Study on the linkages between microstructure and permeability of porous media using pore network and BP neural network

Hao Liu, Ying Xu, Chengyong Wang, Feng Ding and Haishan Xiao

1 Department of Electromechanical Engineering, Guangdong University of Technology, Guangzhou, People’s Republic of China
2 Sanying Precision Instruments Co. Ltd, Tianjin, People’s Republic of China

E-mail: 15521395668@163.com

Keywords: permeability, porous media, porous air bearings, pore microstructure, BP neural network

Abstract

In applying porous media air bearings (PMABs), designing the pore microstructure of porous media to obtain the desired permeability is challenging. The key parameters in this design are to map the pore microstructure characteristics to permeability and adapt to manufacturing process with the characteristics. For this purpose, a framework is proposed to characterize pore microstructure with morphology descriptor and predict permeability. 3D digital images of porous media are obtained using X-ray micro-computed tomography and various image construction techniques. The complex pore microstructure of porous media is represented with a pore network. Permeability is calculated based on the pore network. Sixteen pore microstructure morphology descriptors are initially calculated to characterize pore microstructure. A back-propagation neural network (BPNN) is built to learn the correlation between morphology descriptors and permeability. Pearson correlation coefficient (PCC) and feature importance scores of morphology descriptors are obtained based on the dataset and trained BPNN. The results demonstrate that the prediction performance of BPNN is excellent. The following six morphology descriptors (porosity, coordination number, average pore diameter, average throat diameter, average pore throat ratio, average throat length) are reserved to characterize pore microstructure. Finally, two types of pore microstructure are designed with the help of knowledge obtained by this research.

1. Introduction

Porous media air bearings (PMABs) are often used in many Original Equipment Manufacturer (OEM) precision machine applications such as metrology equipment, semiconductor wafer manufacturing machines, and precision machine tools due to their advantages of near zero friction and wear. The PMABs can obtain good stiffness and capacity when the permeability of porous media inserted in it ranges from $3.3 \times 10^{-15} \text{ m}^2$ to $8.4 \times 10^{-14} \text{ m}^2$ [1, 2]. It is well-known that permeability is solely determined by the pore microstructure [3]. Many studies have been done with the guidance of PMABs by the reference of papers [4–9]. However, these works mainly focus on the macro-performance such as capacity, stiffness, which cannot provide sufficient knowledge for the design of the pore microstructure of porous media. Therefore, it is worthy of finding a solution to determine the quantitative relationships between pore microstructure and permeability of porous media at the pore scale.

There are usually four methods for calculating the permeability based on the pore microstructure of porous media: pore-scale numerical simulation, pore network modeling (PNM), empirical formula, and convolutional neural network (CNN). The pore-scale numerical simulation approaches mainly include Navier–Stokes’s equations (NSEs) and Lattice Boltzmann equations (LBEs). NSEs or LBEs are solved on the pore microstructure geometry to obtain the flow rate [10–14]. The principle of PNM is to obtain the pore network of pore microstructure and then solve the transport equations on the pore network to determine the flow rate [15–18]. Darcy’s law [19] is employed to calculate permeability using the flow rate. Kozeny-Carman equation may be the
prominent empirical formula [20] that calculates the permeability with empirical coefficient, specific surface, and porosity. CNN has achieved significant success in image classification [21, 22]. CNN has been used to predict permeability of porous media from images with the inspiration of image classification [23–25]. CNN has also been used to predict other properties of materials directly [26, 27].

Generally, the pore-scale numerical simulation method provides a way to calculate the permeability value of porous media accurately. The solution of LBEs and NSEs is obtained using computational fluid dynamics (CFD) techniques. However, CFD requires a high computational cost, which limits the application of this method. The PNM can characterize the pore microstructure with morphology parameters and calculate the permeability, significantly reducing the computational cost with acceptable accuracy. CNN provides a novel way to predict permeability from pore microstructure images.

Some other pore microstructure descriptors can also characterize the pore microstructure, such as tortuosity [28], percolation threshold [29–31], and two-point correlation functions [32]. Permeability can also be calculated from these descriptors.

