جامعة خليفة
Khalifa University

Physics-augmented Machine Learning Classification of 3D Vision Morphology for Digital Rock Typing

Omar Alfarisi

Ph.D. Thesis

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A thesis submitted to Khalifa University of Science and Technology in accordance with the requirements of the degree of Ph.D. in Interdisciplinary Engineering in the Department of Mechanical Engineering.

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by

Omar Alfarisi

A thesis submitted in partial fulfillment of the
requirements for the degree of

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Masdar Institute in collaboration with MIT
Massachusetts Institute of Technology**

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Abstract

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Reservoir Simulation models require Rock Types with their petrophysical properties as an input to perform fluid flow predictions that direct the reservoir development plans. Each rock type represents a unique set of static and dynamic properties: Capillary Pressure (P_c), Permeability (k), Initial Water Saturation (S_{wi}), and Lithology, and a set of dynamic properties like Relative Permeability (k_r) and Wettability. Geoscientists find it very difficult to perform Rock Typing in carbonate, especially in linking P_c to k to S_{wi} to Lithology. This linkage dilemma is mainly due to three reasons — first is rock heterogeneity. Second is the measurements of P_c and Permeability, which cannot capture heterogeneity in an integrated manner as both correspond to different Representative Elemental Volume (REV). However, on a limited scale of ~ 0.2 " (0.5 mm), P_c and k analysis are at the same REV. The third is the control over the selection of Representative Elemental Volume, which is not easily definable. We can notice that the first reason (heterogeneity) leads to the second and third ones.

This thesis explored an alternative to REV with Controllable Measurable Volume (CMV). Experimental, analytical, Image Processing, and Machine Learning tasks have proven that CMV can solve the inherited problems that conventional REV cannot define. The REV deficiency is apparent in the oil industry with difficulty achieving

appropriate up-scaling from the thin section scale to the reservoir scale. It is essential to analyze the microscopic rock features with this difficulty by combining image processing, machine learning, and human expertise. The applicability of CMV is demonstrated at all scales if each scale volume property is measurable with a controllable boundary.

Furthermore, in this research, we introduced the concept of Pore Throat Network (PorThN) as a substitute to typical Pore Network. PorThN suits the carbonate heterogeneity owing to the domination of the pore throat effect rather than the porosity. We also introduced Digital Rock Typing (DRT) to show the ability of the digital world to classify rock. Despite the current focus of this research on reservoir rock typing application, the proposed methodology is extendable to other sectors, including medical and planetary exploration, especially heart vessel examination and Mars exploration. Therefore, enhancing our capabilities in analyzing these images to extract natural resources' physical and chemical properties will help humanity reach uneasy longevity goals.

Indexing Terms: Machine Learning, 3D Printing, Random Forest, 3D Vision, 3D Image Processing, 3D Micro Model, Image Recognition, Image Analysis, Digital Rock Physics, Digital Rock Typing, Pore Throat Network, Porous Media, Petrophysics, Rock Typing, Permeability Prediction, MRI, μ CT, Cretaceous Carbonate, Heterogeneous Carbonate, Capillary Pressure, Morphological Machine Learning Image Analysis, 3D Morphology, Complex Morphology, Geometrical Analysis, Physics, Mineralogy, Lithology, Geoscience, Reservoir Engineering, SCAL, Petroleum Engineering, Mechanical Engineering, Electronics Engineering, Interdisciplinary Engineering, and Reservoir Characterization.

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Omar Al-Farisi

Masdar City, May 23, 2019

Declaration and Copyright

Declaration

I declare that the work in this thesis was carried out in accordance with the regulations of the Khalifa University of Science and Technology. The work is entirely my own except where indicated by special reference in the text. Any views expressed in the thesis are those of the author and in no way represent those of Khalifa University of Science and Technology. No part of the thesis has been presented to any other university for any degree.

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1.1 Background

Reservoir Simulation models require Rock Types with their petrophysical properties as an input to perform fluid flow predictions that direct the reservoir development plans. Each rock type represents a unique set of static and dynamic properties; Capillary Pressure (P_c), Permeability (k), Initial Water Saturation (S_{wi}), and Lithology, and a set of dynamic properties like Relative Permeability (k_r) and Wettability. Geoscientists find it very difficult to perform Rock Typing in carbonate, especially in linking P_c to k to S_{wi} to Lithology. This linkage dilemma is mainly due to three reasons — first is rock heterogeneity. Second is the measurements of P_c and Permeability, which cannot capture heterogeneity in an integrated manner as both correspond to different Representative Elemental Volume (REV). However, on a limited scale of ~ 0.2 inch (0.5mm), P_c and k analysis are at the same REV. The third is the control over the selection of Representative Elemental Volume, which is not easily definable. We can notice that the first reason (heterogeneity) led to the second and third reasons.

Therefore, in our research, we explored an alternative to Representative Elemental Volume with Controllable Measurable Volume (CMV). We performed experimental, analytical, Image Processing & Machine Learning tasks to prove that CMV can solve

the inherited problems of not defining the right or suitable REV. The REV deficiency is apparent in the oil industry with the difficulty of achieving appropriate up-scaling from thin section scale (40um thickness) to core plug size of 1.5inch (38.1mm) to the well-logging resolution of ~2ft (~0.61m) to perforation interval of ~30ft (~9.14m) to well production testing of ~1km. This scale effect is explained (Al-Farisi, O. - 2004) [1] and considered one of the uneasy challenges in the oil industry. With this difficulty, we realized the need for micro-scale rock and fluid imaging in addition to machine learning algorithms that can learn from the human expert and apply the learning to high-resolution images. In this research, we demonstrated the applicability of CMV at all scales if each scale volume property is measurable with a controllable boundary.

Despite the advancement in measuring devices (i.e., Imaging Devices), the analysis focused on solving every Pixel or group of pixels in an image rather than understanding what each part of that image represents. That traditional approach of pixel analysis can consume very high computing power. It may not reach the required target due to the lack of the Petrophysical representation of each part in the image. Therefore, we ensured the collective wisdom of research background in this interdisciplinary research to solve heterogeneity, image interpretation, and computing power challenges. We realized that achieving our research goal requires a multidisciplinary approach or a multidisciplinary collaboration of three Engineering and Science sectors: Mechanical Engineering, Petroleum Engineering (Reservoir Engineering and Geoscience), and Computer Science. An amalgamated knowledge is vital to delivering the CMV-based solution. We integrated fluid dynamics, reservoir characterization (rock typing and petrophysical analysis), image processing, and machine learning.

The high potential of Imaging technology in providing static and dynamic petrophysics properties is evident due to the ability of such technology to be more informative, fast,

and efficient in delivering these properties. In contrast, physical measurements may take years to complete for flooding experiments. In carbonate, imaging is vital due to heterogeneity and the same for the unconventional oil and gas sector (Prasad, M. - 2009) [2].

As we will see in this research, Artificial intelligence played a non-replaceable role. Our ability to teach the machine to perform extensive data analysis provides an efficient, fast, more productive, and systematic approach to deliver results. At the same time, quality for these deliverables is also essential. We developed a new verification approach that relies upon experimental data.

1.2 Literature Review and Technical Challenges

As the knowledge of Dynamic Flow Property at any one cross-section is a must when studying fluid behavior in porous media, it becomes more challenging in the case of micro-scale geometry with heterogeneous morphology. Therefore, the need to peruse a micro-level understanding of reservoir rock and fluid behavior is inevitable. Moreover, the first step was to identify the scientific community and oil industry's challenges concerning image processing and analysis at the micro-level.

In this research, we can see that the current wisdom challenge is in more than one domain; Rock Texture complexity (Heterogeneity), Imaging tools capabilities and limitation, image analysis automation, and finally, the interpretation of the image data. So quality static and dynamic petrophysical properties determination and integration via Micro-Computed Tomography (μ CT), Nuclear Magnetic Resonance (NMR) & Magnetic Resonance Imaging (MRI) measurements with artificial intelligence aided image processing is a challenging task. However, we decided to deliver in this research. In reviewing current literature, earlier research has revealed the pressing challenges of

performing 3D image processing instead of 2D (Dernaika M. - 2018) [3]. While we use dual-energy X-ray CT scanning data to perform rock properties characterization, (Dernaika – 2018) [3] claims reasonable matching between core plug helium porosity and DRP μ CT porosity, and the same for permeability. The drawback is that there is no blind test; instead, this work appeared as a learning and exploring μ CT capabilities. 2D images cannot predict the petrophysical properties in carbonate due to the limited representation of the rock heterogeneity. Lately, Major oil firms have stated that no commercial vendor is yet able to measure porosity and permeability (Chhatre, S. - 2018) [4]. The focus on simulation was apparent in several studies, which held other running time challenges, computing power, and representativeness of the models.

