# Numerical strategies for characterizing fractured rock from heat tracer experiments

**Delphine Roubinet*[,1], Zitong Zhou[2] and Daniel M. Tartakovsky[2]**

[1] Geosciences Montpellier, University of Montpellier-CNRS, Montpellier, France; [2] Department of Energy Resources Engineering, Stanford University, Stanford, CA, USA

* Presenting and corresponding author: delphine.roubinet@umontpellier.fr; Poster doi: 10.5194/egusphere-egu2020-13699

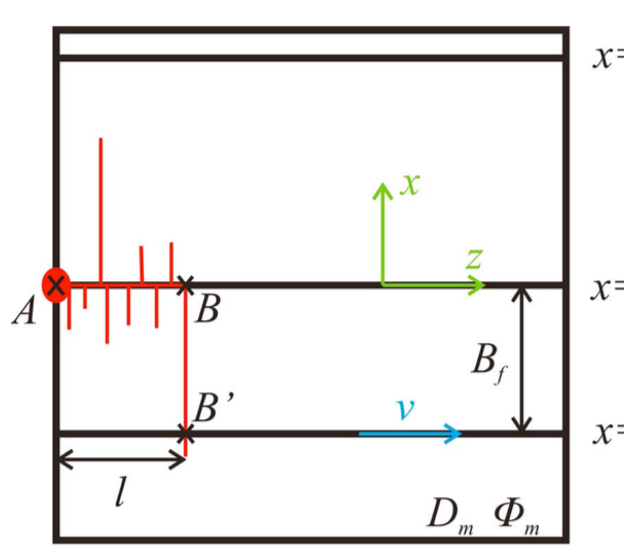
## Framework

Amongst the numerous methods that are used to characterize fractured rocks, the development of advanced field techniques such as active line source (ALS) borehole heating and the distributed temperature sensing (DTS), brings to light the potential use of heat as a tracer. However, there is so far a limited number of theoretical and numerical studies on how thermal experiments could be used for estimating both fracture-network and rock-matrix properties. Here, we wish to evaluate how deep neural network methods can be utilized to analyze synthetic heat tracer test datasets obtained from a particle-based forward model of transport processes in heterogeneous fractured rocks, define surrogate forward models for this problem and perform data inversion.

## Methodological background

- **Particle-based forward transport model**

Model description [Roubinet et al., 2010, 2013; Gisladottir et al., 2016]: Fluid flow in the fracture network; Particle displacement in the fractures; Delay time due to diffusion in the free-mesh matrix; Application to complex fracture networks for solute and heat transport problems; Numerical efficiency suited to parametric analysis and inverting procedures




1. Stochastic definition of the diffusion time spent in the infinite matrix:

$$t_{AB} = t_a + t_{diff}.$$

$$t_{AB'} = t_a + t_{transfer}$$

$$P(t < T) = erfc\left(\frac{\phi_m \sqrt{D_m}}{2b\sqrt{T}} t_a\right)$$

2. Truncation of the diffusion time due to particle transfer to nearby fractures:

$$L\left(P^1_{transfer}\right) \quad \exp\left(l_1\sqrt{\lambda/D_m}\right) \quad 1-\exp\left(-2l_2\sqrt{\lambda/D_m}\right)$$

$$L(P^2_{transfer}) = \frac{\exp\left(l_2\sqrt{\lambda/D_m}\right)}{\lambda} \frac{1-\exp\left(-2l_1\sqrt{\lambda/D_m}\right)}{1-\exp\left(2(l_2-l_1)\sqrt{\lambda/D_m}\right)}$$

- **Deep neural network method**

1. Convert CDF to discrete inverse CDF(ICDF):

$$CDF : F_X(x) := Pr(X < x) = p,$$
$$ICDF : Q(p) := inf\{x \in \mathbb{R}, p \le F_X(x)\}$$
$$ICDF_d : \{Q(p_1), Q(p_2), ...Q(p_N)\},\ p_n \in [0,1]$$