It should be noted that characterization is a comprehensive concept. All the methods mentioned above can characterize the pore microstructure in some way. However, this study aims to establish the relationship between pore microstructure characteristics and permeability. Furthermore, link the characteristics with the porous media manufacturing process. The morphology descriptors, shown in Table 1, are intuitive for characterizing pore microstructure with the help of X-ray micro-computed tomography technology. Notably, compared with the two-point correlation function, mapping these morphology descriptors to process steps is simple. For example, the pore diameter can be controlled by changing the size of the glue particles.

With the development of three-dimensional imaging technology, the pore microstructure of porous media can be seen on a large scale [33]. X-ray micro-computed tomography technology can obtain 1500^3 voxels of porous media with a spatial resolution of 1 μm. An image contains rich information about the pore microstructure of porous media. The advances in imaging techniques for analyzing complex pore microstructure have revolutionized our ability to characterize various porous media systems [34, 35]. The X-ray data of pore microstructure can be converted to a three-dimensional matrix for many analyses.

Two problems need to be solved. First, how to characterize pore microstructure of porous media; second, what is the proper mathematical model related to the characteristics and permeability. This study presents a research framework consisting PNM and BPNN to characterize porous media effectively and predict permeability. The PNM is used to represent pore microstructure with morphology parameters. The BP neural network (BPNN) is built to map the morphology parameters to permeability. Pearson correlation coefficient (PCC) is calculated to determine the linear relationship between pore microstructure and permeability. Feature importance scores are calculated to show which morphology parameters have a significant effect on predicting permeability.

| Table 1. Morphology descriptors selection. |
|-------------------------------------------|
| Morphology descriptors | ID |
| Number of pores | X1 |
| Number of throats | X2 |
| Coordination number | X3 |
| Maximum pore diameter | X4 |
| Average pore diameter | X5 |
| Maximum throat diameter | X6 |
| Average throat diameter | X7 |
| Maximum pore volume | X8 |
| Average pore volume | X9 |
| Maximum throat volume | X10 |
| Average throat volume | X11 |
| Maximum throat length | X12 |
| Average throat length | X13 |
| Maximum pore throat ratio | X14 |
| Average pore throat ratio | X15 |
| Porosity | X16 |

Mater. Res. Express 9 (2022) 025504 H Liu et al
2. Materials and methods

As mentioned above, two problems need to be solved: characterization and mapping. The pore network simplifies the complex geometry of the pore space with a regular node and channel, which can characterize porous media with morphological parameters. BPNN makes it possible to find relations between variables from large amounts of data. The framework presented in this paper includes four parts shown in figure 1.

2.1. Building the dataset of porous media samples

Four methods, shown in figure 1(a), are used to obtain the dataset, including natural and synthetic porous media samples.

2.2. Extracting the pore networks of porous media samples

The watershed algorithm is used to obtain the pore network from images of porous media. The morphology parameters of the pore microstructure are calculated based on the pore network shown in figure 1(b).

2.3. Training the BPNN model

A Multi-layer perception model is built. The model inputs are the morphology parameters, and the output is labeled as permeability (X17), shown in figure 1(c).

2.4. Explaining the trained model

The correlation between the pore microstructure morphology parameters and permeability is analyzed. The performance of the BPNN is evaluated. The feature importance scores are calculated based on the trained model to investigate which morphology parameters are important role in predicting permeability. The degree of linear correlation between morphology parameters and permeability is measured by Pearson correlation coefficient (PCC), which provides a reference to check the morphology parameters for desired permeability.