There is another work performed (Byrnes – 2018) [5] that used FIB-SEM and μ CT in combination with CFD (Computational Fluid Dynamics) simulation to produce porosity, permeability, P_c , and relative permeability. Measuring porosity and pore size distribution leads to calculating porosity and P_c curves, while permeability and relative permeability result from simulated work. While the work of (Liu Z. - 2016) [6] focused on the use of NMR for saturation measurement, the paper showed the relation between Relaxation time and Pore Size using an equation (Ausbrooks – 1999) [7] that converted T2 relaxation to Pore Size Distribution. Earlier (Marschall – 1995) [8] used the same equation. While we know every well in heterogeneous rock, the pore size alone cannot lead to other petrophysical properties like Permeability and Capillary Pressure Curves. Then, Relative permeability determination from Image data is approached in the industry (Li, H. – 2016) [9] by analyzing the fluid flow in a micro model that mimics the rock. A hi-resolution optical Confocal camera tracks the fluid flow inside the micro models to find the relative permeability in a 2D plane.

Carbonate is hard to measure using image analysis (Saxena 2018) [10] to determine porosity and permeability. The work concluded that image processing only suits clastics (Sandstone). We could see that AI and Image processing are used mainly for the 2D image, not 3D. Therefore, we ensured performing the tasks in 3D rather than 2D in our research work. AI, primarily machine learning, performed rock properties characterization (Alqahtani – 2018) [11] by analyzing 2D micro CT images to produce porosity and pore size distribution where segmentation calculated porosity, then Convolutional Neural Network (CNN) performed the pore size distribution. It is helpful as a procedural reference for conducting 2D image analysis using ImageJ software and the open CNN source Tensor Flow software. Image with 3D analysis (Dong – 2007) [12], using micro CT images, and an approach called Maximal Ball algorithm, perform topological extraction of pore network by analyzing the connectivity between each pore, which is very important to calculate the dynamic properties of the rock. The paper also highlights the effect of vugs that acts as large channels or massive connectivity between matrix porosity, putting a way forward to build a predictive dynamic property estimator for relative permeability and capillary pressure. All challenges we stated above are a different reflection of the main problem of the reservoir characterization, which is the ability to determine what we call Pore Throat Network (PorThN), a term we introduced. Finding PorThN of a rock is the key to all the required static and dynamic properties for rock typing and reservoir simulation. PorThN can deliver Permeability, Capillary Pressure, Relative Permeability, and even Wettability Deformation Effect (WDE).

1.3 Research Objectives

We defined the objective of this research to be: Quality Static and Dynamic Reservoir Properties Determination and Integration via μ CT (Micro Computer tomography),

NMR (Nuclear Magnetic Resonance), and MRI (Magnetic Resonance Imaging) measurements with Artificial Intelligence Aided Image Processing. Figure 1.1 shows the sequence of objectives to be delivered in a reservoir characterization project, starting from Porosity, Pore Throat Size, Permeability, Capillary Pressure Curve (including Water Saturation), and finally to Relative Permeability. Our project will focus mainly on the first four: Porosity, Pore Throat Size, Permeability & Capillary Pressure Curve.

Figure 1. 1. Reservoir Properties Deliverables in a Characterization Project.

1.4 Reservoir Characterization Rock Typing Conventional Wisdom

One of the most critical tasks in Reservoir Characterization is Rock Typing. Correct rock types hold the suitable petrophysical properties (static and dynamic) that the Reservoir Simulation Model needs. For Reservoir fluid flow simulation purposes, relative permeability is one of the most critical inputs. To identify multi-phase k_r , we realized the need to honor all factors influencing the k_r curve. These parameters are fluid viscosity, absolute permeability, and wettability. These parameters suggest that we need to determine the rock type, where pore throat influences permeability, capillary

pressure, and initial water saturation. As per (Al-Farisi - 2009) [13], the ability to find a representative permeability, then with the aid of lithology and porosity, the value will enable determining P_c and S_{wi} using the C-Function (Carbonate Capillary Function) (Al-Farisi – 2013) [14]. Lithology and porosity data are available for each well with logging.

In contrast, cored wells have lithology and porosity data in both formats, logging and coring domains. Where k_r data is limited, the thin section is widely available. Therefore, we initiated this digital image processing research to generate a vast amount of k_r curves for the thousands of thin-section data. This first step is to acquire and analyze μ CT images of core plug aiming to find permeability, representing one of the static properties that k_r . Then by moving to 3D, we capture the deformation in pore throat shape due to wettability.

In this research, we build a new MRI flooding system in our university facility. As will be explained thoroughly in the next chapter, this setup provides a unique in-situ visualization of fluid flow changes.

1.5 References

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Experimental Setup and Image Acquisition

In our research, after the literature review, we decided to use two types of images, μ CT (Zhang – 2017) [1] and MRI (Wang – 2017) [2], to enable characterizing the carbonate rock from 3D vision. In 2016, we acquired eight rock samples from Abu Dhabi's marine operating companies (core plugs). Each of these eight samples is sister plugs (within <1 ft distance). One of the sister plugs is preserved with polymer and aluminum foils and sealed with wax. The other sister plug is bare. These eight plugs are Lower Cretaceous carbonate have their static properties measured by Weatherford ResLabTM in Abu Dhabi.

2.1 μ CT Image Acquisition System

To acquire the 3D vision of our carbonate core plug, we used the existing μ CT setup in an Abu Dhabi-based Research Center operated by Khalifa University of Science and Technology, The Petroleum Institute, in Abu Dhabi. The resolution of the μ CT image voxel is 40 x 40 x 40 μ m. We acquired it with ZEISS Xradia 520 VersaTM, as shown in Figure 2.1, at the research center. We have also obtained a higher resolution image, using an Ingrain μ CT device to achieve an image voxel resolution of 28 x 28 x 28 μ m. We used the 40 μ m image for porosity determination; however, for permeability determination, we used 28 μ m. To visualize the difference between both resolutions, we

displayed them back to back, as shown in Figure 2.2. The μ CT instrument we acquired in the INGRAINTM facility in Abu Dhabi is like in Figure 2.3.

The fluid is invisible in the μ CT vision; therefore, this measuring technique provides an excellent path to characterize the rock morphology. Therefore, solid can be recognized as a gray shade while the pore spaces appear black. The μ CT image in μ CT image intensity ranges from “0” to represent black and “255” to describe white, and in between, the intensity values would vary over gray shades.

Figure 2. 1. We used the Research Centre μ CT laboratory device, ZEISSTM, to acquire the 3D vision.

Figure 2. 2. Two μ CT images with two different resolutions. The left image has a 40um voxel resolution, and the right is a 28um voxel resolution.

Figure 2. 3. The INGRAIN™ μ CT machine

2.2 MRI Image Acquisition System

We built an MRI laboratory to visualize the fluid inside the pore space inside the rock sample for our research. We used the Suzhou Niumag™ NMR system (0.5 Tesla). The MRI instrument setup consists of three main parts, the magnetic field with the core holder, the NMR radio frequency and temperature controller, and the 3-phase pressurized flooding system, as shown in Figure 2.4.

Figure 2. 4. Bench Top NMR and MRI Analyzer (MesoMR) Niumag™ and Pressurized Flooding System.

The diagram of the high-pressure flooding system shows a detailed description of its components, as shown in Figure 2.5. Two high-pressure gas cylinders (nitrogen and carbon dioxide) are available for performing gas flooding. The flooding system is a gas booster for reaching supercritical carbon dioxide. Also, two cylinders are available for liquid flooding. These two liquid cylinders can handle water flooding, including saline water that contains MgSO_4 and oil flooding like Decane and crude oil. The MRI flooding system has an analytical balance to measure the recovered liquids' weights during flooding. An additional pump in the flooding system maintains the confining pressure over the core plug holder to ensure no fluid leakage during the flooding. This NMR/MRI core flooding system mimics our reservoir conditions up to 3626psi, equivalent to 250bars.

Figure 2. 5. Diagram of high-pressure 3-phase core flooding with NMR and MRI measuring devices.

We see in Figure 2.6 the MRI images of one of the preserved core plugs (Plug 9) in multi-angle views. In the exact figure (Figure 2.6), we also see the core holder with cartesian coordinates. The fluid is visible to MRI and presented in gray shades while

the solid is black, “0” intensity value. This image representation of MRI vision is opposite to μ CT expression. While in Figure 2.7, we see three consecutive 2D MRI slices that we use to build the MRI 3D vision.