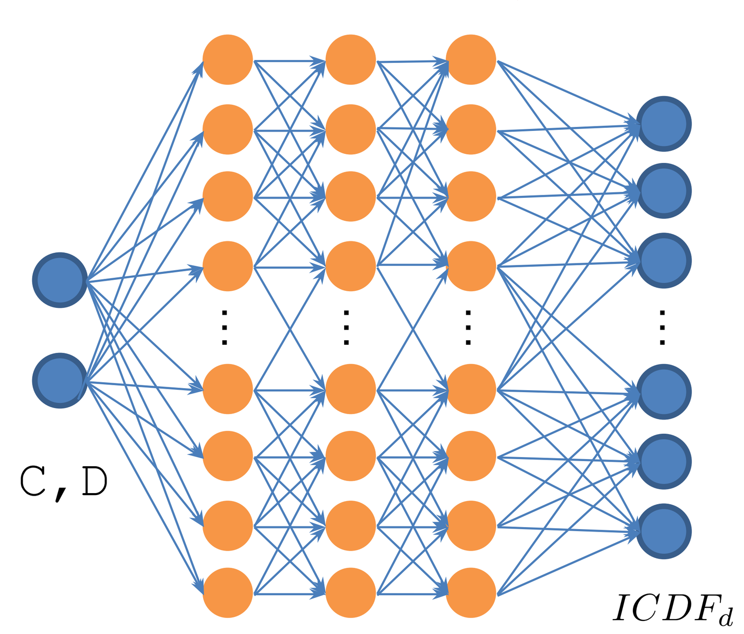
2. Construct Fully connected Neural Network:

$$\mathbf{N_f} : \{C, D\} \xrightarrow{NN} \widehat{ICDF}_{\mathrm{d}}$$
$$\mathbf{N_f}(\mathbf{m}; \mathbf{\Theta}) \equiv (\sigma_{N_l} \circ \mathbf{W}_{N_l - 1}) \circ \ldots \circ (\sigma_2 \circ \mathbf{W}_1)(\mathbf{m}),\ m = (C, D)$$

3. Parameter estimation to obtain $\mathbf{\Theta}$ :

$$Loss(\mathbf{\Theta}) = \frac{1}{N}\sum_i^N \left\| ICDF_d^i - \widehat{ICDF}_d^i \right\|_2^2$$
$$\hat{\mathbf{\Theta}} = \underset{\mathbf{\Theta}}{\mathrm{argmin}}(Loss(\mathbf{\Theta}))$$

Figure 1: Illustration of NN.




## Experiments & Results

- **Forward transport model applied to fractal fracture networks** [Watanabe and Takahashi, 1995]

Input parameters:

Fracture density: $C_i \in [2.5, 6.5],\ i = 1, ..., 10000,$

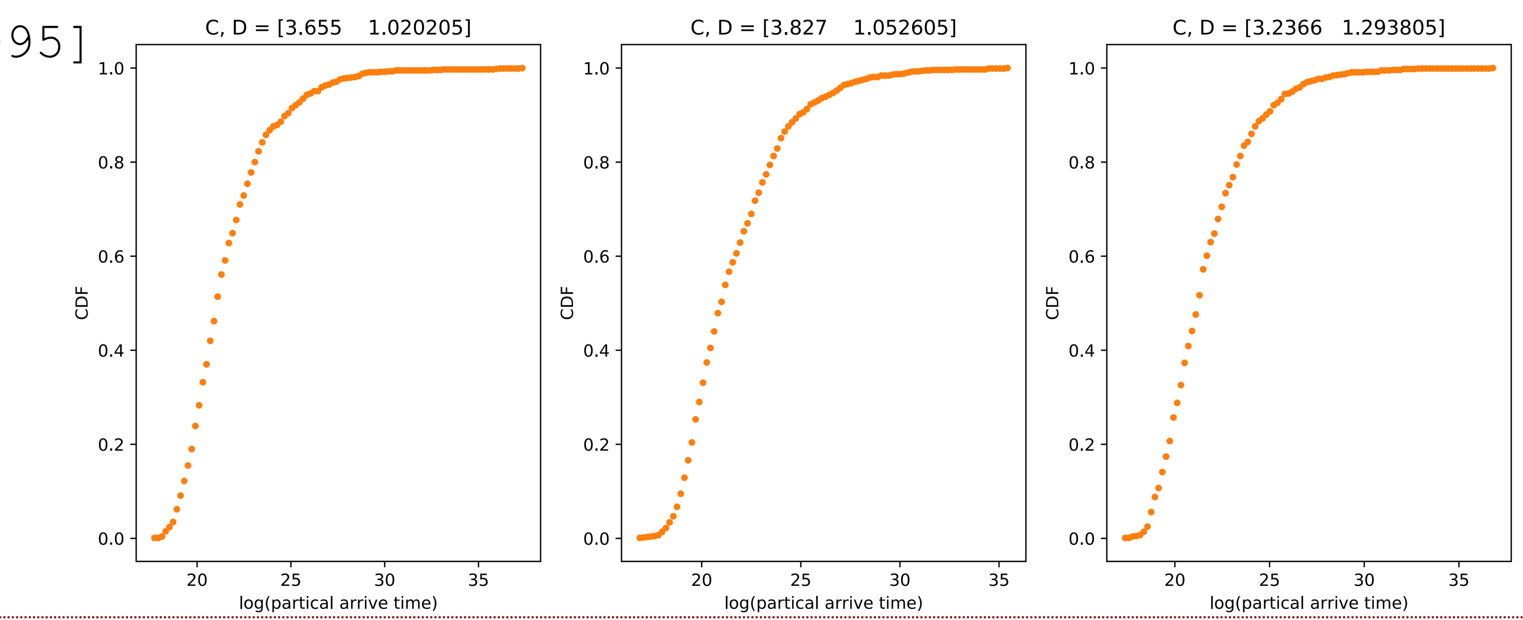
Fractal dimension: $D_i \in [1, 1.3],\ i = 1, ..., 10000.$

6 sets of simulations are done:

Number of particles: nb_part $\in \{1, 10, 100\}$

Discretization of fractures: p_lim $\in \{0, 0.1, 0.2, 0.5, 1\}$

Figure 2: 3 examples of simulation outputs.