Figure 1. Overview of the framework, including (a) obtaining porous media images, (b) extracting pore network of each porous media, (c) using the morphology parameters and permeabilities to train BP neural network, (d) explaining trained BP neural network model with feature engineering approaches.
2.5. Dataset

441 natural porous graphite images are obtained using 3D X-ray. However, to provide reliable training to BPNN, the 441 samples are not sufficient to define the morphological variability that can be seen in graphite. Therefore, throur methods are employed to increase the number of images. Figure 2(a) shows the proportion of the used methods to generate porous media. The proportions of Boolean and GRF are 72.4% totally since their construction speeds are very fast. The CT-Based method can obtain natural porous media images, but it is time-consuming, so it takes the smallest proportion at 8.4%. The QSGS method simulates the growth process of porous media, but its computation time is also high. The proportion of QSGS method is 19.1%. Finally, 5240 porous media images with the sizes of 2503 voxels are generated. The pore microstructure patterns obtained by the four approaches are significantly different, as shown in figure 3. Figure 2(b) shows the permeability distribution of all samples. The range of permeability values is $10^{-17}$ to $10^{-13}$ m$^2$.

2.5.1. CT-Based approach

X-ray microcomputed tomography was accomplished at Guangdong University of Technology, using a μm-CT scanner (nanoVoxel-3000) produced by Sanying Precision Instruments Co., Ltd. The μm-CT features a combination of microfocus tube, a diamond-coated anode target with a focal spot of a few μm, and a flat-panel detector of 244 mm × 195 mm with 1920 × 1536 pixels. The samples were scanned with an X-ray set to 60 kV voltage and a current of 50 μA at the target. During a rotation of 360° of sample stage, 1440 projections were obtained, corresponding to a 0.25° step-size. Three projections were obtained and averaged for each rotation step to reduce noise. Slice images were recorded with a pixel size of 1 μm, the spacing of inter-slice was also 1 μm, resulting in a voxel volume of 1 μm$^3$.

---

Figure 2. (a) The proportion of porous media generated by the four methods, (b) the permeability distribution.

Figure 3. Examples of 3D porous media images with a size of 2503 voxels. The colourful region is pore space, and other is solid matrix, showing (a) Boolean porous media with porosity = 0.19, (b) Gaussian random field porous media with porosity = 0.26, (c) QSGS porous media with porosity = 0.28, (d) CT-Based structure with porosity = 0.11.
2.5.2. Boolean method
In this model, white noise is built with a size of $N^3$. The Gaussian blur filter is performed on the white noise. The anisotropic Euclidean Distance Transform (EDT) is calculated. Peak point method is performed on the EDT images to find the sphere centers, allowing spheres to overlap. The density of sphere centers, or the sphere volume fraction, is used to generate a parametric model. The volume fractions of spheres and embedding medium are denoted by $1-q$ and $q$, respectively. Two kinds of models are considered, where spheres are either ‘solid’ or ‘pore’. In the model (A), flow is outside the spheres entirely; in the model (B) it is only inside the spheres.

The specific surface area $\gamma$ is calculated using the following formula:

$$\gamma = -4 \frac{\partial C(h)}{\partial h} \bigg|_{h=0}$$

(1)

where $C(h)$ is the covariance function that has a different formula for models (A) and (B)

$$C_A(h) = q^{\frac{1}{\alpha^2}} \frac{h^3}{2D}$$

(2)

$$C_B(h) = 1 - 2q + q^{\frac{1}{\alpha^2}} \frac{h^3}{2D}$$

(3)

where $D$ denotes spheres diameter

2.5.3. Gaussian random fields
According to Lang and Potthoff [36], gaussian random fields are created. Assuming a gaussian random field $\mathcal{G}(x)$, $x \in \mathbb{R}^3$ to be simulated, with a mean of zero and a covariance function $\Psi(x, y)$. The covariance function can be written as:

$$\Psi(x, y) = \int_{\mathbb{R}^3} e^{-2\pi (p \cdot x - y)} \gamma(p) dp$$

(4)

$$\gamma(p) = \exp \left[ -\alpha^2 (p_1^2 + p_2^2 + p_3^2) \right]$$

(5)