Figure 2. 6. Multi-angle MRI view of the preserved carbonate core plug. The right-side image shows the MRI device's core plug holder.

Figure 2. 7. Lower row: three 2D MRI slices in a cross-sectional view of a core plug (preserved Lower Cretaceous carbonate) show the fluid (crude oil) in gray shades and solid in black shade. Top row: The red lines show the 2D slices markings.

One of the uniqueness of the MRI set up in our laboratory is measuring the fluid changes in-situ and at reservoir conditions. This feature in the system is vital for tracking, visualizing, recoding then molding multi-phase flow dynamics.

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Porosity Determination Using Machine Learning Assisted 3D Image Processing

This chapter delivers porosity determination using mainly two methods; the first is standalone image processing, and the second is machine learning-assisted image processing. These methods are built based on experimental results.

3.1 Machine Learning Image Processing

3.1.1 Machine Learning

Machine Learning, as we define it here, is the ability of a machine to build models as good as the training set delivered and run the model on a new collection of data faster and more accurately than human experts. In a more engineering sense, the definition stepwise appears like the following:

- (1) Step 1: Input a training data set of a knowledge domain to the machine.
- (2) Step 2: The human domain expert selects one or more learning algorithms for the machine.
- (3) Step 3: The machine performs the learning task from the provided data using the selected algorithms to build a model and test the

model to know model accuracy. The Model runs for classification or regression prediction problems.

- (4) Step 4: The machine uses the model developed in step 3 above on new data set to perform the prediction.

Other definitions of Machine learning in literature is, (Mitchell T. – 1997) [1], “A computer program is said to learn from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E.”

3.1.2 Image Processing

We define image processing here as the tasks a human expert performs on the input image (2D, 3D) that produce a new set of information or images that provide more insight to a human expert. In a more engineering sense, the definition stepwise appears like the following:

- (5) Step 1: Input to machine an image (2D, 3D).
- (6) Step 2: Human domain expert selects and runs suitable filtering, segmentation, analysis, and measuring algorithms to achieve the image processing objective.
- (7) Step 3: The human expert learns new insight and generates new data (Numerical or Image) as a result of step 2 above.

Other definitions of image processing are, as per (Gonzalez R. – 2009) [2], “...Image Processing encompasses processes whose inputs and outputs are images and, also, encompasses processes that extract attributes from images, up to and including the recognition of individual objects.”

3.1.3 Combining Machine Learning and Image Processing

We call the combination scenario Machine Learning Image Processing. We define it as the machine's ability to perform learned tasks from the training set delivered from a human expert image interpretation on a new collection of images faster and more accurately than a human expert. Other definitions also describe a combination of Machine Learning and Image Processing as Image Analysis, as per (Gonzalez R. – 2009) [2].

3.2 Porosity Determination

Porosity measurement from rock core plugs uses helium gas, and this is what we consider the ultimate porosity measurement. Also, we performed μ CT and MRI imaging for the same core plug. The porosity determination, in our research, consists of two parts, Experimental and Machine Learning Image Processing.

3.2.1 Porosity from Experimental Measurements

In the experimental part, we measured the porosity of the rock core plug with three different methods. The first measurement method is a weight difference of rock under dry and wet conditions. The second method is NMR of the same rock filled with fluid (crude oil). After cleaning and drying, the third method is helium gas on the same rock.

3.2.2 Porosity from Machine Learning

We performed 3D μ CT image processing using a Random Forest machine learning algorithm in machine learning. The primary Machine Learning tasks were as per the following:

(1) Human Expert (Geoscientist), a Petrophysicist in our case, provided data set to Machine. Our Petrophysicist identified two types of minerals (limestone and pyrite), two physical statuses (pore and solid), and four image intensities. The data set contains:

- i. “Independent Parameters data columns”; Image identified properties with Black Color, Dark Gray Intensity, Light Gray Intensity, and White.
- ii. “Dependent Data Column,”; Containing the desired classes of limestone, pyrite & pore. Solid here include the limestone and pyrite.

(2) Human Expert chooses a Machine Learning Algorithm; in our case, we choose the “Random Forest” algorithm owing to its superior capability in performing Classification.

(3) The Computer uses the Random Forest algorithm to learn from the data set and build the Prediction Model with all its Governing Equations.

(4) The Computer inputs new data set, 3D μ CT Image, and uses the learned Prediction Model with its Governing Equations to predict output classes.

In this research, we used mainly three software; Microsoft Office 365™ [3], Python [4], and Imagej [5] for Machine Learning, Image Processing, Mathematical Modeling, and Graph Generation.

3.2.3 Initiating and Utilizing 3D Micro Model

We realized that without proper measurement control, the complexity of interpreting image data (μ CT and MRI) would continue without a solution. Therefore, we developed a 3D Micro Model (3DMM) with various micropore sizes as measurement control in this research. The micro model we developed are three types:

- (1) Bundle of Capillary Tubes 3D Micro Model.
- (2) Spherical-Glass-Beads' 3D Micro Models.
- (3) Multi-Geometry 3D Micro Models.

3.2.3.1 Bundle of Capillary Tubes 3D Micro Model

The image resolution is one of the main challenges in the 3D morphological recognition process—naturally, the better the image resolution, the better the segmentation. However, not every image has the desired resolution for optimal image analysis. In 3D rock images, identifying 10^6 s of micropores and quantifying their morphology is a pressing challenge. The resolution does blur the feature of interest. Numerically, the pixel color value does not represent the actual value. Figure 3.1 shows how natural rock micropores (void space) appear in more than one gray value. The exact representation of pore is black, which is a value of 0. We must assign the real value to each of these pores, 0. In Figure 3.1, we see the resolution effect. In Figure 3.1, the Top image shows a 38mm diameter sample acquired with 40um resolution (each pixel is 40 um). The image inside the red circle is our zone of interest for identifying pore (Dark shade) and solid (light shade). To solve the resolution effect, we innovated a novel convoluted image processing algorithm for improving the resolution of 3D images. Figure 3.2 shows three

MRI cross-section images for natural rock we acquired with three different sampling rates. By different sampling rates, we mean a different thickness of the z-axis along the sample cylinder. We acquired all images with 400um resolution, but the width of the cross-section along the z-axes (along the core plug cylinder z-axis) is; 3.5mm for the Left image, 3.5mm for the middle image, and 1.5mm for the Right image.

Figure 3. 1. The resolution effect is evident in three zooming factors.

It is noticeable that to bring the right-side image, in Figure 3.2, to be as bright as the left-side image is essential, analyzing thinner slices for monitoring fluid behavior inside microporous media. The intensity of the left image is much lower than the image intensity of the left image. The

contrast between the dark and light of the three is increasing towards the left. Light color represents void, while dark color represents solid.

Figure 3. 2. MRI for the core plug with three different sampling rates.

3.2.3.1.1 3D Micro Model 3DMM Experiment Design and Imaging

We built a 3D micro model (3DMM) with a known dimension of pore and solid. 3DMM enables constructing and verifying IROGA in a controlled environment. Figure 3.3 shows the 3DMM cross-sectional and longitudinal structure that contains 26 tubes. Each tube is of a 790um void diameter and 50mm length. The calculated value of void to total volume is 7.21%. We use a 0.5 Tesla MRI device. We collected 3D MRI images of nine 2D slices, as shown in Figure 3.4. In Figure 3.4, the small light dots represent void, black represent solid, and gray rectangles represent separators between each 2D image slice. Each dot represents one of the tubes. We displayed one of the nine MRI 2D slices in an enlarged view, as shown in Figure 3.5.

Figure 3.3. 3D physical micro model with cross and longitudinal sections.

Figure 3.4. 3D MRI cross-section images of nine 2D slices for the 3D micromodel.

Figure 3.5. Enlarged MRI slice shows an unwanted resolution defect in gray shade.

3.2.3.1.2 3DMM Experiment and Construction of Mathematical Algorithm

We analyzed 3D MRI images and 3D micro CT images using three different Machine learning methods.

3.2.3.1.2.1 The First Method – Machine Learning Gaussian Random Forest

We used traditional Gaussian Random Forest (Polan – 2016) [6] as part of open-source ImageJ (Abràmoff – 2004) [7] software. We trained an algorithm with a data set generated by associating labels with human expert visual labeling. Then, we selected the Gaussian Probabilistic to build the best representative model and perform the classification. Figure 3.6 (a) shows that the black and white MRI image is the raw acquired image with 400um resolution. Each light color dot of the 26 dots represents a 600um void (pore) of the 3D micromodel. The model's prediction produces Figure 3.6 (b) with red and green colors. We noticed that the void area is large, and the accuracy was 53.1%, which is unacceptable.

