# Uncertainty of stochastically generated fracture networks for the SA of a subsurface radwaste repository

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# 1. Introduction

The characterization of a fracture system is important for the safety assessment of a subsurface repository for radioactive waste. A discrete fracture network approach describes the geometry and hydraulic properties of individual fractures and thus, it can account for transport phenomena of nuclides through these fractures. In this approach, fractures can be populated based on the characterization of the fracture network. The characterization of fracture networks can be classified into a deterministic or statistical characterization according to the type of information collected. The deterministic characterization represents the explicit acquisition of information on the geometry and hydraulic properties for individual fractures and the statistical characterization indicates collection of implicit group information for a population of fractures. In the real-world applications, the stochastically generated fracture network from the statistical characteristics is mostly used to simulate the fracture system near a repository. In this study, we define different network structures stochastically with power law fracture size distributions and then, analyze the ensemble mean and variability of the effective connectivity of the networks for different structural characteristics. From the ensemble behaviors of the effective connectivity, we discuss the uncertainty of the stochastically generated fracture network.

### 2. Methods

There is increasing field evidence that fracture trace lengths and fracture sizes are distributed according to a power law [1], defined as

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

where n(l)dl is the probability of a fracture having a size in the range [l, l+dl],  $\alpha$  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. Fracture size (l) is defined as a diameter of the smallest circle, which can include the fracture. In this study, Fracture networks with power law exponents of 1.0, 2.5, 3.5, and 4.5 are considered for the simulations of different network structures, and Fractures of the hexagonal shape with unit aspect ratio are generated in a

three-dimensional domain ( $L \times L \times L$ ). Using the generated fracture networks, we calculated the effective connectivity that reveals the hydraulic property of a fracture network. Then, in order to quantify the system variability for given network structures, we analyze the ensemble mean and standard deviation of the effective connectivity for realizations of fracture networks with various power law exponents and with different fracture density values.

# 3. Results

The ensemble mean and variability of the effective connectivity are calculated for various power law fracture networks with different fracture densities. Fracture density or the number of fractures for various network structures is ranged in order that the percolation probability of the networks ( $\Pi$ ) can vary from near 0.1 to close to 1.0 for each network structure. The percolation probability of the fracture networks are calculated with various mean effective connectivity values. It is shown in Fig. 1 that percolation probability and mean effective connectivity ( $\Lambda$ ) have similar relationships for all power law exponents. This result indicates that the connectivity of different network structures is well represented by mean effective connectivity.

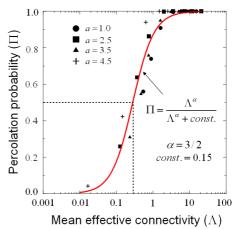


Fig. 1. The percolation probability of the networks with the ensemble mean of the effective connectivity for the networks with power law size distributions.

The relative variability of the effective connectivity can be represented by the coefficient of variation (CV) – standard deviation divided by mean. When the ensemble mean of the effective connectivity increases, the absolute value of standard deviation can increase but the relative value to the mean may decrease. In this case, the coefficient of variation is a measure of the uncertainty or the inverse of the predictability for the average behavior of the effective connectivity: as the system varies more among realizations and the coefficient of variation becomes larger, it becomes more difficult to estimate the system properties with given statistical properties.

The change of the coefficient of variation with fracture density (Fig. 2) shows that the standard deviation of the effective connectivity ranges from 10 % to several times of the ensemble mean for given power law fracture networks. In sparse fracture networks where the coefficient of variation is larger than unity, it is unlikely to predict the order of magnitude of the network connectivity with given power law exponent and fracture density. On the other hand, in highly dense fracture networks where the coefficient of variation becomes smaller than 0.1, the effective connectivity can be safely inferred from fracture density.

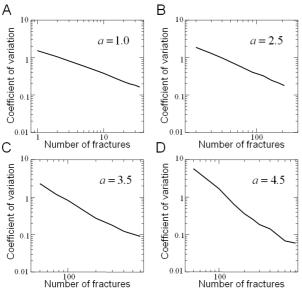


Fig. 2. Coefficient of variation (CV) of the effective connectivity with fracture density for the networks of power law exponents of (A) 1.0, (B) 2.5, (C) 3.5, and (D) 4.5.

The coefficient of variation, plotted with the mean effective connectivity in Fig. 3, linearly decreases with the mean effective connectivity in the log-log scale and when the power law exponent becomes larger, it becomes smaller. The results imply that statistics may be sufficient for characterization in denser fracture networks, especially when the fractures have similar geometry. In general, when the mean effective connectivity is greater than a percolation threshold ( $\approx$ 

0.3 in Fig. 1), the coefficient of variation becomes smaller than unity for all given network structures and when the effective connectivity approaches unity, the coefficient of variation decreases rapidly (Fig. 3).

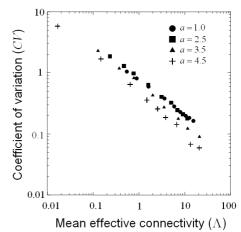


Fig. 3. Coefficient of variation (CV) of the effective connectivity with the effective connectivity of the power law networks.

### 4. Conclusions

In a highly fractured system where the network is likely to percolate the domain ( $\Pi \rightarrow 1$ ), statistical characteristics of the networks are sufficient information to estimate the transport properties as they are similar among realizations, which means that the uncertainty of stochastically generated networks are small. In sparsely fractured rocks where fracture density is below percolation threshold ( $\Pi < 0.5$ ), most pathways need to be explicitly identified as a small number of unidentified pathways can significantly change the transport properties, which means that the uncertainty of stochastically generated networks is large. Therefore, when  $0.5 < \Pi << 1$ , statistics can be considered as necessary information and the identification of main pathways is most critical to reduce the uncertainty in estimation of transport properties. Overall, it is concluded that the proper estimation of the percolation probability of a fracture network is a prerequisite for an appropriate conceptualization and further characterization.

#### REFERENCES

[1] N.E. Odling, Scaling and connectivity of joint systems in sandstones from western Norway, J. Struc. Geol., Vol.19, p. 1257-1271, 1997.