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Evaluation of Porous Media Using Digital Core Analysis by Pore Network Modeling Method: A Comprehensive Review

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ABSTRACT

Digital rock technology has emerged as a powerful tool for analyzing reservoir rocks in the petroleum industry. Technically, Digital Rock Physics (DRP) is an effective method for determining reservoir rock properties. The article reviews the history of digital rock, from its origins in the study of porous media to its development into a practical tool for the petroleum industry. The features of digital rock are discussed, including the use of X-ray microcomputed tomography and pore-scale modeling, which allow for the analysis of rock samples at the pore-scale. The philosophy and science behind digital rock are explored, emphasizing the importance of understanding the fundamental physics of fluid flow in porous media. The applications of digital rock in the petroleum industry are discussed, including its use in reservoir characterization, fluid flow simulation, and enhanced oil recovery. The benefits and limitations of digital rock are examined, highlighting the need for careful interpretation of results and the importance of complementary laboratory techniques. The role of pore network modeling in digital rock technology is also discussed, which allows for the simulation of fluid flow in porous media at the pore-scale. Finally, the article discusses future directions for digital rock, including the development of new imaging and modeling techniques and the integration of digital rock with other data sources. Overall, digital rock technology, including pore network modeling, is a promising tool for the petroleum industry that has the potential to improve the understanding of reservoir rocks and enhance hydrocarbon recovery.

Introduction

Energy markets are greatly affected by the development of hydrocarbon resources. Petroleum engineering has seen significant growth in the field of digital rock technology. This

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involves creating 3D digital replicas of rock samples, which can then be analyzed in detail to gain insights into their properties and behavior. In the petroleum industry, digital rock technology is used for reservoir analysis, production optimization, and enhanced oil recovery. Using the spatial distribution of the connected pore space, it is possible to predict a rock sample's properties. So far, systematic upscaling of predictions has been impossible due to limitations in feature resolution and approximations. In porous media research, structural information is obtained from tomographic images. The extraction of pore networks enables pore network modeling simulations, which are invaluable for predicting transport properties and simulating entire device performance.

Several technologies and businesses rely heavily on porous materials. In the contexts of oil recovery and aquifer management, naturally existing porous media such as rock and soil have been intensively studied [1]. Several industries, including electrodes [2], membranes [3], biomedical applications [4] and others [5], have benefited from engineered or produced porous materials. The design of porous materials poses a traditional optimization challenge: The existence of the solid is required to perform a crucial job, such as providing reactive surface area, yet also impedes flow and transport. Porous materials are characterized by the fact that the pore structure may have a decisive effect on the transport processes. Depending on how the pores are spatially dispersed, how they are linked, their forms, size distribution, and so on, two materials with the same porosity will have significantly different transport characteristics. As a result of this reliance on pore structure, visualization is a crucial aspect of porous media investigation. High-resolution x-ray tomography is especially beneficial since it provides images of the inside structure [6]. Benchtop x-ray tomography scanners that can create pictures with 1-nano meter voxel resolution are now commercially accessible, while the most recent generation can acquire images with 100-nm or lower resolution [7]. Extraction of the large quantity of data contained in such photos is a current endeavor [8]. The study of digital rock characteristics is an area of research that is undergoing significant development. This area of study includes the use of sophisticated imaging and modeling methods in order to investigate the physical and mechanical properties of rocks on a pore-scale level. The optimization of the design and operation of oil and gas reservoirs is one of the most important uses of digital rock properties [9], and one of the primary applications of digital rock properties is in the area of reservoir engineering. Digital rock characteristics may assist to enhance reservoir performance, cut production costs, and prolong the life of mature fields [10], since they provide extensive insights into the qualities of the rock. In digital rock properties, one of the primary areas of study is on the fracture characteristics of the rock. Fractures are an important factor in defining the permeability and porosity of rocks, and they may have a considerable influence on the flow of fluids inside reservoirs [11]. Fractures also play an important part in the formation of faults. Recent developments in high-resolution imaging methods, such as X-ray computed tomography (CT), have given researchers the ability to view and measure fractures and fissures in rocks on a scale that is micron and sub-micron in size [12]. Digital rock characteristics may give useful insights into the flow behavior of fluids inside reservoirs by studying the shape, distribution, and connectivity of fractures within rocks. This can assist to improve recovery procedures [13]. In digital rock properties, petrophysical characteristics are another essential field of inquiry that should be carried out. These characteristics include metrics that are essential in establishing the viability and productivity of hydrocarbon reservoirs, such as porosity, permeability, and capillary pressure. It is possible to employ digital rock characteristics to extract these qualities from high-resolution photographs of rocks, which enables a more in-depth knowledge of how reservoirs behave [9]. This information can be used to optimize the design of well completion and stimulation techniques, such as hydraulic fracturing, and to predict the performance of enhanced oil recovery (EOR) methods [14]. Another use for this information is in the context of predicting the performance of enhanced oil recovery (EOR) methods. The study of rock mechanics may also benefit from an understanding of digital rock characteristics, notably in the subfields of deformation and failure. Digital rock characteristics may be used to anticipate the initiation and propagation of fractures, as well as to assess the potential for reservoir compaction and subsidence [15]. This is accomplished by modeling the behavior of rocks under various stress circumstances. These insights have the potential to assist in the optimization of drilling and completion operations, the reduction of the risk of production-related concerns, and the extension of the useful life of reservoirs [16]. In conclusion, digital rock properties provide an effective tool for the characterization and management of reservoirs. Researchers are able to gain an in-depth understanding of the physical and mechanical properties of rocks by employing sophisticated imaging and simulation techniques. They can then use this knowledge to improve the performance of reservoirs and increase the number of hydrocarbons that can be extracted from them. The representation of a porous structure by a network of pores and throats has been the subject of extensive study for many decades (e.g. [17, 18]), and this work is still being done by a large number of researchers in a wide variety of fields today (e.g. [19-21]). Recent developments in pore-scale modeling have shown that in order to study the flow and transport processes that occur in any disordered porous media, it is necessary to have a detailed description of the medium's morphology [22]. This comprises the determination of the porous internal structure, shape, and size of pore bodies or big void spaces (geometry), as well as the manner in which the thin channels or throat bodies link these vast void spaces together (topology), in order to characterize the pore connectivity [23]. The mapping of the porous medium onto a network of pores and throats, on the other hand, demands a degree of arbitrary decision making over what constitutes a pore or a throat, in addition to how and where these pore-throat constrictions intersect [23]. The implementation of different transport laws into a representative network of pores and throats might in practice enable the estimation of such macroscopic properties of porous media as permeability, effective diffusivity of fluids, and resistivity of the pore medium. This is possible given that the macroscopic properties of porous media may be sensitive to only some microstructural details (pore size and throat length distributions, average connectivity, among other things) [23], but not all. Before we can create a network of pores and throats, we need to begin by constructing a realistic sample of a porous medium.

There are clear advantages in utilizing PNM that has attracted oil companies and researchers to this technology. First off, it eliminates the requirement for destructive testing. Thus, the same sample can be investigated repeatedly and more accurate results can be obtained. Second, complicated fluid interactions and behavior in porous media such as flow patterns and surface tension effects can be assessed using PNM. Additionally, other DRP methods such as DNS can be restrictive in large scale models because of computational cost and complexity of such models. Furthermore, DNS does not readily provide information on macroscopic properties, such as permeability which is crucial in petroleum engineering [24-27].

In this paper, first a comprehensive review on DRP is given. Then regarding the importance of PNM, it is investigated in further detail. PNM applications, features and limitations are explored. Finally, we concentrate on the future steps in imaging techniques considering the rapid growth of AI techniques and integration between this technology and other approaches used in petroleum engineering.

History

The concept of digital rock technology was first introduced in the early 2000s by researchers at Lawrence Berkeley National Laboratory (LBNL) in the United States. They developed a technique called "virtual core analysis" (VCA), which involved using X-ray computed tomography (CT) to create 3D digital images of rock samples [28]. These images were then used to simulate fluid flow through the rock and to study the properties of the rock at the pore scale [29].