Figure 3. 6. 3D MRI cross-section images of one of its 2D slices.

3.2.3.1.2.2 The Second Method – Constructing Novel Optimized Gaussian Image Resolution Enhancement Algorithm

We thought that innovating a universal image enhancer would enable a natural way forward for utilizing it in all future MRI images without the need for human expert labeling. So, based on 3DMM MRI images, we produced enhanced image resolution that is universal in use within time-invariant systems. In time-invariant, we meant here that no other changes in the system might occur with the time that influences the image intensity (i.e., temperature, signal strength, and acquisition parameters setting do not change with time for the system). We construct IROGA, Image Resolution Enhancement with Optimized Gaussian Algorithm, as shown in Figure 3.7. IROGA is an image processing algorithm that replaces machine learning for image recognition, like a Random Forest (Sommer et al. 2011) [8] or others. IROGA is a recursive image processing algorithm that achieves the primary purpose of image resolution enhancement. Let us keep in mind that IROGA as a standalone algorithm is useful when we perform one or more of the following tasks:

- 1- If we want to enhance the resolution of an image.
- 2- If we want to differentiate between two labels (binary).
- 3- If we want to make points (1) and (2) above.
- 4- If we want to determine porosity.

We design IROGA with several experimental verification steps. We use an experiment to build and verify the IROGA. IROGA has two loops, as shown in Figure 3.7:

- 1- The Small Loop: also we call Enhanced Convoluted Gaussian (ECG).
- 2- The Large Loop: also we call Image Processing Based Porosity Determination (IPBPD).

Figure 3. 7. IROGA Algorithm Block Diagram

We constructed IROGA, our new Image Resolution Optimized Convolved Gaussian, by learning from 3DMM MRI images, by continuous iterations with changing the gaussian matrix values to reach the optimum. Figure 3.8 (a) shows the original raw MRI image of the 3DMM. Figure 3.8 (c) is the final image of IROGA after applying the algorithm, while Figure 3.8 (b) is the first IROGA iteration. We achieved very high accuracy, equal to 96.2%.

Figure 3. 8. 3DMM MRI cross section images of one of its 2D slices. (a) original image, (b) image after 1st IROGA iteration and (c) is the final image result.

3.2.3.1.2.3 The Third Method – Machine Learning Difference Gaussian Random Forest

We used Machine Learning with Random Forest, but this time with a different algorithm called Difference Gaussian (Lindeberg - 2015) [9] and (Lowe - 2004) [10]. Figure 3.9 (a) shows the original 3DMM MRI image; black represents solid, and light represents void. While in Figure 3.9 (b), we see the enhanced resolution image using Machine learning Difference Gaussian Random Forest, red color represents solid and green color represents void. This methodology produced a comparable higher accuracy of 97.1% to be the best method for accuracy for Resolution enhancement and hence, for porosity determination. By performing analysis of the comparison between IROGA and machine learning methods (Method 1 and Method 3) shown in Figure 3.10., the traditional Gaussian Random Forest approach is the worst among others, while Difference Gaussian Random Forest and IROGA showed the best results with 97.1% and 96.2% accuracy respectively.

Figure 3. 9. 3DMM MRI image (a) The original image. (b) The enhanced resolution image using Machine learning Difference Gaussian Random Forest.

Figure 3. 10. Machine Learning Random Forest (Gaussian & Difference Gaussian).

3.2.3.1.3 IROGA Validation

We performed the prediction and validation of IROGA on carbonate core plug MRI images. Figure 3.11 (a) is the raw MRI image of lower cretaceous carbonate rock, saturated with crude oil; black represents solid, and light represents void filled with crude oil. Figure 3.11 (b), the image is the final MRI IROGA results, red color is solid, and green color is void filled with crude oil. The validation of IROGA shows an accuracy of 93.9%.

Figure 3. 11. Lower Cretaceous Carbonate Rock MRI image (a) Raw image, (b) enhanced resolution image, and (c) rock and oil separation.

A summary of the experiment, modeling, and utilization of IROGA is below:

- 1- Built 3DMM with 600um inner diameter tubes.
- 2- Flooded 3DMM with Crude Oil collected from a lower Cretaceous Offshore Abu Dhabi formation.
- 3- Acquired 3D stack MRI Images ($\sim 400\mu\text{m}$) resolution for 3DMM.
- 4- Structured an Iterative Image Resolution-enhancement Convolutional Gaussian Matrix Algorithm (IROGA).
- 5- Recorded 3D-MRI of Carbonate Rock.
- 6- Applied IROGA to get the resultant Micro Fluid Distribution Map.

3.2.3.2 Glass Beads 3D Micro Model Experiment

We worked on the glass to understand the effect of void size on MRI. Here we started emphasizing void size rather than the porosity because porosity can be the same even with different void sizes. We will discuss and explain this difference further in Chapter 4. Figure 3.12 shows a different image view for the same glass beads of $\sim 1500\mu\text{m}$. From Figure 3.12, we could notice the sorting of these glass beads to follow what is known as poor sorting. The poor sorting leads to a geometrical configuration called Rhombohedral (Serra - 1985) [11].

Figure 3. 12. Glass Bead images, (a) UV light with Crude Oil, (b) MRI with crude oil, (c) optical without crude oil, and (d) optical with crude oil.

In this experiment, we care about the effect of the void size on MRI images, and Figure 3.13 shows the void size effect on MRI intensity is very clear. In Figure 3.13, the experiment setup used three different glass bead sizes. These sizes are Large (~1500um), medium (~400um), and small (~50um). We notice that the intensity of MRI images in Figure 3.13 is not the same for the different glass beads, despite the porosity being the same for the same poor sorting. Nuclear Magnetic relaxation time differs between different sizes of the void. The larger the pore, the slower the relaxation time (Sprawls – 2000) [12], and the type of fluid affects the MRI signal.

Figure 3. 13. Three Different Sizes of Glass Beads MRI Images.

We will expand our experiments on the glass beads in the next chapter (Chapter 4) by using more glass beads and building based on Pore throat and permeability determination models.

3.2.3.3 Multi-Geometry 3D Printed Micro Models

To understand further the effect of geometry on the MRI signal, we conducted a third experiment that confirmed the previous experiments and provided new insight. Figure 3.14 shows the Multi-Geometry, (a) is the 3D Geometrical design, (b) is the MRI image, and (c) is the MRI image processed with colored intensity to identify the variance due to geometry. One of the new findings regarding the symmetrical Box shape is that MRI records higher intensity at the center along the Y-axis. The cubic box is diagonal when placed in the MRI device. We relate the change of intensity to the fluid's thickness (along the signal direction), as shown in Figure 3.14 (c). This phenomenon resolves another petrophysical property of wettability; however, it is not this research target. While another observation from Figure 3.14 shows that the smaller the pore throat, the less MRI intensity, where the tubes are considered pore throat and pore are the ovals, sphere, and Box shape. In chapters 4 and 5, we use this phenomenon to solve for pore throat size and permeability determination.

Figure 3. 14. Multi-Geometry 3D Printed Model, (a) Desgin, (b) MRI image, and (c) MRI Intensity Histogram to identify signal variance due to geometry and position.

3.3 References

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Pore Throat Determination from Image Processing

In literature, we can find the term Pore Network, a novel concept we introduce in this research is the Pore Throat Network (PorThN). To build PorThN, we will integrate several concepts in geometry, machine learning, and image processing. We see the integration in Figure 4.1 as a closed-loop. The numbers inside the figure show the flow sequence of the different concepts to reach Pore Throat size determination.

Figure 4. 1. Integration of Concepts to reach Pore Throat Size determination.

Then once we reorganize Figure 4.1, we can produce another chart that takes the analysis to start from fundamental basic blocks, as shown in Figure 4.2. The analytical

approach tries to understand the physical phenomena of the geometrical effect on fluid flow. This approach will perform two main tasks: identifying the pore throat as an object from other objects in the space. This Identification can help us use it for object-oriented programming, like Python, in machine learning utilization. It also helps in image recognition. Then we move to Quantification to reach our final goal of measuring pore throat.

Figure 4. 2. Solving Pore Throat Size in five Methods. Our research focuses on methods 1, 2, 3, and 4.

Identification of pore throat using the analytical method will require observing our space, then putting some assumptions to ease dealing with space. Once we put the assumptions, we can deduce some Axioms that help solve more complicated issues. Finally, we build our model with its governing equations.