- **Deep neural network method**

Training set: 7535 simulations,

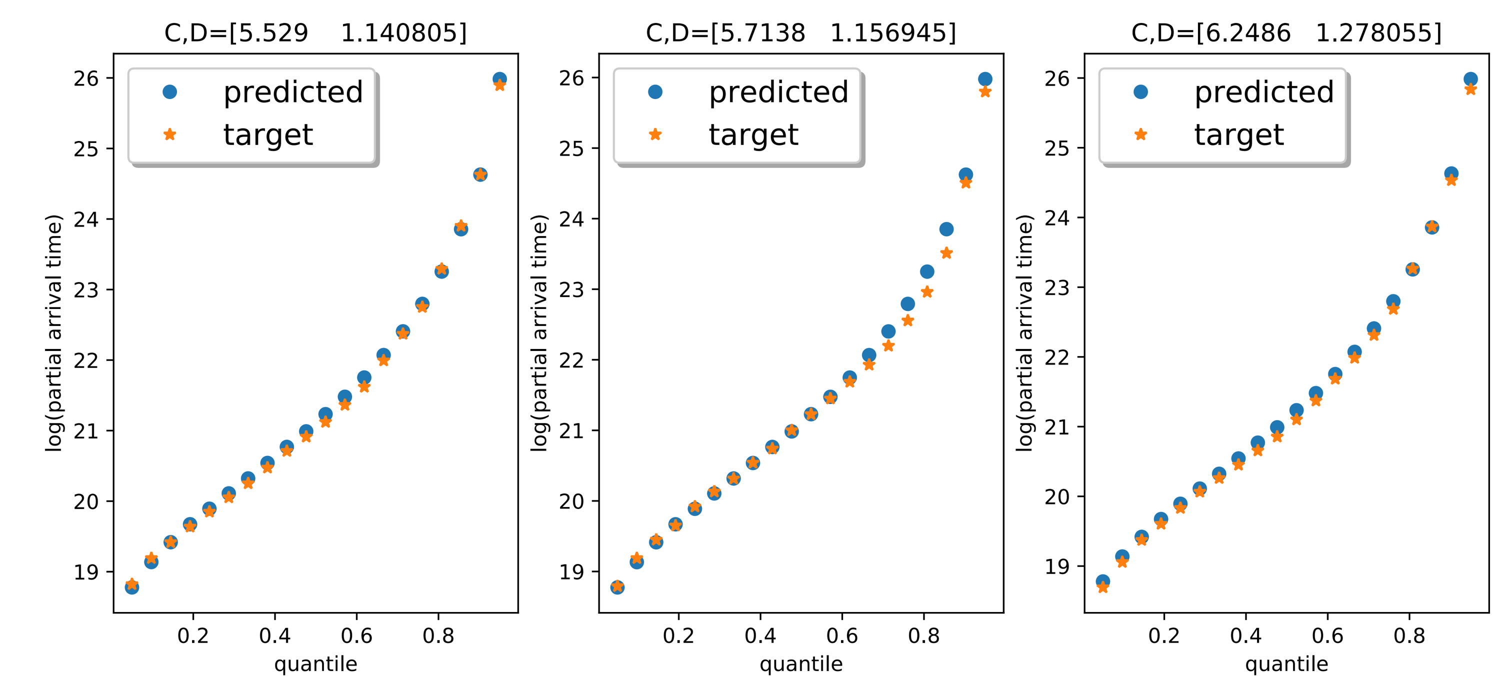
Dimension of ICDF: $ICDF_d : \{Q(1/21), Q(2/21), ...Q(20/21)\},$

Number layers: $N_l = 11$

Number of neurons: $W_1 \in \mathbb{R}^{300\times 2},\ W_{n_l} \in \mathbb{R}^{300\times 300},\ n_l = 2, ..., 9,\ W_10 \in \mathbb{R}^{300\times 20}.$

Loss: 0.336, on a test set: 1884 simulation.

Figure 3: 3 NN prediction examples.




## Conclusions & future work

- **Conclusions:**

1. Particle-based forward transport model are used to construct simulations covering (C, D) ranges with different nb_part, p_lim.

2. The output particle arrival time CDF are converted to discrete ICDF.

3. A surrogate Neural Network is obtained with reasonably good predictions of the ICDF.

- **Future(ongoing) work:**

1. Analyze the well-posedness of the model.

2. Perform direct inversion with a neural network, which predict (C, D) given ICDF.

3. Perform grid sampling with the surrogate forward model: sample the prior distribution of (C, D), compute the corresponding ICDF. For ICDF with unknown (C, D), use the sample set to provide the candidates of (C, D).

## Reference

Roubinet, D., H.-H. Liu, and J.-R. de Dreuzy (2010), **A new particle-tracking approach to simulating transport in heterogeneous fractured porous media**, Water Resources Research, 46, W11507, doi:10.1029/2010WR009371

Roubinet, D., J.-R. de Dreuzy, and D. M. Tartakovsky (2013), **Particle-tracking simulations of anomalous transport in hierarchically fractured rocks**, **Computers and Geosciences**, 50(SI), 52-58, doi:10.1016/j.cageo.2012.07.032

Gisladottir, V. R., D. Roubinet, and D. M. Tartakovsky (2016), **Particle methods for heat transfer in fractured media**, Transport in Porous Media, 1-16, doi:10.1007/s11242-016-0755-2

Watanabe, K., Takahashi, H. (1995), **Fractal geometry characterization of geothermal reservoir fracture networks**, J. Geophys. Res. Solid Earth 100(B1), 521-528