In 2004, researchers at the University of Texas at Austin unveiled a new digital rock technology called "pore-scale modeling." This technique involved using computational fluid dynamics (CFD) simulations to model the behavior of fluids in a rock sample at the pore scale [30]. This allowed researchers to gain insights into the complex interactions between fluids and rock, and to develop more accurate models for predicting fluid flow in reservoirs [31].

Since then, digital rock technology has continued to evolve and gain popularity in the petroleum industry [32]. In 2007, Schlumberger, one of the world's largest oilfield services companies, launched a digital rock analysis service called "Rock Physics Labs" [33]. This service uses advanced imaging and modeling techniques to provide detailed analysis of rock samples [34], helping oil and gas companies to optimize production strategies [35] and reduce exploration risks [36].

In recent years, researchers have continued to develop new digital rock techniques, including the use of artificial intelligence and machine learning algorithms to analyze and interpret digital rock data [36-38]. These techniques are helping to drive innovation in the petroleum industry and to improve our understanding of the complex processes that govern fluid flow in reservoirs [39, 40].

Digital rock technology has rapidly evolved over the past two decades and has become an important tool for petroleum engineers [41]. The technology was first introduced in the early 2000s by researchers at Lawrence Berkeley National Laboratory and the University of Texas at Austin, and has since been adopted by major oil and gas companies such as Schlumberger [42, 43]. As the technology continues to develop, it is likely that we will see more widespread adoption of digital rock techniques in the industry, leading to improved reservoir analysis and production optimization [44-47].

There are several companies and research centers that provide commercial digital rock analysis services. These services involve the use of advanced imaging techniques and computational methods to analyze the three-dimensional microstructure of rock samples. Corelab, FEI (now part of Thermo Fisher Scientific) and Digital core are some of the active centers which provide digital rock services to oil and gas companies. Additionally, there are Some universities and research centers that have launched laboratories which specialize in digital rock analysis, such as University of Texas at Austin, Imperial College London and University of Oklahoma. These companies and research centers offer micro-CT scanning, image processing, and pore network modeling as part of their digital rock analysis services [8, 48-50].

Features

Digital rock properties are a rapidly evolving field of research that involves the use of advanced imaging and simulation techniques to analyze the physical and mechanical properties of rocks at the pore scale [51-53]. One of the key applications of digital rock properties is in the field of reservoir engineering, where it is used to optimize the design and operation of oil and gas reservoirs [9, 54, 55]. By providing detailed insights into the rock's properties, digital rock properties can help to improve reservoir performance, reduce production costs, and extend the life of mature fields [10, 55].

Fracture properties are one of the key areas of focus in digital rock properties. Fractures play a critical role in determining the permeability and porosity of rocks, and can have a significant impact on fluid flow within reservoirs [11, 56-58]. Recent advances in high-resolution imaging techniques, such as X-ray computed tomography (CT), have enabled researchers to visualize and quantify fractures and cracks in rocks at the micron and sub-micron scale [12, 59, 60]. By analyzing the geometry, distribution, and connectivity of fractures within rocks, digital rock properties can provide valuable insights into the flow behavior of fluids within reservoirs, and help to optimize recovery strategies [13, 61, 62].

Petrophysical properties are another important area of investigation in digital rock properties. These properties include parameters such as porosity [62], permeability [63], and capillary pressure [64], which are critical in determining the feasibility and productivity of hydrocarbon reservoirs [65, 66]. Digital rock properties can be used to extract these properties from high-resolution images of rocks, enabling a more detailed understanding of reservoir behavior [9]. This information can be used to optimize the design of well completion [67] and stimulation techniques, such as hydraulic fracturing [68], and to predict the performance of enhanced oil recovery (EOR) methods [14, 69].

Digital rock properties are also relevant to the study of rock mechanics, particularly in the areas of deformation and failure [70]. By simulating the behavior of rocks under different stress conditions, digital rock properties can be used to predict the onset and propagation of fractures, and to evaluate the potential for reservoir compaction and subsidence [15, 71, 72]. These insights can help to optimize drilling [73] and completion operations [74], reduce the risk of production-related issues, and extend the life of reservoirs [16].

Understanding the electrical properties of a reservoir can help engineers determine the type of fluid contained within the rock, estimate its volume, and ultimately determine the overall viability of the reservoir. Accurately estimating electrical properties has become critical, particularly in identifying bypassed or remaining oil and gas within a reservoir. DRP can be used to investigate the electrical properties of rocks. Generally, rocks are composed of minerals with different electrical properties, including dielectric constant, conductivity, and polarization behavior, which can be influenced by a range of factors, including mineral composition, porosity, and fluid content. By measuring the electrical conductivity of the rock in response to the fluid flow, researchers can extrapolate the electrical properties of the rock itself. DRP can be used to investigate the polarization behavior of rocks in response to an applied electric field. In addition, it can measure the dielectric properties of a rock sample as a function of frequency and temperature, providing information about the distribution and behavior of polar molecules within the rock.

Knowing how rocks fail is crucial for geologists and engineers working in fields such as oil and gas exploration, mining, and geohazard assessment. One way to investigate the damaging mechanisms of rock is through pore network modeling. The use of Digital Rock Physics (DRP) in combination with theoretical rock physics has gained significant interest as a supplement to traditional laboratory measurements. DRP approach accompanied by other novel methods such as machine learning can help to build reliable rock mechanical property models. These models can predict Young's modulus and other rock mechanical properties with good agreement with actual traditional laboratory outputs [75].

Digital rock properties can be used to estimate stimulation techniques of porous media, particularly those that involve reactive flow. The modeling helps estimate where and how stimulation, such as hydraulic fracturing, can be most effective. Using digital rock properties for stimulation techniques can help reduce costs and improve the effectiveness of the process. DRP can be a reliable tool for visualizing and characterizing acid fracturing operation and analyzing the results of acidizing tests with more accuracy [76]. An application of PNM in visualizing acidization is show Fig. 1.

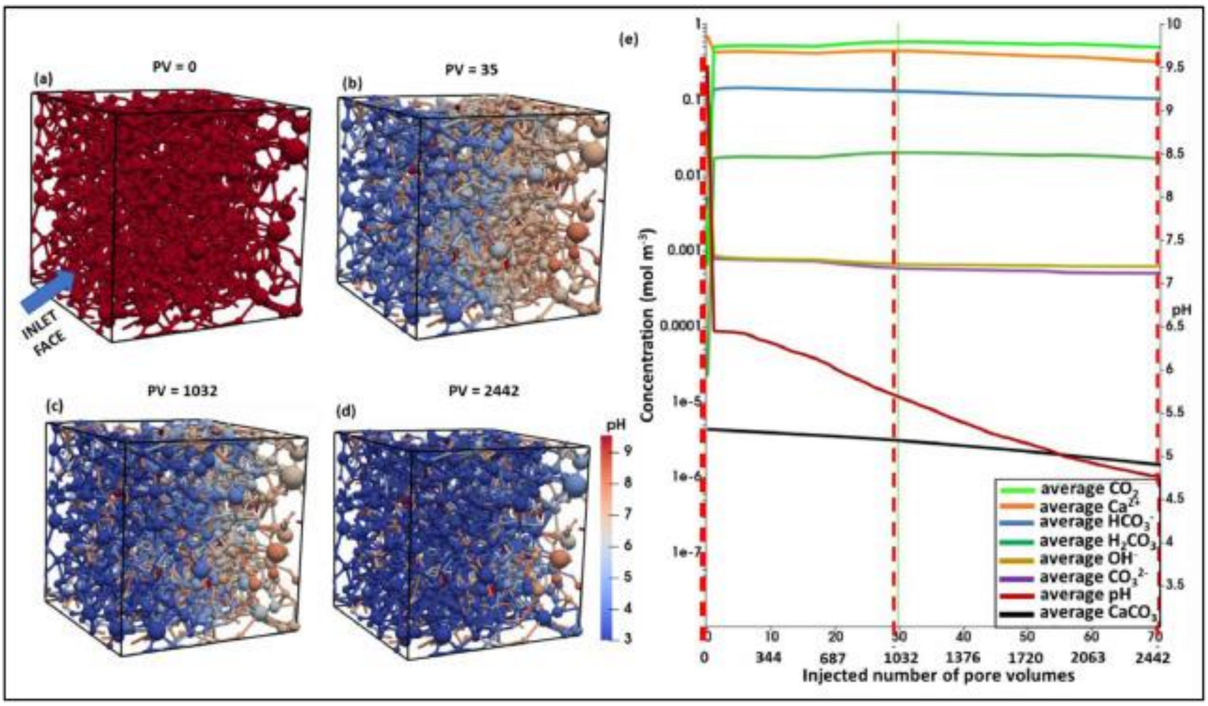

Fig. 1. Concentration fields. (a-d) show 3D distribution of pH within the reactive transport pore network model (rtPNM) corresponding at times corresponding to pore volumes of (a) 0, (b) 35, (c) 1032, and (d) 2442. (e) evolution of the concentration of aqueous species with the injected number of pore volumes [77]