where $\gamma(p)$ is the spectral density of the gaussian random field, and $\langle \cdot, \cdot \rangle$ is the inner product. A pore microstructure with length scale parameter $L$ and resolution $N^3$ is to be created. Letting $\delta = L/N$, $\alpha = 1.25$. FFT and FFT-1 denote the forward and inverse three-dimensional Fourier Transforms, respectively. It can be performed as follows: Generating an array $W$ where all components are independent and getting a gaussian distribution with a mean of zero and a standard deviation of $\delta^2$ (white noise). The Fourier space grid is defined as $p = (p_1, p_2, p_3)$ to use FFT($W$), where $p_1 \in (-N/(2L), (-N/2 + 1)/L, ..., (N/2 - 2)/L, (N/2 - 1)/L)$ and likewise for $p_2, p_3$. By using the commutation relation $\gamma(p)$ on the grid, $U = \text{FFT}(W) \times \gamma(p)^{1/2} / L^3$. Finally, the gaussian field is obtained as $\text{FFT}^{-1}(U)$. After that, the scale fields are converted to two-phase media using the threshold method. The threshold is chosen as an acceptable value to procure a specified porosity. The execution time is approximately 1 s for each porous media sample by using Python programming.

2.5.4. Quartet structure generation set (QSGS)
QSGS is a method based on stochastic clustering theory to generate stochastic porous media [37]. Four major factors primarily regulate the formation of porous media. The implementation strategy is explained below with numbered sentences. (1) An array of zeros $M$ with a size of $N^3$ is generated. (2) Solid seeds are randomly spread in the array depending on a distribution probability, $C_0$, which is lower than the target porosity of porous media.

![Figure 4](image-url) In 2D, a pore’s connectivity and size are shown, (a) the pore regions with number 34 is chosen as the focal point, as well as neighboring pores 6, 68, and 90, where equivalent diameter refers to the diameter of a ball with the same volume of the pore, (b) the pore and throat size information is determined using the image’s Euclidean Distance Transform (EDT), the white throat regions are discovered by dilating region 34 and using the watershed algorithm to classify overlapping regions, (c) the extended pore diameter extends into the adjacent pore while the global distance map is used, (d) using the local EDT of the specific pore to determine the inscribed pore diameter.
This is accomplished by assigning a random virtual number to each element then selecting the elements whose number is less than $C_d$ as the solid seed. The value of the seed elements in the array $M$ become one. (3) The directional growth probability $P_i$ is used to check these seeds expanding their neighboring components. In this checking process, each of the neighboring elements of the solid seeds is assigned a random virtual number, then compared with $P$. Only the number of neighboring elements is less than $P_i$ becomes part of the growing solids. (4) Repeat steps (2) and (3) until the target porosity is achieved in the array $M$.

2.6. Pore network
A pore network is made up of nodes that represent individual pores in pore space and links that connect the nodes of neighboring pores. Physical properties such as local permeability can be assigned to these links. The pore network is a simplified representation of the natural pore space. Different approaches using different definitions for a pore have been proposed. The definition proposed by Piovesan [16] is used in this study. Prefiltering the distance diagram, deleting peaks on saddles and plateaus, mixing peaks that are too close, and

![Figure 5. PNMs of the samples shown in figure 3.](image)

![Figure 6. (a) The Berea sandstone, where the colorful region is pore geometry, (b) the pore network extracted by watershed algorithm, (c) pressure distribution of the pore network.](image)
assigning void voxels to appropriate pores using a marker-based watershed are the four key steps of the algorithm. Figure 4 illustrates how the pore microstructure is divided into individual pore bodies and throats. The pore body with voxels labeled $i$ can be isolated to compute morphology properties. Figure 5 shows the PNM obtained by applying the watershed algorithm to the pore microstructure of porous media. The spheres represent the position and size of the pores, while the cylinders represent the throat. After obtaining the pore network, permeability can be calculated based on it. Figure 6 shows the calculation process from porous media image to permeability. The steady-state condition, mass conservation at the nodes is assumed to model single-phase fluid flow. Flowing in $x$-axis is simulated by adding a pressure drop between inlet and outlet; the other sides are impermeable. Since the links are saturated with fluid, the flow rate $Q_{ij}$ from pore $i$ to pore $j$ is given by:

$$Q_{ij} = G_{ij}(P_i - P_j)$$

where $G_{ij}$ stands for the channel hydraulic conductance and the pressure values registered in pore $i$ and $j$ are $P_i$ and $P_j$ respectively. Hydraulic conductance of a fluid-filled link determined by applying Poiseuille’s Law with the condition of laminar flows in a cylindrical cross-section:

$$G_{ij} = \frac{\pi r^4}{8\eta l}$$

where $r$, $l$ and $\eta$ denote the throat radius, length, and dynamic fluid viscosity, respectively. The next step is to apply mass conservation to pores, which is mathematically expressed for pore $i$ in the conditions of the incompressible fluid:

$$\sum_j Q_{ij} = 0$$

From the mass conservation hypothesis, a linear system equation is written:

$$GP = -Q$$

where the pressure values at each pore are stored in the vector $P$, $Q$ represents the flow rate at each pore of the pore network, and their summation is equal to zero, according to equation (8). The conductance matrix $G$ is a sparse, symmetric matrix with non-diagonal elements expressed by the cylindrical hydraulic conductance. The diagonal elements are computed as:

$$G_{ii} = -\sum_j G_{ij}$$

The volumetric flow rate $Q$ through the domain is calculated after the linear system equation is solved. Darcy’s law is used to determine the permeability, $K$:

$$K = \frac{\eta LQ}{A\Delta P}$$

where $L$ and $A$ are the sample length and cross-section area, respectively. $\eta$ is dynamic fluid viscosity set to 0.001 Pa s, $\Delta P$ is the pressure difference applied to the sample.

The watershed algorithm is applied to Berea sandstone to verify the permeability prediction. The Berea sandstone is a standard material used in geosciences known for its permeability. Figures 6(a) and (b) show the pore microstructure of Berea sandstone and the pore network extracted by the watershed algorithm, respectively. The pressure distribution can be seen in Figure 6(c). The experimental permeability of the Berea sandstone is $1.3 \times 10^{-12}$ m$^2$, and it is calculated from the pore network as $1.6 \times 10^{-12}$ m$^2$. The difference is close to the experimental value.

A further function of the pore network is to characterize the porous media explicitly. Therefore, sixteen morphology parameters shown in Table 1 are produced with a statistical method.

### 2.7. BP neural network

BPNN is a mathematical representation of the biological neural network. The BPNN can be used to learn and store a lot of mapping relationships from the input-output dataset. In the beginning, the identification of the mathematical equation which describes the relationships is not needed. In this paper, the inputs are morphology descriptors (X1-X16) and the output is permeability (X17). The relations between the inputs and output are very complicated without any explicit mathematical equation. BPNN has the potential to find relationships hidden under a big dataset.

There are sixteen neurons in the input layer and one neuron in the output layer. The key point is to determine the number of hidden layers, and neurons in all layers included hidden. Generally, there are no exact rules for designing BPNN except for some basic rules: (1) If the dataset is linearly separable, there is no need to introduce a hidden layer. (2) If the dataset dimension or feature is fewer, it means less complex, and BPNN
would work with 1 to 2 hidden layers. 3 to 5 hidden layers can be used for a complex dataset. (3) The number of hidden neurons should be between the size of the input layer and the output layer. Based on these rules, initially, two hidden layers are selected, each hidden layer with sixteen neurons. The performance of BPNN is compared with linear regression, decision tree, random forest, gradient boosting, support vector machine [38–41].

### 2.8. Matrix
The Pearson Correlation Coefficient (PCC) is a statistics function that measures the linear correlation between two variables. It is calculated by the covariance of two variables divided by the product of their standard deviations. The value of PCC ranges from $-1$ to $1$ because it is essentially a normalized measurement of the covariance. When applied to a sample, PCC is commonly represented by $r_{xy}$ and may be referred as the sample correlation coefficient or the sample Pearson correlation coefficient. Given paired data $(x_1, y_1), \ldots, (x_n, y_n)$ consisting of $n$ pairs, $r_{xy}$ is defined as:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2} \sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

(12)

where $n$ is the sample size, $x_i$, $y_i$ are the individual sample points indexed with $i$, $\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i$ is the mean value of variable $x$, and similarly for $\bar{y}$.

