carlo simulation (Fig. 2). At large a, the transition becomes sharp. In Fig. 2. (b), I_c of the network and the a can be represented with power law:

$$I_c \propto a^{1.06} \tag{2}$$

Ensemble mean of the effective conductivity and its variability are calculated as a function of $I - I_c$ (Fig. 3). A power law governs the effective conductivity. However, the exponent changes from 0.62 to 1.25 at an inflection point. This result is agreed with that of Ji (2001). It can be inferred that the location of the inflection point is determined by the relation between the correlation length of the system and the system scale based on results of Ji (2001):

$$K_{eff} \propto \begin{cases} (I - I_c)^{0.62}, & L < \xi \\ (I - I_c)^{1.25}, & L > \xi \end{cases} \tag{3}$$



(a) (b)

Fig. 2. Determination of the percolation threshold: (a) variation of the probability that the system is percolated at various power law exponents. (b) calculated percolation threshold at various power law exponents.

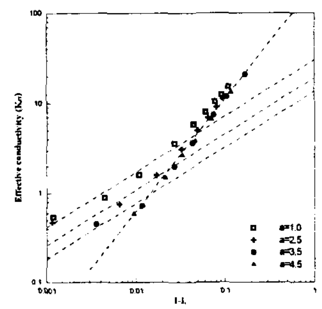


Fig. 3. Plots of the effective conductivities with $I - I_c$

The variability of the effective conductivity can be represented by the coefficient of variation (CV). As the fracture intensity increases, variability of K_{eff} deceases (Fig. 4). When $I < I_c$, CVs are greater than 1 generally. This means that it is unlikely to predict the order of magnitude of the network conductivity with given power law exponent and fracture intensity when $I < I_c$. And the CV decreases, as a becomes larger. However, CVs mostly ranges from 0.1 to 1 and the system properties are not likely to be understandable within an order in any given fracture intensity. To reduce CV, we assume that the geometry of some portion of fractures is a priori known and the results of the conditional simulations are described (Fig. 5). The results show that when the system scale is smaller than the correlation length of the system or when

$I < I_c$, no significant reduction in CV is observed.

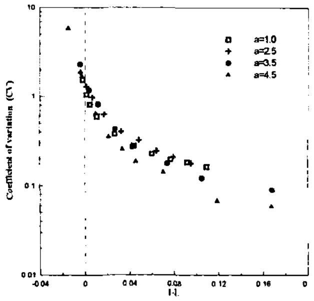
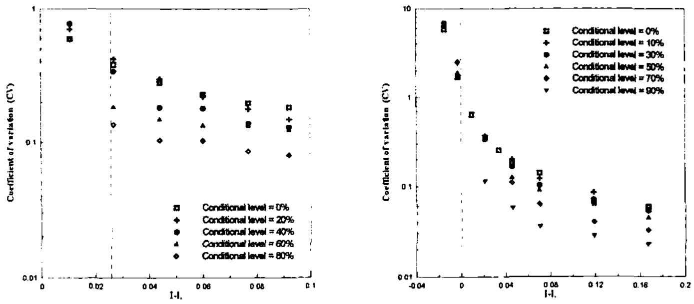


Fig 4. Plots of the coefficient of variations (CV) of the effective conductivities with $I - I_c$. The dashed line is at the location of $I = I_c$.



(a) (b)

Fig 5. Plots of the coefficient of variations for conditional simulations; (a) when $a = 1.0$. Dashed line is at the estimated location of $L/l = \xi$; (b) when $a = 4.5$. Dashed line at the location of $I = I_c$

Based on these results, it is suggested that the percolation threshold, the correlation length, and the characterization level can be criteria to evaluate which model is appropriate to describe the flow system for a given fracture network.

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