In conclusion, digital rock properties offer a powerful tool for reservoir characterization and management. By using advanced imaging and simulation techniques, researchers can gain a detailed understanding of the physical and mechanical properties of rocks, and use this information to optimize reservoir performance and enhance hydrocarbon recovery [54, 78, 79].

Philosophy and Science Behind

Digital rock is a field that involves using advanced imaging technologies to study the properties and behavior of rocks at the microscale. One of the key techniques used in digital rock is X-ray computed tomography (CT), which involves taking multiple X-ray images of a rock sample from different angles and using computer algorithms to reconstruct a 3D image of the internal structure of the rock [80]. Other techniques used in digital rock include focused ion beam scanning electron microscopy (FIB-SEM) [9] and micro-CT [81], which can provide even higher resolution images of rock samples.

The philosophy behind digital rock is to gain a better understanding of the properties and behavior of rocks that can affect the flow of fluids through subsurface formations [82]. This is important for a variety of applications, including oil and gas exploration, groundwater management, and carbon sequestration [83, 84]. By studying the microscale properties of rocks [85], researchers and engineers can develop more accurate models of fluid flow in the subsurface and better predict the behavior of rock formations under different conditions [80].

One of the key benefits of digital rock is the ability to study rock properties in a non-destructive manner [86]. Traditional laboratory techniques for studying rocks, such as thin-section microscopy and permeability measurements, typically involve cutting or drilling into the rock sample, which can alter its properties [87, 88]. Digital rock, on the other hand, allows researchers to study the internal structure of the rock without altering it [89]. This is particularly important for studying the behavior of rocks under in situ conditions, where the properties of the rock may be different than those observed in the laboratory [8].

Another important aspect of digital rock is the integration of data from multiple imaging techniques [42]. For example, X-ray CT can provide information on the porosity and mineralogy of a rock sample, while FIB-SEM can provide information on the pore network connectivity and grain structure [90]. By integrating data from multiple techniques, researchers can gain a more comprehensive understanding of the properties and behavior of rocks at the microscale [35, 91, 92].

In conclusion, digital rock is an interdisciplinary field that combines philosophy and science to study the properties and behavior of rocks at the microscale. By using advanced imaging technologies like X-ray CT and FIB-SEM, researchers can gain a better understanding of the subsurface properties and behaviors of rocks, which is critical for developing effective strategies for resource extraction and management [61, 93-96].

Despite its high accuracy and reliability, pore network modeling can be time-consuming and computationally intensive, especially for large-scale systems. This is where the Multi-Resolution Approach (MRA) comes into play. MRA refers to a technique in which an image is analyzed at different scales, each having different levels of detail. It enables us to quickly capture the essential features of a complex structure and generate an accurate 3D representation without the need for the high computational cost. Of course, blending all this data together can be quite the challenge. That's where AI techniques come in handy. Machine learning algorithms can be trained to analyze and interpret the data from various sources, allowing us to create a cohesive 3D reconstruction of the porous media under study. Deep learning can create large 3D continuum-scale models with spatially varying flow and material properties when paired with pore scale simulations such as OpenPNM [97]. Generally, with AI, researchers have gained the ability to produce 3D images of porous material at a faster pace and with more precision.

Statistical methods can be utilized to generate 3d images from known distribution functions. One common statistical method for 3D image reconstruction of porous media is the random sequential adsorption (RSA) method. In this method, particles are randomly placed in the image space, and then allowed to move until they reach a stable, non-overlapping configuration. The resulting configuration is representative of the underlying pore structure. Gaussian Random Field (GRF) can be used to create a 3D image by generating a random field based on a specified covariance function. Markov Chain Monte Carlo (MCMC) which involves generating a sequence of random samples probability distribution based on a Markov chain is another statistical approach being used. Fourier Transform-based methods involve generating a random field in the Fourier domain, and then transforming it back to the spatial domain to create a 3D image. Sequential Gaussian Simulation (SGS) generates conditional simulations that honor specified statistical properties at multiple scales. The generated simulations are then combined to create a 3D image that satisfies the specified statistical properties.

As an alternative to solving nth-order partial differential equations (PDEs), we apply finite difference schemes to solve 1D analytical solutions to relevant transport equations. Multiphase transport can be accurately predicted with PNMs despite their simplification [9]. In this way, the structure and flow characteristics interact based on the size and configuration of the pores and throats. A variety of imaging techniques [98, 99] and computer-generated structures can be used to obtain the structural properties of porous materials [100-102]. Models reproduce experimental properties by arbitrarily adjusting pore and throat sizes [103]. The PNM is naturally suited to percolation calculations [104], which makes them easy to simulate [105]. As a result, fluid distribution within media can be described at pore scale, which affects almost all other transport processes. As long as pores and throats filled with one phase are labeled as closed in PNMs, experimentally inaccessible multiphase parameters can be predicted [106-108]. Literature reviews and comparisons of pore network modeling are extensive [1, 20, 109]. For one selected generated porous medium, Fig. 2 shows pores and throats in three dimensions.

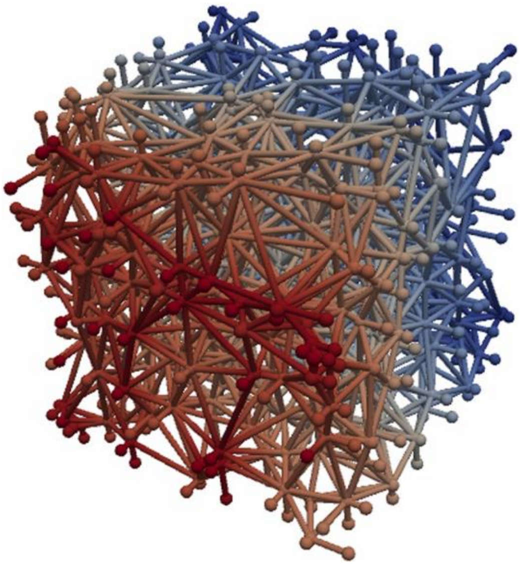

Fig. 2. Network of pores and throats in porous media

Different computational techniques have been created and utilized for examining flow and transport phenomena at the pore scale [110]. Generally, there exist two types of pore scale modeling. The first type of model is commonly known as direct numerical simulation (DNS) [111, 112], which consists of standard computational fluid dynamics (CFD) , lattice Boltzmann method (LBM) [113, 114], and smoothed particle hydrodynamics (SPH) [115]. The second type, which represents the pore space as a network connected by simplified pore bodies and throats, is the aforementioned term, pore network modeling (PNM). Gridding the domain directly solves the governing equations for transport in DNS. Formerly, Navier-Stokes equations were numerically solved [116, 117], while latter methods used kinetic models to achieve the same results [118-120]. With DNS, one-phase or multiphase fluid flow in conjunction with diffusion, sorption, and reactive transport can be simplified [121-124]. The most common application of direct numerical simulation is when porous media is considered as a volume average continuum without microscale features determined. The mathematical complexity of continuum models limits their practical use. Experiments must be conducted to measure the appropriate relationships to describe porous media's macroscopic transport properties [125]. It is difficult to measure these properties, especially if there is multiphase flow, for example, permeability coefficient or effective diffusivity. Models that calculate the average amount of fluid based on volume average do not identify discrete pore-scale events; they calculate the average amount of fluid based on volume average instead. We need more comprehensive formulations to describe fluid distributions within a continuum since Darcy's law cannot accurately describe fluid distributions within a continuum. This issue can be addressed through porous network modeling; however, it removes the tricky math [126]. In comparison with other methods, PNM is extremely computationally efficient and thus may be highly suitable for quickly evaluating different options or conducting large simulations in situations where a slight overestimation of dispersive transport is not a concern. However, this superiority in computational cost sacrifices the physical complexities of fluid flow [127]. Thus, it is a debatable issue how to apply PNM in more complex samples such as carbonates accompanied with fractures. A brief review on different pore scale modeling techniques is given below:

Table 1 Different pore scale modeling techniques.