### 3. Results and discussion

#### 3.1. Prediction performance
Table 2 presents the coefficient of determination $R^2$ for the proposed BPNN and surveyed methods. All the models give high values of $R^2$. Gradient boosting and BPNN have the best values. The performance of the Gradient boosting and BP neural network could be demonstrated by plotting predicted values versus the actual values shown in figure 7. Sklearn library includes Linear regression method, Decision tree method, Random Forest method, Gradient boosting method, Support vector machine method. The most straightforward Linear

| No | Model                  | $R^2$ |
|----|------------------------|-------|
| 1  | Linear regression      | 0.867 |
| 2  | Decision tree          | 0.801 |
| 3  | Random forest          | 0.823 |
| 4  | Gradient boosting      | 0.952 |
| 5  | Support vector machine | 0.871 |
| 6  | BP neural network      | 0.964 |

Figure 7. Comparison of predicted and real permeability. (a) BP neural network, (b) gradient boosting.
Figure 8. (a) The correlation matrix among X1-X17, (b) the features importance scores of morphology descriptors in predicting permeability.

Table 3. Comparison of FI rank and PCC rank.

| FI rank | Value | PCC rank | Value |
|---------|-------|----------|-------|
| X16     | 23.7  | X16      | 0.73  |
| X3      | 20.9  | X5       | 0.56  |
| X5      | 19.0  | X9       | 0.49  |
| X7      | 16.7  | X7       | 0.48  |
| X15     | 16.2  | X11      | 0.46  |
| X13     | 5.0   |          |       |

Figure 9. The irregular pore network with permeability of $1.1 \times 10^{-15}$ m$^2$. 
regression gives 0.867 for $R^2$. The $R^2$ of BPNN is 0.964. That indicates the used mathematical model shows a good correlation between input and output.

3.2. Feature importance

Feature importance (FI) is a category of feature selection that assigns scores to input features in a predictive model, indicating the importance of each feature when making a prediction. Figure 8(b) shows the importance scores of all morphology descriptors. Some morphology descriptors have a high degree of linear correlation. Therefore, it is necessary to select important features considering the PCC. Only one of the highly linearly related parameters remains, such as X1, X2, and X3 have high PCC values. Therefore, X1 is selected. On the other hand, the morphology parameters with maximum value, such as X4, X6, X8, X12, and X14 are ignored due to their low probability of these values. Finally, X16, X3, X5, X7, X15, and X13 are selected to represent the pore microstructure of porous media, and the rank of PCC and FI can be seen in table 3.

3.3. Design of pore network

Two types of pore networks are designed. The first type has irregular pore and throat distribution with the permeability of $1.1 \times 10^{-15}$ m$^2$ shown in figure 9. The pore network is the representative elementary volume (REV) with a size of $0.4 \times 0.4 \times 0.4$ mm$^3$. It is concluded that X16, X3, X5, X7, X15, and X13 are suitable for representing the pore network. The distributions of these parameters are shown in figures 9(b)–(f). The equivalent pore diameter follows Gauss distribution with $\sigma = 2$, $\mu = 8$, and the pore throat ratio follow Gauss distribution with $\sigma = 2$, $\mu = 2.5$.

$$y = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{1}{2} \left( \frac{x-\mu}{\sigma} \right)^2}$$

The second type has regular pore and throat distribution with the permeability of $4 \times 10^{-16}$ m$^2$, as shown in figure 10(a). The pore network is the REV with a size of $10 \times 10 \times 10$ mm$^3$. The coordination number is shown in figure 10(b). The other important morphology parameters are shown in table 4. In the future, 3D printing technology may be used to manufacture porous graphite materials with controlled permeability.
4. Conclusions

Mining from big data explains the relationship between pore microstructure and permeability for porous media manufacturing, and it presents a design method for porous media. This method will reduce the possibility of trial-and-error, so lead to fast developments in porous media with tailored permeability. In this paper, several well-developed methods are employed with pore microstructure morphology descriptors to predict permeability accurately. The framework can easily apply general procedures to other permeability-like transport properties of porous media by replacing the permeability label. In particular, the three construction methods (GRF, QSGS, and Boolean) can also be used to generate different realizations of porous media for investigating a diversity of transport properties, such as diffusivity, electrical and thermal conductivity.