We developed a new theory to analyze the image data to produce Pore Throat Network, leading to permeability determination. In this theory, the permeability value is the 3D Permeability. 3D Permeability explicitly informs us that the direction we consider for the permeability value will give us different permeability. 3D Permeability is a new concept, as in the past, the focus was on the variance between vertical and horizontal permeability (Zahaf, K. – 1999) [1]. The new theory is DimAmp (Dismissing-Amplification Theory). We define DimAmp as the minimum diagonals' gradient chain among neighboring elements. The main contribution of DimAmp is in the calculation

of 3D permeability. We detail DimAmp here, which works with another novel concept we introduce: Dual Physics Enclosure (DuPhE). DuPhE is a dual representation for one measurement physics to another reciprocally, producing measurement physics with indispensable complementary parts. The first enclosure is represented by the enveloping of an MRI stack of images by μ CT to define the zone of Morphological Similarity Enveloping (MorSE). MRI can determine the Pore Throat Size, the open vugs, and close vugs based on fluid contents, while μ CT can provide the MorSE for the MRI.

The MRI would deliver the 2nd physics of measurement DuPhE to μ CT, where μ CT enveloped zone can now hold labels with the proper pore throat size. Then by teaching the Machine to learn what is the appropriate labeling (pore throat size) each MorSE to enable moving to the next step, which is DimAmp, like the building blocks that mimic reality (Lego™) [2], then can be upscaled to any needed size. The mathematical formulation of DimAmp is:

$$DA_{chain_Cum} = \sum_{P=1}^n [\nabla_{N_{min}}(Mijk)] \quad (4.1) \text{ or (DimAmp)}$$

Where;

P : N_{min} frame Index number

n : number of N_{min} frames

$\nabla_{N_{min}}$: the minimum gradient among neighbouring element

$Mijk$: 3D [3x3x3] matrix

The initial demonstration of DimAmp is used based on random data shown in Figure 4.4. This figure shows that the red boxes are the pore throats, while the green is the porosity. This concept is a new 3D image analysis theory from which we can identify the pore throat from the pore and measure the pore throat size, leading to permeability by using DuPhE and MorSE. The pore throat is not more than the minimum

perpendicular area (cross-section) enclosure on the flow path. This chapter performed geometrical, analytical, and experimental proof of DimAmp. This concept led us to the next chapter to determine the permeability value. A practical and simulation validation of this concept is noticed in the 2D micro model flooding and simulation using LBM (Lattice Boltzmann Modeling), (Li – 2015) [3] and later in internal ADNOC RTD TECOM review meeting 16-May-2019, presented by (TieJun Zhang – 2019). DimAmp theory has no wettability element yet, but wettability can significantly enhance it.

Figure 4. 3. DimAmp theory conceptual representation, where Pore Throat is shown in Red Color, while the Pore is the green color boxes.

4.1 Assumptions of DimAmp

For DimAmp analysis, we have put the following Assumptions:

- (1) Irrotational flow.
- (2) The pore throat plane is perpendicular ($\perp$) to Flow.
- (3) There is no transient flow; it is a steady-state flow.
- (4) The flow is a piston-like flow.
- (5) Internal Pore throat within the grain is not a pore throat between two grains and is not part of DimAmp focus as sub microscale has a marginal impact (nano $\ll$ Micro).

4.2 DimAmp Integrations of Concepts

The μ CT image provides information about the solid part of the porous media. When this porous media is heterogeneous, then the impact quantification of the pore throat network is not an easy task.

4.2.1 MRI is the Pore Throat Size and Network Determination Tool

So, the need for MRI becomes vital to solving for the PorThN. The MRI can see the fluid distribution inside the rock. Each rock fabric, or rock type, has a different PorThN. PorThN is the primary driver of rock permeability value. At the same time, the rock typing process depends on permeability and capillary pressure curve (Al- Farisi - 2009) [4]. We can see that MRI image intensity changes with the PorThN with known sizes of glass beads. We used different sizes of capillary tubes; all contain crude oil. The difference between these tubes represents the oil volume inside these tubes. The glass beads experiments provide a great reference on how the MRI intensity can change with the different pore sizes. We used glass beads as learning for the MRI image processing algorithm. Two additional factors we needed to solve. First, more than one type of fluid in the rock (Water, Oil, and Gas). The 2nd factor is the relation between pore size and pore throat size. The link between these two petrophysical properties in carbonate rock is unclear. To solve the first factor, multiphase fluid existence in the rock, we conducted experiments that used all of these fluids separately. These experiments provided information about the intensity range of each fluid type for different types of glass bead sizes. Then we worked to solve the relation between Pore Throat size and Pore size by geometrical analysis.

4.2.2 Pore Size and Pore Throat Size Interdependency Investigation

The main reason for developing the DimAmp theory is to define the relationship between pore throat size and pore size. In DimAmp, we quantified the value of pore throat size for each pore size. Then we connected these pore throats to the other pore throats to produce the PorThN that leads to the determination of Permeability. Now, instead of analyzing every pore throat and pore, which will be a time-consuming task even for high-performance computers, we did a Pore to Pore Throat Network pre-clustering called CMV. This step utilizes both μ CT and MRI image coupling to produce the clusters. Then we populated the findings by expanding the results with 3D CMV using DuphE and MorSE. The porosity of that cluster MorSE is known, and we calculated the pore throat size for each cluster. We connected all the clusters; then, we calculated the total pore throat distribution and permeability using DuPhE.

4.3 Analyzing Pore Throat from Homogenous to Heterogenous Rock

The MLIR porosity is total porosity, while the effective porosity is different as a secondary porosity (Intragranular) exists. We call a pore system heterogenous if it contains more than one porosity type. We start from homogenous well-sorted grain. In Figure 4.4, we can see the blue square, which connects the centers of the circles, represents the largest perpendicular plane to the center of the four circles. This plane will help us image processing as the starting point for image analysis. This plane is considered the X-Y plane, and the image analysis will move perpendicular to this image. This blue square also represents the largest plane of the porosity, so the lateral size is the diameter of the circle and the pore size. The orange curved diamond shape is the

pore throat. In 3D, the form will produce a square base and top of a curved diamond. The void volume for well-sorted eight spheres will be an area smaller than the cube containing the eight spheres (Thomas G. – 1984) [5].

Figure 4. 4. Four spherical grains represent the most basic homogeneous rock configuration.

The void volume equals the difference between the cube and the eight spheres. In Figure 4.4, we see that the edges of the circle are also the edges of the pore throat. We deduced Axiom 0; a pore throat is a morphological plane that has enclosure from all directions:

Axiom 0: Pore Throat has an enclosure from all directions.

We can also derive the first mathematical governing equation, as shown in Equation (4.2). Where the Pore Size area is defined, and r is the Grain Size (grain radius):

$$\text{Pore Size} = \text{Small Blue Square Area of Figure 4.4} = 4r^2 \quad (4.2)$$

While Equation (4.3) shows the Pore Throat Size area determination:

$$\text{Pore Throat Size} = \text{Small Square Area} - \text{Circle Area}$$

$$\text{Pore Throat Size} = 4r^2 - \pi r^2 = (4 - \pi)r^2 = 0.858 r^2 \quad (4.3)$$

To know the relation between the pore size and the pore throat size in 2D, we ratio the two sizes as shown below:

$$\text{Pore Throat Size} / \text{Pore Size} = 0.858 r^2 / 4r^2 = 0.2146 \quad (4.4)$$

We know that the porous system is of 3D configuration, not 2D, and this requires the calculation of volume rather than area. In Figure 4.5, we can see the same porous system in 3D. To proceed further in the 3D configuration, we need to consider the structure that dominates our reservoir. Our reservoir rock porosity ranges from 18 to 32 p.u. (porosity unit). This range gives an average porosity of 25 p.u. for our reservoir. (O. Serra -1985) [6] Reflecting on (Graton & Fraser – 1935) [6], the pore structure of Rhombohedral configuration, as shown in Figure 4.6, is our rock structure.

Figure 4. 5. Four spherical Grains in 3D represent the most basic homogeneous Rock configuration called Cubic Grain Sorting.

Figure 4. 6. Rhombohedral configuration of grains for the pore system reflects our reservoir pore system.

4.4 Porosity and Pore Throat Size Non-Interdependency

The porosity value does not change with grain size changes if the grain structure is the same, while the change in grain size impacts the pore throat size. Therefore,

porosity does not directly relate to pore throat size in carbonate. So, we cannot use porosity to identify rock types in carbonate, pore throat size, and PorThN influence fluid flow rather than the porosity value. We know that porosity is the void ratio to the total bulk volume (void + solid). Therefore, porosity will not change with the change of the grain size but only with the structure because the grain structure determines the transformation of the ratio between void and the total bulk volume (O. Serra -1985) [6].