Name	Base	Further explanation	Reference
CFD	DNS, Continuum approach	-Utilizes a range of numerical discretization techniques. Such as finite element and finite difference to solve the partial differential governing equations such as Navier Stokes. - the mass-conservativeness of this approach gives it superiority over other approaches. For a comprehensive revie of formulation of CFD method readers can refer to Clemens et al. [128]	[127, 129]
LBM	DNS, particle based	-It can represent complicated physical phenomena in irregular geometries using simple Cartesian grids. - This method solves a discretized Boltzmann equation that describes the movement and interaction of fluid particles on a regular lattice with minimal degrees of freedom. For each node on the lattice, a particle distribution is defined for every possible particle velocity vector. The number of these vectors is restricted by allowing particles to move to a neighboring node within a single time step. - The Multi-Relaxation-Time (MRT)-LBM model, which has multiple relaxation times, is reported to show better accuracy than the Bhatnagar-Gross-Krook (BGK)-LBM model, which only has a single relaxation time. For a comprehensive revie of formulation of CFD method readers can refer to Golparvar et al. [127]	[129-131]
SPH	DNS, particle based	- The meshless nature of SPH enables a more convenient simulation of movable or deformable boundaries, while the LaGrange nature of SPH makes it easier to incorporate additional physical effects at a fluid-fluid interface. - Unlike LBM, SPH solves discretized versions of the Navier-Stokes equations directly, similar to Computational Fluid Dynamics (CFD) methods. For a comprehensive revie of formulation of CFD method readers can refer to Zhu et al. [132]	[129, 132]
PNM	Network based	-By utilizing a network of interconnected pores and throats, PNM represents a sample's pore and simulates multiphase flow by solving flow and transport equations on this network. - PNM have proven to be the most effective models for conducting pore-scale simulations of two- and three-phase flow in the geological researches.	[127, 130]

Applications

Digital rock has numerous applications in the oil and gas industry. Some of the key applications of digital rock include:

Monitoring of oil and gas wells: Digital rock can be used to monitor the production of oil and gas wells by studying the properties and behavior of the reservoir rock. This can help in identifying any changes in the flow characteristics of the reservoir, such as changes in porosity or permeability, which can affect the production of oil and gas [133].

Systematic analysis of rock structure: Digital rock can be used to analyze the rock structure systematically, which can help in identifying the composition, texture, and properties of the rocks that make up the reservoir. This information can be used to develop better geological models of the reservoir, which can aid in resource extraction [83].

Specialized investigation of mobility conditions: Digital rock can be used to investigate the mobility conditions in the reservoir, which can help in optimizing the production of oil and gas. For example, digital rock can be used to study the flow of fluids through the reservoir rock under different conditions, such as changes in pressure or temperature. This can help in identifying the most effective techniques for enhancing the recovery of oil and gas from the reservoir [134, 135].

Identification of carbon injection processes: Digital rock can be used to identify the processes involved in carbon injection, which is a technique used for enhancing the recovery of oil and gas from the reservoir. Digital rock can help in understanding the flow of fluids through the reservoir rock under different carbon injection conditions, which can aid in optimizing the process [136-138].

Learning from development conditions: Digital rock can be used to learn from the development conditions of oil and gas reservoirs. For example, digital rock can be used to study the properties and behavior of rocks that have been subjected to various types of stress or deformation, such as those caused by hydraulic fracturing. This information can be used to develop more effective hydraulic fracturing techniques and to optimize production from the reservoir [139, 140].

Overall, digital rock has numerous applications in the oil and gas industry. By using advanced imaging technologies to study the properties and behavior of rocks at the microscale, digital rock can help in developing more effective strategies for resource extraction [141], optimizing production [142], and enhancing recovery from oil and gas reservoirs [143].

Benefits and Limitations

Digital rock technology offers several benefits to the oil industry, including:

Cost savings: Digital rock technology can save costs by reducing the number of physical samples required for testing. This can also reduce the need for costly and time-consuming laboratory experiments [36, 75, 144]. For example, a study by Ghanbarian et al. (2015) showed that digital rock technology reduced the number of core samples required for permeability testing by up to 80%, resulting in significant cost savings [145].

Faster analysis: Digital rock technology can provide results more quickly than traditional laboratory experiments, enabling faster decision-making and reducing the time required for reservoir characterization and production optimization [82, 146, 147]. For example, a study by Clarkson et al. (2017) showed that digital rock technology enabled faster analysis of rock properties compared to traditional laboratory experiments, reducing the analysis time from several weeks to a few days [148].

Improved accuracy: Digital rock technology can provide more accurate and precise measurements of rock properties, such as porosity and permeability. This can improve the accuracy of reservoir models and reduce uncertainty in production forecasting [149, 150]. For example, a study by Tariq et al. (2019) showed that digital rock technology provided more accurate measurements of porosity and permeability compared to traditional laboratory experiments [151].

Limitations: Need for specialized expertise: Digital rock technology requires specialized expertise in image analysis and numerical simulations. This expertise can be expensive and may not be readily available within an organization [152-154]. For example, a study by Babak et al. (2018) highlighted the need for specialized expertise in digital rock technology and the potential cost of hiring external experts to perform the analysis [155].

Need for calibration and validation: Digital rock technology requires calibration and validation to ensure that the results are accurate and reliable. This can be time-consuming and may require the use of physical samples [156-159]. For example, a study by Li et al. (2016) showed the importance of calibration and validation in digital rock technology and the potential impact of inaccurate calibration on the results [160].

Limited applicability: Digital rock technology may not be applicable to all types of rocks and reservoirs. Some rocks may have complex pore structures that are difficult to image and analyze using digital rock technology [161, 162]. For example, a study by Khatibi et al. (2018) showed that digital rock technology was not effective in analyzing complex carbonate reservoirs due to the limitations of image resolution [163].

Pore Network Modeling (PNM)

Several disciplines have studied porous structures using a network of pores and throats (e.g. [17, 18]) and continue to do so (e.g. [19-21]). The morphology of any disordered porous medium must be realistically described in order to understand flow and transport phenomena [22]. To specify the pore connectivity, it is necessary to identify the porous structure, shape, and size of pore bodies and their large void spaces (geometry) [23]. It is necessary to make some arbitrary decisions about what constitutes a pore and a throat, as well as where and how these pore-throat constrictions meet, when mapping porous media onto pores and throats [23]. Computer simulation can be used to estimate the macroscopic properties of porous media, such as permeability, effective diffusivity, and resistivity, at a reduced computational cost with acceptable accuracy [22]. Porous media must first be sampled realistically in order to have a network of pores and throats [23].