5240 images of porous media are obtained. Sixteen morphology descriptors are extracted from the pore network as input variables for BPNN training. The permeability, treated as the output of BPNN, is calculated based on the PNM. The $R^2$ between actual and predicted permeability achieves 0.964, indicating that the proposed BPNN is proper and efficient. The investigation of feature importance scores demonstrates that porosity, coordination number, average pore diameter, average throat diameter, average throat length, and average pore throat ratio are suitable for characterizing pore microstructure. Therefore, a designer should focus on linking these parameters with the specific manufacturing processes in practical application. The investigation of the Pearson correlation coefficient demonstrates that average throat length is inversely proportional to permeability. Porosity, average pore diameter, average throat diameter are highly proportional to permeability. In the same way, the designer should map these parameters to the process steps and obtain tailored permeability by adjusting these steps.

Acknowledgments

This project is supported by Tianjin Key Program (Grant No. 18YFZCGX00240), Guangdong Province Key Field Program Project (Grant No. 2020B090924005).

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

ORCID iDs

Hao Liu  @ https://orcid.org/0000-0002-5837-3868
Chengyong Wang @ https://orcid.org/0000-0001-6785-9491

References

[1] Durazo-Cardenas I S et al 2014 Permeability and dynamic elastic moduli of controlled porosity ultra-precision aerostatic structures Ceram. Int. 40 3041–51
[2] Cui H et al 2018 A fractal method to calculate the permeability for compressible gas flow through a porous restrictor in aerostatic bearings Int. J. Heat Mass Transfer 121 437–52
[3] Wu J et al 2018 Seeing permeability from images: fast prediction with convolutional neural networks Sci. Bull. 63 1215–22
[4] Silveira Z C et al 2010 Ceramic matrices applied to aerostatic porous journal bearings: material characterization and bearing modeling Cerâmica 56 201–11
[5] Mingming X 2021 Study on static performance of gas-lubricated thrust bearing based on multi-microporous stainless steel plate J. Braz. Soc. Mech. Sci. Eng. 43 1–4
[6] Cui H et al 2017 Effects of manufacturing errors on the static characteristics of aerostatic journal bearings with porous restrictor Tribology 115 246–60
[7] Cui H L et al 2018 Numerical simulation and experimental verification of the stiffness and stability of thrust pad aerostatic bearings Chin. J. Mech. Eng. 31 1–2
[8] Feng K et al 2018 Theoretical investigation on porous tilting pad bearings considering tilting pad motion and porous material restriction Precis. Eng. 53 26–37
[9] Luong T S et al 2004 Numerical and experimental analysis of aerostatic thrust bearings with porous restrictors Tribology 37 825–32
[10] Thovrild J F et al 2001 Grain reconstruction of porous media: application to a low-porosity Fontainebleau sandstone Phys. Rev. E 63 061307
[11] Zhang D et al 2019 Relative permeability of three immiscible fluids in random porous media determined by the lattice Boltzmann method Int. J. Heat Mass Transfer 134 311–20
[12] Rao P et al 2020 Permeability estimation on tomographic images using curved boundary schemes in the lattice Boltzmann method Adv. Water Resour. 143 103685
[13] Rabbani A and Bahaed M 2019 Hybrid pore–network and lattice–Boltzmann permeability modelling accelerated by machine learning Adv. Water Resour. 126 116–28
[14] Li Z et al 2018 A lattice Boltzmann investigation of steady-state fluid distribution, capillary pressure and relative permeability of a porous medium: effects of fluid and geometrical properties Adv. Water Resour. 116 153–66