4.5 Grain Size and Pore Throat Size Interdependency

We can deduce that the grain size impacts pore throat size for the same grain structure, as shown in Equation (4.3). So, we need to derive the equation for the Rhombohedral configuration to determine Pore Throat Size (PorTS) based on the derived relation. We started with a more straightforward structure than Rhombohedral, the Triclinic, as shown in Figure 4.6, which is the 2D illustration. The equations that govern the pore and pore throat size is derived below from Figure 4.6, where r is the grain size (Grain Radius):

$$\text{Pore Size} = \text{Triangle Area} = \sqrt{3} r^2 \quad (4.5)$$

$$\text{Pore Throat Size}_{\text{Triclinic}} = \text{Square Area} - \text{Circle Area}$$

$$\text{PorTS}_{\text{Triclinic}} = \sqrt{3} r^2 - \frac{\pi}{2} r^2 = \left(\sqrt{3} - \frac{\pi}{2}\right) r^2 = 0.162 r^2 \quad (4.6)$$

Figure 4. 7. Triclinic configuration of grains for the pore system. The green triangle shows the pore size, while the orange color shows pore throat size, and we can see that both are dependent on Grain size, but porosity does not depend on Grain size.

Also, we can determine the length of the fluid path at the center of the PorThN for this configuration, which we derived from the geometrical structure shown in Figure 4.8 to produce the following governing equation, where r is the grain size:

$$\text{PorThN Center Fluid Flow Path length} = 2r \quad (4.7)$$

Then we moved to our desired geometrical configuration (Rhombohedral), more complex than Triclinic, as shown in Figure 4.6. We calculated the pore throat size for Rhombohedral by reducing the pore throat size when moving from Triclinic to Rhombohedral. We built the geometrical shape of the rhombohedral using glass beads.

Figure 4. 8. We used the triclinic configuration of grains for the pore system to derive the PorThN Center Fluid Flow Path length.

From this configuration, we found the reduction, as shown in Figure 4.9. The top image in Figure 4.9 is a top view, and the middle image is a side view to see the pore throats of the two different grain configurations, Triclinic and Rhombohedral. In the central image (side view), the first three balls from the left form Triclinic, while for the same image, the other three balls construct the proper Rhombohedral form. While the bottom image of Figure 4.9 is also a side view of the two configurations (Triclinic and Rhombohedral) with both pore throat types measured. Now we can deduce the ratio between the two configurations, as shown in equation (4.8):

$$\text{Ratio of Rhombohedral to Triclinic} = 0.47/0.70 = 0.6667 \quad (4.8)$$

Figure 4. 9. Deducing two different grain configurations (Triclinic and Rhombohedral). The top image is a top view, while the middle and bottom images show a side view (image flipped upside-down for measurement).

We calculated Rhombohedral pore throat size $PorTS_{Rhombohedral}$ from equation (4.9):

$$PorTS_{Rhombohedral} = 0.6667 * 0.162 r^2 = 0.109 r^2 \quad (4.9)$$

Where r is grain radius, and in the next chapter, Chapter 5, we described the permeability determination.

4.6 References

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3D Permeability Determination

The Permeability from pore throat size is essential to produce a new petrophysical link between these two properties to provide the freedom for the geoscientist in defining rock types and fluid flow behavior. We called it 3D permeability; as stated earlier in Chapter 4, its determination came from the 3D geometrical analysis. Also, we calculated the final value of permeability using a 3D reconstruction (LEGO™) [1] concept.

5.1 Integrating Geometrical and Analytical Approaches

From the geometrical analysis of pore throat size in Chapter 4, we deduced equation (4.9) for Rhombohedral grain configuration. This equation represents the pore throat area for Rhombohedral configuration, and this area is the minimum Area facing the flow direction. We rewrote equation (4.9) as shown in equation (5.1) below:

$$PorTS_{Rhombohedral} = Area_{min} = 0.109 r^2 \quad (5.1)$$

Where r is the grain radius. Then we defined the flow geometrical determining parameter. We started analytically from Darcy Equation shown in equation (5.2) below:

$$k = \left(\frac{q \cdot l \cdot \mu}{A \cdot \nabla p} \right) \quad (5.2)$$

We factored the equation to most fundamental measures, as shown in equation (5.3), where we substituted “ q ” (Flow Rate) of equation (5.2) with “ A ” (Area), “ l ” (length), and “ t ” (Time). Also, we substituted “ μ ” (Viscosity) and “ p ” (Pressure) with fundamental measures as we did for “ q ,” as shown in equation (5.3) below:

$$k = \left(\frac{q \cdot l \cdot \mu}{A \cdot \nabla p} \right) = \left(\frac{A \cdot l^2 \cdot \mu}{t \cdot A \cdot \nabla p} \right) = \left(\frac{t \cdot A \cdot l^2 \cdot F}{t \cdot A \cdot l^2 \cdot \nabla p} \right) = \left(\frac{t \cdot A^2 \cdot l^2 \cdot F}{t \cdot A \cdot l^2 \cdot F} \right) = A \quad (5.3)$$

or $Permeability (mD) = Area (um)^2$

or $k = A$

In verifying (5.3), we identified (Ezekwe – 2011) [2] in the book chapter “Permeability and Relative Permeability” that permeability delivers a proportional relation to the area. Then by equating equations (5.1) and (5.3), we deduced the generalization of permeability determination in an equation that links permeability to grain size with Rhombohedral configuration, as shown in equation (5.4) below:

$$k_{20190mar} = 0.109 r^2 \quad (5.4)$$

Where: r is the grain radius.

5.2 Validation of the Permeability Equation

Then we validated equation (5.4) with experiments done (Bread and Wely – 1973) [3] on different sizes of grain which recorded the permeability for these different gain sizes

with poor sorting of grains (Rhombohedral), as shown in Table 5.1. We calculated the permeability using Equation (5.4) and tabulated the results for validation, as shown in Table 5.1 below.

Table 5. 1. Permeability determination based on geometrical analysis ($k_{2019Omar}$) compared to experimental data (Bread and Wely - 1973).

Grain Diameter (um)	Grain Radius (um) (Note: we deduced Grain Radius from Grain Diameter), where [Grain Radius = 0.5 Grain Diameter]	Permeability (mD) based on (Bread and Wely - 1973) various Grain sizes Experiments	Permeability (mD) $k_{2019Omar}$ (this research) based on Geometrical and Analytical Approaches
62	31	100	104.79
83	41.5	210	186.00
125	62.5	420	421.88
177	88.5	830	845.88
250	125	1700	1687.50
350	175	3300	3307.50
500	250	6600	6750.00

5.3 Permeability Determination for Heterogeneous Carbonate

In the previous section, we established an essential relation between permeability and grain size, as described in equation (5.4), and we called this permeability $k_{2019Omar}$ to use it further in our research. We call it essential because this equation acts as one of

the cornerstones of the Heterogeneous Carbonate Permeability (k_{HeC}). Another critical cornerstone in determining k_{HeC} is the Differentiating Heterogeneity Zones (DHZ) concept, where Machine Learning Image Processing plays a role in deciding DHZ. MRI Image Intensity (MRIII) plays a vital role in $k_{20190mar}$. Other cornerstones, described in Chapter 4, are; MorSE, Morphological Similarity Enveloping, and DuphE; Dual Physics Enclosure. Together, all these models build what we have submitted a patent invention disclosure for, the Permeability Imaging Logging Tool (PERIL). We displayed the interconnectivity between the cornerstones in Figure 5.1.

Figure 5. 1. Permeability Imaging Logging Tool (PERIL) measurement physics flowchart.

For achieving the road map shown in Figure 5.1, we detailed the validation of porosity determination in Chapter 4, $k_{20190mar}$ in Chapters 4 and 5. CMV, DuphE, and MorSE in Chapter 4, and DHZ is in Chapter 5 that we will describe in the next section.

5.4 Differentiating Heterogeneity Zones (DHZ)

As we have stated earlier, μ CT plays a valuable role in DHZ. We acquired very high-resolution images, 28 μ m, and we can even go lower than that $\sim$ 4 μ m, which is suitable for more detailed CMV. We recoded $\sim$ 400 μ m MRI image resolution for DHZ in case μ CT images are not available. We have also put porosity as another replacement for μ CT; because, for the actual porosity value, honoring the right DuphE is vital; otherwise, there will be no porosity value reconstruction. To further explain this point, when we have a grain size, we can calculate the Pore Volume ($\forall\phi$), which we identified within a CMV for a DuphE. We also found the porosity from the ratio of $\forall\phi$ to CMV. Now, if we have identified other types of PorThN within DuphE (i.e., Connected Vugs), then the porosity value will not reconstruct for that MRIII type. So, based on the non-reconstruction of porosity, we can infer the difference in porosity as the value of the second PorThN. Porosity plays multiple roles in Digital Rock Typing, which is easier to determine among other petrophysical properties.