PNM Generation Methods

On a pore space, a PNM is composed of discrete networks of pores and throats. Mass balance equations are applied to each pore and Poiseuille-type equations are solved to calculate the flow in the throats. In addition to simulating drainage, imbibition, and single permeability, these simulations have also studied relative permeability [164]. Petrochemical [165-167], geological [106, 168, 169], filtration [170, 171], and fuel cell [172] applications use porous network models. For predicting macroscopic petrophysical and transport properties, porous structures, permeabilities, diffusivities, formation resistivity factors, breakthrough capillary pressures, and thermal conductivities are calculated. In addition, pore network modeling provides accurate descriptions of microscopic fluid flow mechanisms, such as multiphase flow, wettability, capillary trapping, dissolution, diffusion, and convection. A pore network should have the same morphology and size distribution as a real porous media for which it is constructed. In order to construct a model of a pore network, both statistical and process-based methods can be used. Based on measured statistical properties, such as porosity and pore size distribution, the statistical methods generate random pores and throats [173-175]. The network generation process requires core plane images to extract effective statistical information. The morphology of porous networks obtained from statistical methods may differ from that of the original sample, even though their statistical characteristics may be identical (compared with 3-D tomographic images [103, 176]). Using this method, a two-dimensional computed tomography (CT) image is combined with information regarding the main processes in the formation of rock, including sedimentation, compaction, cementation, and diagenesis [169]. As a result, process-based methods can underestimate pore connectivity and associated transport properties; however, they provide valuable insights into how geological processes affect pore structure. [176]. Deep oil reservoir rocks are often heterogeneous and diagenetic, making reproduction difficult.

Pore network models can be constructed using a variety of methods. However, imaging techniques are the most common methods of analyzing pore structure and algorithms for network extraction (e.g., SEM, TEM, and X-ray micro-CT scan) [177, 178]. Numerical algorithms, such as medial axis (skeletonizing) [179, 180], watershed segmentation [181-184] and maximal ball [185] have proved their importance in pore network extraction after image analysis [186]. Many researchers have adopted other techniques for pore size distribution, such as gas adsorption and mercury intrusion porosimeter. A pore size distribution is most commonly obtained by imaging or gas adsorption in pore network modelling [187].

Three main components of porous media modeling are defined and solved: the geometrical and structural characteristics, the governing equations, and the macro properties. [188]. By doing so, larger scales can incorporate porous medium properties that are underappreciated. Using pore-scale modeling, you can estimate the dynamic properties of porous structures by distributing fluid phases heterogeneously inside voids. As Blunt and coworkers describe in detail, it involves various disciplines, such as spatial statistics, imaging, and mathematical modeling, which help characterize the desired phenomenon [9, 106, 189-193]. Three-dimensional objects can be scanned and reconstructed in porous media using techniques he has developed. Okabe and Blunt (2004), Valvatne et al. (2005), Mostaghimi et al. (2012), and Blunt et al. (2013) have used these reconstructions and mathematical models to study Newtonian and non-Newtonian flow in several rock samples.

Single Phase and Two/Three Phase Flow Approaches

Pore network modeling has gained great importance and interest over the last two decades. In principle, this can be attributed to two factors: computational developments and improvement in rock-fluid system descriptions. It is possible to model some of the proposed EOR mechanisms at pore scale that have yet to be fully explained at larger scales, such as wettability alteration. Using adsorption particles, polymer entrapment, and viscous forces, Bolandtaba and Skauge (2011) investigated residual oil mobilization by polymer injection [194]. The surfactants in the rock-fluid system produced oil mobilization and wettability change, as studied by Hammond and Unsal (2012) and Qin and Hassanizadeh (2015) [195, 196]. Using a model for in situ combustion of forward filtration, Lu and Yortsos (2001) investigated the effects of porous microstructure on filtering combustion dynamics [197]. Multi-physics models were carried out to reduce potential risks related to high combustion temperatures and low oxygen rates in practical applications by Xu et al. [198]. LSWF occurs due to theoretical considerations at the pore scale, according to Sorbie and Collins (2010). [199]. A commonly discussed mechanism in LSWF is wettability alteration. The authors assessed the degree of uncertainty associated with this mechanism. Oil-water-rock parameters are investigated systematically using the generated network [200]. An analysis of LSWF effects on oil recovery was conducted by Boujelben et al. (2018) under dynamic flow conditions. This method tracks salinity spatial distributions during recovery, and fluid distributions are updated based on capillary and viscous forces. Contact angle and local injected water concentrations are related to capillary effects and salinity [201].

By using X-ray images or numerically constructed porous materials, this method extracts pore networks directly from X-ray images. Micro-CT or other X-ray imaging facilities are necessary for image-based methods to obtain three-dimensional (3-D) images. Pore networks are constructed from 3-D images using an extraction algorithm [186, 202]. Several image processing techniques are used to prepare 3-D images, including cropping, noise removal, and phase segmentation. Using binary images as void spaces and connections, the 3-D network of pores and throats is created. Lindquist et al. developed an algorithm to calculate geometrical properties from CT-images, including geometric tortuosity and how pores are connected, based on a topological skeleton (medial axis) [203].

CT images can be analyzed using several algorithms [204]. Flow studies involving two phases (gas-water) frequently use the maximum ball algorithm. Silin and Patzek used this algorithm [205]. AlKharausi and Blunt then improved the maximal ball algorithm [186]. Multiple spheres (called maximal balls) are generated by the maximum ball algorithm in pore space. Big spheres represent pores. Throats are small spheres that connect large spheres. Cylindrical throats are formed by small spheres between these large ones. The maximal ball algorithm extracts pore network from 3D CT images. There are spheres and cylinders in this pore network [98, 206]. With transport equations and extracted pore networks, porosity, absolute permeability, and relative permeability can be measured [207]. Fig. 3 describes the procedures to estimate transport properties by PNM.

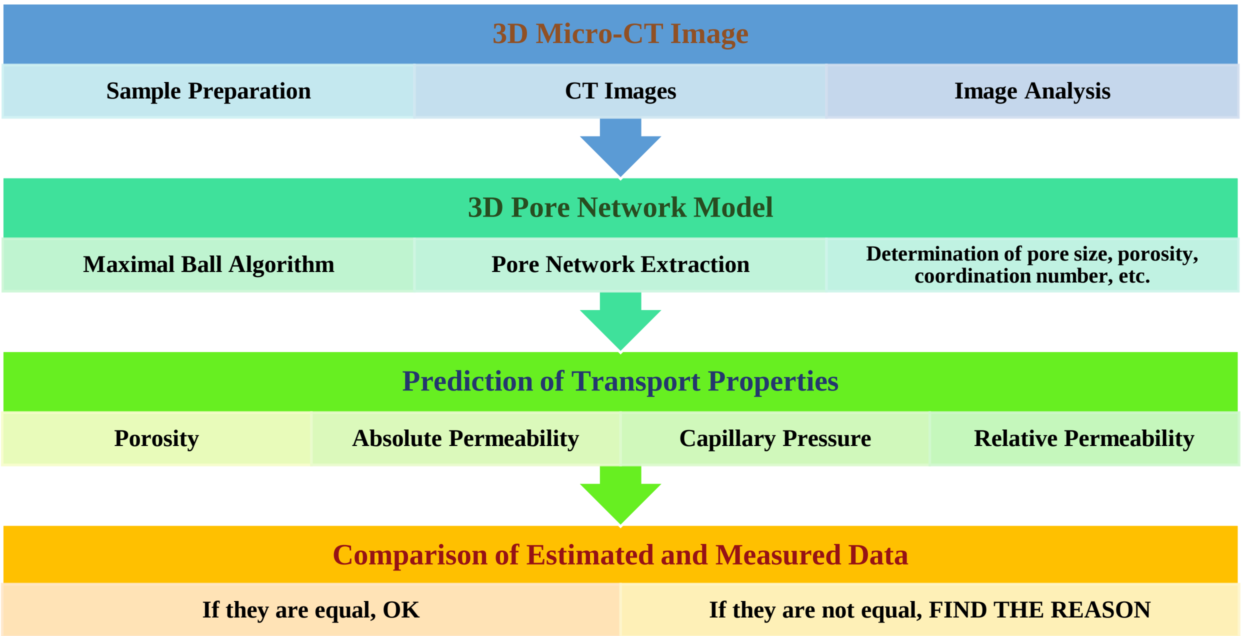

Fig. 3. Estimation of transport properties using porous network modeling

PNM Types and Software

There are two primary approaches to PNM: the quasi-static method and the dynamic method. Quasi-static PNEMs assume that the fluid flow is slow enough to be considered in equilibrium with the porous material [208, 209]. This approach is often used in applications where the fluid flow is slow, such as in groundwater management or membrane filtration. Quasi-static PNEMs are computationally efficient and can provide valuable insights into the behavior of fluids in porous media. Dynamic PNEMs, on the other hand, account for the unsteady nature of fluid flow and are often used in applications where the fluid flow is fast [209, 210]. This approach is more suitable for studying dynamic processes, such as fluid injection or production in oil and gas industry, and for predicting the behavior of reservoirs under different operating conditions. However, it requires more computational resources and may be more complex to implement than quasi-static methods. Thus, choosing the proper approach is dependent on the objectives defined for a project in which PNM is being utilized [208-211].