[15] Khan Z A et al 2019 Dual network extraction algorithm to investigate multiple transport processes in porous materials: image-based modeling of pore and grain scale processes Comput. Chem. Eng. 123 64–77
[16] Piwesas A et al 2019 Pore network model for permeability characterization of three-dimensionally-printed porous materials for passive microfluidics Phys. Rev. E 99 033107
[17] Gostick J T et al 2017 Versatile and efficient pore network extraction method using marker-based watershed segmentation Phys. Rev. E 96 023307
[18] Rabbania A et al 2017 Estimation of carbonates permeability using pore network parameters extracted from thin section images and comparison with experimental data J. Nat. Gas Sci. Eng. 42 85–98
[19] Gray W G et al 2004 Examination of Darcy’s Law for flow in porous media with variable porosity Environ. Sci. Technol. 38 5895–901
[20] Carman P C 1937 Fluid flow through granular beds Trans. Inst. Chem. Eng. 15 150–66
[21] Krizhevsky A et al ImageNet classification with deep convolutional neural networks Adv. Neural Inf. Process. Syst. 25 1097–105
[22] LeCun Y et al 2015 Deep Learning Nature 521 436–44
[23] Hong J et al 2020 Rapid estimation of permeability from digital rock using 3D convolutional neural network Comput. Geosci. 24 1525–39
[24] Kamrava S et al 2020 Linking morphology of porous media to their macroscopic permeability by deep learning Transp. Porous Media 131 427–48
[25] Cecene A et al 2018 Material structure-property linkages using three-dimensional convolutional neural networks Acta Mater. 146 76–84
[26] Cang R et al 2018 Improving direct physical properties prediction of heterogeneous materials from imaging data via convolutional neural network and a morphology-aware generative model Comput. Mater. Sci. 150 212–21
[27] Yang Z et al 2018 Deep learning approaches for mining structure-property linkages in high contrast composites from simulation datasets Comput. Mater. Sci. 151 278–87
[28] Xu W and Jiao Y 2019 Theoretical framework for percolation threshold, tortuosity and transport properties of porous materials containing 3D non-spherical pores Int. J. Eng. Sci. 134 31–46
[29] Li M et al 2021 Effects of the pore shape polydispersity on the percolation threshold and diffusivity of porous composites: theoretical and numerical studies Powder Technol. 386 382–93
[30] Xu W et al 2021 Thermal conductivity and elastic modulus of 3D porous/fractured media considering percolation Int. J. Eng. Sci. 161 103456
[31] Xu W et al 2018 Multiple-inclusion model for the transport properties of porous composites considering coupled effects of pores and interphase around spheroidal particles Int. J. Mech. Sci. 150 610–6
[32] Jiao Y et al 2007 Modeling heterogeneous materials via two-point correlation functions: basic principles Phys. Rev. E 76 031110
[33] Hemes S et al 2015 Multi-scale characterization of porosity in Boom Clay (HADES-level, Mol, Belgium) using a combination of X-ray μ-CT, 2D BIB-SEM and FIB-SEM tomography Microporous Mesoporous Mater. 208 1–20
[34] Bultrye T et al 2016 Imaging and image-based fluid transport modeling at the pore scale in geological materials: a practical introduction to the current state-of-the-art Earth-Sci. Rev. 155 93–128
[35] Wu T et al 2017 Multiscale pore structure and its effect on gas transport in organic-rich shale Water Resour. Res. 53 5438–50
[36] Lang A and Potthoff J 2011 Fast simulation of Gaussian rand-om fields Monte Carlo Methods Appl. 17 195–214
[37] Wang M and Pan N 2007 Numerical analyses of effective dielectric constant of multiphase microporous media J. Appl. Phys. 11 114102
[38] Cortes C and Vapnik V 1995 Support-vector networks Mach. Learn. 20 273–97
[39] Quinlan J R 1986 Induction of decision trees Mach. Learn. 1 81–106
[40] Breiman L 2001 Random forests Mach. Learn. 45 5–32
[41] Friedman J H 2001 Greedy function approximation: a gradient boosting machine Ann. Stat. 29 1189–232