We highlighted that machine learning image processing played an essential role in delivering CMV. Image processing played an indispensable role in providing DuphE. Therefore, we analyzed MRIII using two methods; image processing and Machine Learning Image Processing (MLIP).

In Figure 5.2, the original μ CT image acquired for our carbonate core plug with 28 μ m resolution, as shown in (a). Then we needed to identify DHZ within this core plug. We used the same MLIP process we described in Chapter 2. Figure 5.2 (b) shows the training of MLIP with four critical features or four DHZs that are needed to determine permeability. We displayed the classification results of MLIP for these DHZs in Figure 5.2 (c):

- 1- Pyrite (red color).

- 2- Open-Vugs (Green color).
- 3- Intergranular-1 (Pink color).
- 4- Intergranular-2-Bioclast (Yellow color).

Figure 5. 2. (a) Original μ CT image, (b) Train MLIP with Four Features, (c) MLIP.

We separated each DHZ volumetrically and geometrically as a discrete block. The four DHZ are in Figure 5.3 for Pyrite, Figure 5.4 for Open Vugs, Figure 5.5 for Intergranular-1, and Figure 5.6 for Intergranular-2 Bioclast.

Figure 5. 3. DHZ of Pyrite is separated, as shown in White color shade.

Figure 5. 4. DHZ of Open Vugs is separated, as shown in White color shade.

Figure 5. 5. DHZ of Intergranular-1 is separated, as shown in White color shade.

Figure 5. 6. DHZ of Intergranular-2 is separated, as shown in White color shade.

5.4.1 Cementation Controllable DHZ

Another use of Porosity in this research is detecting and quantifying the rock cementation effect. Cementation (O. Serra) [4] forms around the grain when porous media is active (water is flowing). As cementation forms around the grain, it impacts porosity marginally; however, it affects the pore throat drastically. It is important to note that we discuss the impact of the early stage of cementation formation. Therefore, here we can infer a new utilization for Porosity in determining permeability. Cementation requires NMR Porosity (total porosity) or another measurement physics for porosity like (Density – Neutron) in the logging domain or gas porosity in the core domain. The difference between MRI and NMR's porosity values defines the cementation effect and then determines DHZ.

5.4.2 Vugs and Fractures Controllable DHZ

In the earlier section, we defined DHZ with a different type of morphology (i.e., non-connected vugs, connected vugs. Even fractures (Al-Farisi – 2006) [5] can be part of the DHZ definition. MRIII recognized the more vigorous intensity in the vugs and fractures due to a higher fluid volume. The non-connected-vugs are not invadable by mud filtrate (Al-Farisi – 2011) [6]; therefore, the Resistivity of Invaded Zone (R_{xo}) can differentiate. Thus, for WBM (Water-Based Mud), we invented a new characterization concept for the non-connected vugs in this research. In the logging domain, because the high salinity water cannot penetrate the non-connected-vugs, MRIII does not suffer intensity diming. MRIII recognizes the invasion of mud filtrate effects on the connected vugs and the fractured zones with lower intensity. In the future, we consider researching different zones (i.e., water zone or oil zone) for characterization cataloging of varying fluid types.

5.5 Controllable Measurable Volume (CMV)

We can assign a permeability value $k_{2019O_{mar}}$ for each CMV, as stated earlier. Therefore, it is vital to model MRIII to provide grain size. Moreover, from grain size, we can determine $k_{2019O_{mar}}$ for each CMV. MRI can sense the fluid (containing Hydrogen) rather than anything else. To identify the effect of grain size on MRI, we used glass beads with different grain sizes and with poor sorting. Then we measured the MRIII histogram for each grain size, as shown in Figure 5.7.

Figure 5. 7. MRIII Histogram for six different sizes of glass beads.

Now we have the intensity value linked to grain size. We display findings in Table 5.2.

We built the MRIII Grain Size Model (MGSM), as shown in Figure 5.8. and 5.9.

Table 5. 2. The finding of corresponding MRIII and Gran Size

Grain Diameter (um)	MRIII Intensity, the Mode model for Grain Diameter
1150	196
630	186
260	171
125	161
20	132
5	110

Figure 5. 8. MRIII Grin Size Model (MGSM)

Figure 5. 9. MRIII Grin Size Model (MGSM) in logarithmic scale

To validate the permeability determination using MRIII morphology with pore throat size, we recoded MRI for carbonate rock and analyzed the intensity value. Then we used the data generated and displayed in Chapter 3 and reproduced in Figure 5. 10 to predict permeability and compare results with experimental measurement. The experimental permeability measurement gave 126 mD, and MRIII gave 129.07 mD.

Figure 5. 10. Validation of MRI permeability based on grain size impact on MRIII.

5.6 MRI Permeability

We can measure permeability using MRI; as seen in the previous section, the MRIII can deliver Grain Size through the MGSM model. We have also developed earlier in Chapter 4 a model for determining permeability ($k_{20190mar}$) from Grain Size. We have also demonstrated the ability of MLIP to deliver DHZ from μ CT.

5.6.1 Morphological Similarity Enveloping MorSE

Performing the analysis in 2D is not good enough as per the literature discussed in Chapter 1; this is because 2D does not capture the full plug heterogeneity. Therefore, we introduced MorSE, where each texture can be identified and separated. As we explained MorSE in Chapter 4, the permeability value for each CMV is different from the other CMV while the models for permeability are the same; MGSM and $k_{20190mar}$. The role of MLIP is needed again in delivering the DHZ in 3D rather than in 2D. In Figure 5.11, we have several DHZ; each color is different CMV, which shows how our core plug heterogeneity is unidentifiable if only one 2D is analyzed. For this purpose, again, we called it 3D Permeability determination. Figure 5.12 separated one of the morphologies, pyrite, and we displayed three snapshots from that morphology. The pyrite Morphology in Figure 5.10 is the yellow color patches for the entire plug.

Figure 5. 11. Core Plug MorSE view; the left image is a longitudinal view; the right image is a cross-sectional view, and the images in between are +18° rotation.

Figure 5. 12. Core Plug 3D view of one of the morphologies (pyrite) separated.

5.6.2 3D Flow Upscale Basis (3DFUB)

We linked the two physic, μ CT and MRI, using DuphE. Let us keep in mind that this step is not always necessary shall μ CT images be unavailable because MRI can still perform this task with the different MRIII. Also, we mentioned earlier that porosity is a suitable replacement for μ CT. So, to reach the final stage of permeability determination or delivering k_{HeC} (also called 3D permeability). To achieve this, we need to imagine our 3D rock with different permeability representations at each part of the rock, as shown in Figure 5.11. We performed the aggregation of permeability by using two models of permeability (Ezekwe – 2010) [7], also shown in Equations (5.5) and (5.6), which we called the parallel permeability and the series permeability:

$$k_{avg_Series} = \frac{l_1 + l_2}{\left(\frac{l_1}{k_1}\right) + \left(\frac{l_2}{k_2}\right)} \quad (5.5)$$

$$k_{avg_Paralel} = \frac{h_1 k_1 + h_2 K_2}{h_1 + h_2} \quad (5.6)$$

To demonstrate the concepts of parallel and series Permeability, Figure 5.13 shows both permeabilities in 3D visualization.

Figure 5. 13. The visualization of 3D permeability with series and parallel schemes.

We combined them to produce one calculation flow, the general 3D permeability equation of heterogeneous carbonate rock, which we call k_{HeC} . So, we calculated k_{HeC} as per the following flow behavior, also shown in Figure 5.14:

- 1- We first used the DHZ identification.

Figure 5. 14. 3D Permeability Modeling

- 2- We used the Control Volume (CV) of DHZ based on the continuity of the DHZ feature in parallel and series directions. Best practice, as per fluid dynamics wisdom, is by gridding the CV based on the location and direction of the flow (Farraj – 2017) [8]; visually, we kept the flow direction “arrows” perpendicular to the CV boundary.
- 3- We calculated in Series for each section, then in Parallel (or vice versa), as shown in Figure 5.15, to reflect the best practice mentioned in point 2 above.

Figure 5. 15. 3D Permeability Determination Control Volumes.