PoreXpert is currently the most well-known commercially viable software product, arising from a Plymouth University research group (formerly known as Pore-Cor [212]), although some groups publish overviews of their internal code [188]. PNM is not being developed in any other open-source framework. Compared to computational fluid dynamics, where quite a few powerful open source and commercial frameworks are available [213]. For internal use within their research groups, PNM researchers generally develop their own code. It is also unlikely that existing code is optimized for speed, modularity, extensibility, or maintainability, and it is rarely well documented for future users. Open PNM was developed to address these problems, which are all too common. A general, powerful, and flexible framework will be available to the porous media community to handle all kinds of PNM problems effectively. We will all be able to build on each other's work, allowing researchers to share code, compare models, and speed up research.

Developed at the University of Waterloo, OpenPNM is open source software [214]. Simulation of single- and multiphase transport in porous materials is provided. It has gained popularity among researchers, engineers, and students in various fields, including materials science, chemical engineering, and geology. From simulating blood flow in medical applications to simulating the behavior of membranes and catalysts in materials science OpenPNM has exhibited promising results. Considering the vital need for a profound knowledge of porous media in petroleum engineering, OpenPNM is a topic of interest in oil and gas industry. The software can simulate the behavior of fluids in different types of porous media, including sandstone, shale, and limestone. OpenPNM can also be used to analyze the properties of the rock formations, such as porosity and permeability, and how they affect fluid flow [214-216].OpenPNM has been used by many scholars. In Yang et al., slippage and adsorption effects were considered in pore-scale simulations of shale oil [217]. The geometry variation of carbonate rock during dissolution was studied with OpenPNM [218]. Among the easy-to-implement choices for studying fluid motion and transport, Golparvar et al. [127] reviewed various pore scale modeling methods. A number of applications use PNM [188], including reactive transport. Basically, PNM maps pore space onto a regular or irregular site-bond lattice [107]. With PNM, large scale modeling and repeated simulations are possible due to the lower computational costs. The displacement process through sandstone can be simulated by four types of 2D networks [219]. Chatzis and Dullien [17] developed Fatt's PNM to 3D and simulated mercury intrusion in sandstones. PNM extraction from core samples by Dong and Blunt [98] was modified using the maximal ball algorithm. Mahanta et al. [220] investigated PNM attributes in high-temperature heat-treated sandstones. Foroozesh et al. [221] studied stress-dependent fluid dynamics in shales using PNM. As Mehmani et al. report in [222], PNM has been applied to studying complex pore structures for the past 60 years, including extracting PNM from core samples and constructing stochastic PNM based on specific porosities.

A comprehensive examination of porous media can be done using various modules that OpenPNM software provides. Several modules are designed in this software which can solve specific types of problems in porous media. 'Network Module' allows users to create customized network geometries and topologies and create pores and throats. Creating complex 3D geometries of porous media can be possible with using 'Geometry Module'. In addition, this module can combine with network simulations for more accuracy of the model. 'Physics Module' contains algorithms required for illustrating physical process inside the porous media such as heat transfer, mass transfer and fluid flow equations. The numerical algorithms required for solving equations existing in physics module can be accessed via 'Algorithm Module'. This module consists of solvers for various types of design such as steady state, transient and Multiphysics simulation [214-216].

OpenPNM provides some crucial benefits. Firstly, it is open source which makes it accessible to everyone. In addition, high flexibility of this software enables the customization of the problem based on the user's needs and the special project in hand. However, some limitations can be challenging for using this software such as steep learning curve and limited user support. Thus, it can be slightly challenging for users without a programming background to learn how to employ this software and makes individuals depend on online forums for solving their problems [214-216].

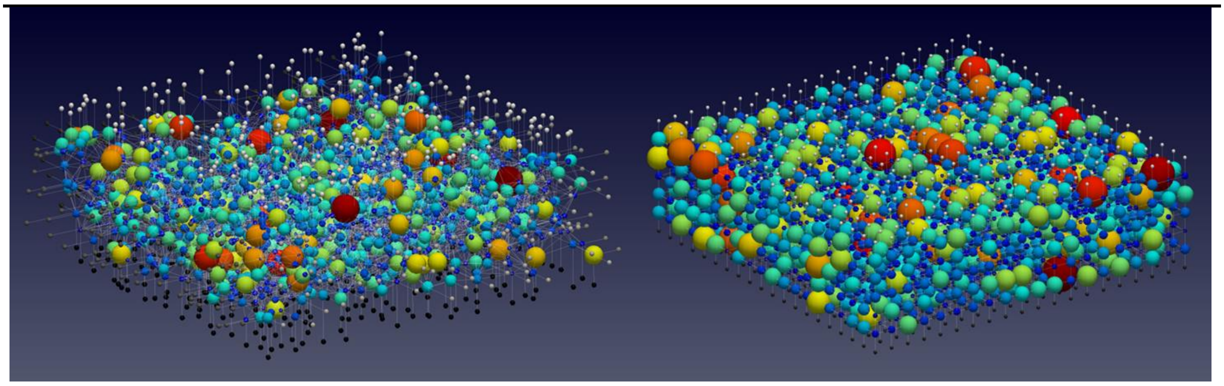

Fig. 4. Output of OpenPNM random and cubic generation algorithms visualized with Paraview [215]

In addition to OpenPNM and PoreXpert there are some other software which provide digital rock analysis and a variety of imaging data, including micro-CT scans. Avizo and Image-J are some of these software. A brief introduction and worthful notes from each one is given in Table 2 [214-216]:

Table 2. The Softwares for applying PNM and DRP

Name	Developer	Commercial / Open source	Features	Reference
OpenPNM	A group of researchers led by Dr. Jeff Gostick	Open source	- The framework is general enough to accommodate any topology. This enables the user to import any topology -To accommodate the vast diversity of networks, systems and applications, OpenPNM is able store an unlimited number of user defined pore and throat properties -OpenPNM is capable of simulating diffusion and permeability in either phase	[214-216]
PoreXpert	PoreXpert Ltd	Commercial	- One of the unique features of PoreXpert is its ability to generate virtual core plugs from the digital rock data - Allows the study of the pore level properties of any mesoporous or microporous solid, i.e. a solid with pore sizes greater than 2 nm	[223, 224]
Avizo	Thermo Fisher Scientific	Commercial	- Generally, contains the following modules: Volume Edit, Interactive Thresholding, Fill Holes, Mask, Separate Objects and Generate Pore Network Model - Can process the data from X-ray tomography: CT, micro-/nano-CT, electron microscope, and synchrotron - Will precisely calculate the porosity, analyze the pore connectivity and skeleton the pore network modeling for the multi-scale and multi-mode data	[225, 226]

Image-J	National Institutes of Health (NIH)	Open source	- Has become a popular platform for image processing and is widely applied in medical, biological and agricultural sciences - Enables processing and analyzing X-ray micro-CT images - Provides 16 different automatic thresholding methods for segmentation, including the widely used “Default”, “Huang” and “Otsu” methods	[227, 228]

Validation Challenges

One of the challenges of pore network extraction methods (PNEMs) is the accuracy of the extracted pore network. The quality of the extracted network depends on the resolution of the image used, the segmentation algorithm used to extract the pores, and the post-processing steps used to remove artifacts and noise. Inaccuracies in the pore network can lead to inaccurate predictions of fluid flow behavior. The segmentation process which comprises of both noises and artifacts in the computing process has been a challenge for researchers. There are several methods which have been applied to overcome the difficulties such as manual thresholding techniques, machine learning and convolutional neural networks (CNN). Another challenge of PNEMs is the choice of model parameters, such as the contact angle and pore size distribution. These parameters can have a significant impact on the predicted fluid flow behavior and must be carefully calibrated to experimental data [159, 229-232].

There have been several modeling techniques developed in recent years to reconstruct pore structure. Process-oriented pore-scale approaches, optimization-based algorithms (OBA), and multiple-point statistics approaches are a few examples [233]. In analyzing the geometry and connectivity of sedimentary rock pores, Silin and Patzek [205] proposed the maximal sphere (or ball) concept. Pore and throat bodies were distinguished and their connectivity was established. Dong and Blunt [98] compared their results with network data extracted by several methods with the maximal sphere algorithm modified by Al-Kharusi and Blunt [186]. A search algorithm was developed instead of layer-by-layer growth of a void ball to reduce memory usage. It is possible to capture pore morphology and understand transport in porous materials using image-based pore network modelling, but how the CT-image is segmented, how the digital volume is extracted, and how it is simulated affect the predictions of macroscopic properties. Moreover, this method is limited without access to sophisticated X-ray imaging equipment. A statistical reconstruction algorithm, like the genetic algorithm, can be used to perform pore network reconstruction without the need for X-rays. Using a random pore size distribution such as normal or Weibull, this approach tunes the geometric parameters of a regular network model [234]. By generating network models, other properties that are difficult to measure can be predicted [20, 235]. Using a network model that was tuned to match capillary pressure measurements, Fischer and Celia [235] were able to predict absolute and relative permeability reasonably well for various rocks. A network model had been tuned to match capillary pressure by Dillard et al. [236] for predicting dissolution experiments. It is very important and challenging to set the initial guess values of the network parameters, though these algorithms are used to generate random pore networks that match some flow properties. This type of analysis requires an understanding of porosity and pore size distribution. The construction algorithm is faster when the network parameter values are reasonable guesses. The most common way of categorizing PNM extraction methods was to divide them into topology-centered and morphology-centered ones [130]. As they are the most widely used methods from both groups, we will discuss medial axis, maximal balls and watershed algorithms below. Topology-central methods such as medial axis extraction belong to this group. They all thin rock surfaces by removing pore space until a medial axis can be identified, i.e., a thin line denoting the pore space's center. Pore identification and partitioning may be difficult with methods that are relying on thinned pores to capture pore interconnections. In most cases, skeletonization-based methods have the downside of being sensitive to small pore defects, which leads to an over-segmentation of pores, making it difficult to identify fake brunches. It is possible to avoid this problem by preprocessing the input images [179, 203]. A maximal ball algorithm (MB) was proposed by Silin and Patzek for modeling pore networks [205]. Using this method, the largest inscribed balls are extracted from each void voxel that touches the grain or a boundary. In order to reduce the complexity of the resulting output, spheres that are completely inside others should be deleted. Families of pores can be formed by clustering them by their common ancestor. It can also be determined that a throat is a child of parents from different origins [205]. In the maximal ball algorithm, pores and throats are explicitly distinguished. The MB method generally works well for finding pores. Due to overlapping smaller spheres, connecting pores can be difficult when building throats [98]. Comparing MB networks to other techniques, some researchers noted small throats [237]. Finally, the pore space can be separated on discrete network elements by applying a watershed algorithm, a method that was proposed by Sheppard et al. [238] and Thompson et al. [239] more than a decade ago. A segmented pore space image can be used to calculate the distance map. Pores can be separated by throats [240]. Using this technique, distance and watershed transforms are combined in order to produce satisfactory results only for images with varying minima and catchment basins. In order to understand this, it helps to imagine two connected objects that have their local deepest points at their centers (these are called catchment basins). Watershed ridge lines are the first contact lines before liquid is mixed in both 'valleys' or peaks when water begins to fill these 'peaks'. In this way, the two touching objects can be marked as pore bodies, and the line between them as a pore throat by cutting the composition along this line [240]. Due to the fact that each local minimum can easily become the catchment basin, watershed segmentation can be sensitive to noise and over-segment input images as a result. Additionally, Gostick [237] noted that the distance transform might include ridges and plateaus as well as peaks at pore centers. As part of SNOW's improved algorithm, spurious local maxima resulting from over segmentation are detected. This method will be discussed in the next subsection.

Most Affecting Parameters That Control PNM Performance

A delaunay tessellation approach was used by Bryant et al. to construct a pore network associated with mono-dispersed packing of spherical grains and calculate their permeability [241]. Models of Berea sandstone were constructed using spherical and ellipsoidal grains by Oren and Bakke and flow simulations were conducted on the models [101, 242]. Various geological and geomechanically processes were also considered using spheres of varying sizes. In their model, only spheres were available in grain shapes, but they pointed out that grain shapes were not an important parameter when estimating permeability. To study the effects of geomechanically deformations on the flow properties of porous media, the Distinct Element Method (DEM) and Pore Network Model (PNM) are used [176, 243]. A sample subjected to shearing was captured using DEM and PNM by Manchanda et al. [244]. Combined rigid spheres form clumps, which are a rigid, non-spherical, whole element, formed by more than one rigid sphere. The distribution of sets of clumps is similar to that of distributing penetrable or impenetrable spherical grains to generate porous media (Fig. 5).

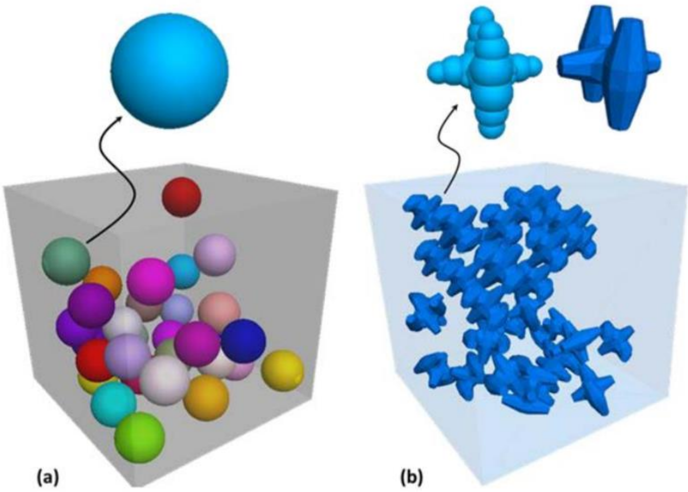

Fig. 5. Generating a porous medium by distributing (a) sets of balls and (b) sets of clumps in PFC_3D

Ramparchikolaee and colleagues calibrated a DEM model based on packed sand/sandstone rock mechanical data to examine the relationship between seismic source mechanisms and permeability in deformed rock joints [245]. A specific stress path was then applied to the sample and flow simulations were run. A more recent study by Yang and Juanes modeled pore pressure effects on fault slip failure modes using the Delaunay tessellation scheme for packing spherical balls in a DEM simulator [246].

Modeling the flow at the continuum scale can be done using Darcy's law. In addition, porous media parameters like porosity and relative permeability affect the accuracy of their models [164]. Rock imaging tools have improved our understanding of porous media flow in recent years by imaging porous rocks and fluids inside them. Simulate the flow in these media using this tool and publicly available numerical tools [206]. Typical conventional relationships are inadequate to quantify transport properties of complex geological materials such as carbonates and tight sandstones. There are numerous different sizes of vugs in multimodal carbonates, from nanometers to millimeters [233]. A significant portion of the world's hydrocarbon reserves reside in such carbonate rocks, so modeling and simulating their multiphase flow is an open challenge [247]. This necessitates pore-scale studies and physics-based transport properties for these complex rocks [248].

Researches Toward Predictive PNM That Relax Experimental Validation

Capillary forces are often taken into account in quasi-static models for slow invasion of a wetting fluid in porous materials. Due to the difficulty of predicting imbibition permeability from pore network models, this approximation has been disputed in the literature. It is possible, nevertheless, for a model to be overfitted if it is compared only with continuum-scale experiments. Therefore, neither network extraction nor pore filling rules have been shown to influence generalizing model performance. By studying continuum-scale fluid distributions, Bultreys et al. investigated the validity of this model [249]. By implementing capillary-dominated pore filling and snap-off, as well as a sophisticated cooperative pore filling model, they compare fluid arrangement evolution measured in fast synchrotron micro-CT experiments on two rock types. Their workflow for validating pore scale multi-phase flow models is shown in Fig. 6. Through numerical simulation or experimental micro-CT imaging, the researchers generated fluid distributions in a pore network model based on a micro-CT scan of the sample.

Their next step is to see if the simulation predicts up-scaled flow properties as well as the experiment does.

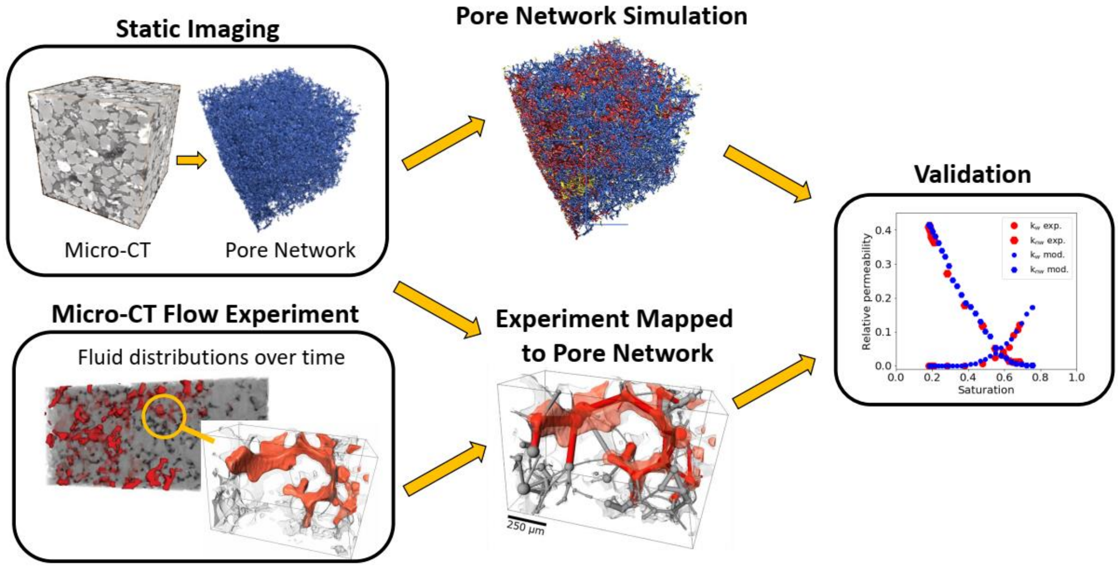

Fig. 6. Bultreys et al.'s workflow for validating multi-phase flow models for imbibition in rocks [177]

In some cases, quasi-static PNMs were able to match experimental relative permeability curves [243, 250], but a substantial body of research has not yet yielded satisfactory predictive abilities [251]. A number of shortcomings have been attributed to inconsistencies in the extracted network or pore filling rules. As a result of X-ray micro-CT experiments [252, 253], viscous and inertial effects, such as ganglion dynamics, have been observed, challenging the quasi-static assumption [254, 255]. At intermediate scales of fluid clusters, the quasi-static approximation may produce fundamentally flawed predictions, but it is unclear how strongly it deviates from experimental reality. Since model simplifications lead to fewer macroscopic parameters, the validation question is complicated by the number of internal microscopic degrees of freedom. As a consequence, when adjusted to experimentally measured continuum scale flow properties, such as relative permeability and capillary pressure-saturation functions, the model may overfit the experimental data. [251]. A system's internal state should be determined by criteria that contain sufficient information [256].

Future Directions

Improved imaging techniques: One of the main challenges of digital rock technology is obtaining high-quality images of the pore structures of rocks. Advances in X-ray CT imaging technology have greatly improved our ability to image rock samples in three dimensions. For example, the use of synchrotron-based micro-CT imaging has allowed for the resolution of sub-micron features in rock samples [257]. Other imaging techniques, such as magnetic resonance imaging (MRI) and focused ion beam scanning electron microscopy (FIB-SEM), may also hold promise for improving our understanding of rock properties [258, 259].

Machine learning and artificial intelligence: Machine learning and artificial intelligence are becoming increasingly important in the oil industry, and there is potential for these technologies to be applied to digital rock data. For example, machine learning algorithms can be used to identify patterns in digital rock data and develop predictive models of reservoir behavior[260]. Artificial intelligence can also be used to optimize drilling and well completion operations [36].

Integration with other technologies: Digital rock technology can be integrated with other technologies to provide a more complete understanding of oil reservoirs. For example, the combination of digital rock data with seismic data can provide a better understanding of the structure and properties of a reservoir [261, 262]. Additionally, the use of well logging data can help validate digital rock models and improve our understanding of the relationship between rock properties and well performance [263].

3D printing: 3D printing technology has the potential to revolutionize the way we study and test rocks. By using digital rock data to create physical models of rocks, we can perform laboratory experiments to validate digital rock models and better understand the properties of reservoir rocks [146]. Additionally, 3D printing can be used to create custom-designed tools for drilling and well completion operations [264].

Applications beyond oil: Digital rock technology may have applications beyond the oil industry. For example, it could be used to study the properties of other porous materials, such as concrete or soil [265]. Digital rock technology could be used in the field of medicine to study the properties of bone and other biological tissues [266].

Conclusion

There is a high correlation between the internal structure of porous media and the morphology of the pore spaces in terms of the flow and transport within them. The size and shape of the solid particles affect how they are arranged in the pores. The size and shape of the solid particles also affect how they are spread out in the pores. The digital core model is an important tool for experimenting with the petrophysics of rocks because it can be used as a simulation platform. It can be used to simulate a wide variety of petrophysical properties and transport processes, including solid mechanics, acoustic transport, electricity transport, fluids, and fluid-solid couplings. In a numerical simulation experiment, the model is constructed using a 3D model of the rock, which must be accurate in order to conduct all the numerical simulation experiments. A variety of different physical and chemical processes have been simulated using porous network models, including phase exchange processes, non-Newtonian displacements, non-Darcy flows, reactive transport, and thermodynamically consistent layers of oil. These models have been applied in many different applications. An overview of how digital rock has evolved from its origins in porous media research to its development into a practical tool Digital rock analysis analyzes rock samples at the pore scale, utilizing X-ray micro-computed tomography and pore-scale modeling. Digital rock is discussed in the petroleum industry and its applications in reservoir characterization, fluid flow simulation, and enhanced oil recovery. A review of digital rock is presented, emphasizing the importance of working with complementary laboratory techniques and carefully interpreting the results. It is also discussed how pore network modeling can be used to simulate fluid flow in porous media. Digital rocks will be integrated with other data sources in the future, including new imaging and modeling techniques.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Nomenclature

Abbreviations

AFM	Atomic force microscopy
DNS	Direct numerical simulation
PNM	Pore Network Model
PVT	Pressure, Volume, and Temperature
SEM	Scanning electron microscopy
XRD	X-ray diffraction
TEM	Transmission electron microscopy
XRF	X-ray fluorescence
LBM	Lattice Boltzmann methods
TDS	Total Dissolved Solids
PV	Pore Volume

Symbols

A	Cross-section area
L	Length of sample
k, k_{abs}	Absolute permeability
K_r	Relative Permeability
P_c	Capillary Pressure
θ	Contact Angle
σ	Interfacial tension (IFT)
$\emptyset$	Porosity
ΔP	Pressure drops across the core
S_i	Saturates of phase i
T	Time

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