For patenting purposes, we put the 3D Permeability, Chapter 5, with the Pore Throat Network, Chapter 4, and the Capillary Pressure Determination, Chapter 6 patenting for joint ownership (ADNOC and Khalifa University) has been submitted under the title “ Permeability Imaging Logging Tool” in Apr 2019. Then we made a 3D printed reference to validate the equations, as shown in Figure 5. 16.

Figure 5. 16. Permeability determination validation of Analytical Equations with 3D designed, printed, measured, and predicted morphology.

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Capillary Pressure Curve Determination from Permeability

Once we determine permeability, then the next is P_c . Several methods have been developed in the past to determine the P_c curve. One of the early ones is the J-function developed by (Leverett - 1941) [1]. This function continued to be the primary function for P_c curve determination, although it was for Clastics rather than Carbonate. The limitation of J-function comes from the assumption of having a bundle of capillary tubes (Al-Farisi – 2013) [2]. [2] introduces a link between permeability and P_c *in the same paper*, called the C-Function. The association with permeability is at two points in the P_c curve. These two points are Transition Zone Top (TZT) and Transition Zone Plateau (TZP). This relation is repeatable in more than one carbonate reservoir. In addition to these two points, we built the shapes of the P_c curves for single PorThN, dual PorThN, and triple PorThN. There was one limitation in this methodology; the geoscientist needs to define a catalog of P_c curves for each permeability value of the single PorThN and generate correlation curves. But these correlation curves are not readily available. The two parts of the P_c curves get a 45-degree splitting line on the P_c, S_w cross plot to derive the equation using a power function. Therefore, the P_c estimation between the known points is a good workaround in delivering acceptable results. It is crucial keeping in

mind that if the P_c curve determination is correct, then every other step before that is right. So, the P_c curve is the most important validation.

6.1 Novel P_c Curve determination; the P-Function

This workaround requires hectic mathematical manipulation to deliver a P_c curve representing a rock type. Here, we added two more points to the P_c equation that replaces the Carbonate Function (C-Function) as per (Al-Farisi – 2013) [2]. We call the P-Function the new function, where P stands for P_c and Permeability. The link between permeability and P_c in the P-Function is not empirical but analytical.

We start with the P_c curve as “developed by Plateau and applied to porous media by Leverett” (Tiab & Donaldson – 2012), as shown in equation (6.1) below:

$$P_c = \frac{2 \sigma \cos \theta}{r} \quad (6.1)$$

Where; r is the pore throat radius,

σ is Interfacial Tension (water_oil),

θ is the Contact Angle (water_oil).

This chapter will link P_c with permeability to generate a new equation that utilizes our new permeability equation $k_{20190mar}$. To achieve this, we need to convert the r in the $k_{20190mar}$ equation from Grain Radius r_g that the $k_{20190mar}$ considers in equation (5.4) to Pore Throat Radius r_{PorTh} , as shown below, starting from equation (5.4), we replaced 0.109 with an equivalence value $(\frac{\pi}{28.8219})$ and replaced r with r_g :

$$k_{2019Omar} = \left(\frac{\pi}{28.8219} \right) r_g^2 \quad (6.2)$$

Now we can equate the right side of equation (6.2) with the equivalent area that is represented by the pore throat area, which is precisely what equations (5.4) and (6.2) mean, leading to the following:

$$\pi r_{PorTh}^2 = \left(\frac{\pi}{28.8219} \right) r_g^2 \quad (6.3)$$

Now we simplify equation (6.3) to solve for r_{PorTh} to get the following:

$$r_{PorTh} = 0.1862681 r_g \quad (6.4)$$

Also,

$$r_{PorTh}^2 = \frac{1}{28.8219} r_g^2 \quad (6.5)$$

Then by substituting equation (6.5) in equation (5.4) or (6.2), we get the following:

$$k_{2019Omar} = (0.109). (28.8219) r_{PorTh}^2 = 3.14159 r_{PorTh}^2 \quad (6.6)$$

We can now substitute the value 3.14159 in equation (6.6) with $\sim\pi$ to have the following equation:

$$k_{Omar2019PorTh} = \pi r_{PorTh}^2 \quad (6.7)$$

Also, equation (6.7) we write it for r_{PorTh} to be as per the following:

$$r_{PorTh} = \sqrt{k_{Omar2019_{PorTh}}/\pi} \quad (6.8)$$

Then to produce the 1st point in the P_c curve, that is the Displacement Capillary Pressure (P_{cd}), we can now substitute equation (6.8) in equation (6.1) to get the following new equation, the P-Function or the P_c Permeability Function:

$$P_{cd} = 2 \frac{\sigma \cos(\theta)}{\sqrt{\frac{k_{Omar2019_{PorTh}}}{\pi}}} \quad (P\text{-Function or } 6.9)$$

We used equations (6.7), (6.8), and (6.9) to produce Table 6.1 to validate these equations with reference experiments data for permeability and grain size as per (Bred - 1973) [4]. While the parameters (σ , θ) for Mercury (Hg), Air, Oil, and Water were as per (Harrison – 2001) [5]. We can see the P_c reference experiment data match very well with the calculated P_c using the P-Function, for one of the offshore Abu Dhabi fields (t different field from the one we built the model with). We displayed the results in Table 6.1.

6.2 The Dual-End Point P-Function P_c curve construction

As we have validated equations (6.7), (6.8), and (6.9), then the next step is to build another P_c point to be able to produce a power function that represents the P_c curve. That point would be another boundary point. We used the point at the ultimate low water saturation (S_w) ~ 0 but cannot be zero as it will be a singularity point because the

power function limit is 0 on the x -Axis. While we also know that we have another limitation for the power function in the y-axis, which is ∞ . We call this point the Ultimate Capillary Pressure (P_{cu}). Therefore, the points of selection can be in the range of $0.01 < S_w < 0.03$ in the x-Axis, while the pressure range ranges $7000 < P_c < 10000$ Psi. We used this pressure range in our research as this pressure is just above the fracturing pressure. So, a higher-pressure range is still valid for formations with higher fracturing pressure. We used these two points P_{cd} and P_{cu} for finding the power function because any power function requires at least two known points to reconstruct.

Table 6. 1. Validating equations (6.7), (6.8), and (6.9) with reference experiments.

Reference r_Grain (um) Experiment	Derived r_PorTh (um) using r_PorThOmar2019	Reference Experimental Permeability (mD)	K_Omar2019 (mD) using r_Grain	K_Omar2019 (mD)_using r_PorTh	pc_Omar201 9 (psi) for Hg/air	Reference Pc (psi) for Hg/air	sigma	Theta	pc_Omar2019 (psi) Reservoir water/ oil
31	5.77	100.00	103.79	104.75	9.69		30	30	0.807
41.5	7.73	210.00	186.00	187.73	7.24		30	30	0.603
62.5	11.64	420.00	421.88	425.78	4.80		30	30	0.400
88.5	16.48	830.00	845.88	853.72	3.39		30	30	0.283
125	23.28	1700.00	1687.50	1703.13	2.40		30	30	0.200
175	32.60	3300.00	3307.50	3338.13	1.72		30	30	0.143
250	46.57	6600.00	6750.00	6812.51	1.20		30	30	0.100
							30	30	0.261
							30	30	0.370
							30	30	0.413
						5.01	30	30	0.415
							30	30	0.523
							30	30	0.584
							30	30	0.675
							30	30	0.826
							30	30	0.924
							30	30	1.067
						12.52	30	30	1.114
							30	30	1.306
							30	30	1.509
							30	30	1.848
						30.85	30	30	2.426
							30	30	2.613
							30	30	2.921
							30	30	3.695
							30	30	4.770
						87.04	30	30	6.983
							30	30	8.263
							30	30	11.685
							30	30	26.129
							30	30	36.952
							30	30	82.626

Legend	
	Given Refenece Parameter
	Our Research Derived equations and Calculation
	Establishing Catalog data
	Experimental Reference
	Converted to Reservoir Condition Field application

6.3 The Dual-End Point P-Function Further Validation

We did additional validation for P-Function using the two endpoints only; we compared the P-Function results with the C-Function (Al-Farisi – 2013) [2]. The match is evident, as shown in Figure 6.1. For the reference C-Function, we used two rock types referencing C-Function: a high-quality rock type (blue) and a medium quality (orange). The results of the P-Function are (gray color) for high-quality rock and in light orange color for the medium rock quality. Here, we considered the primary-drainage capillary curve. We suggest adding the C-Function points to the P-Function to have a four-point Function for future research.

Figure 6. 1. The novel P-Function (gray and light orange) is validated with literature wisdom C-Function (blue and orange), respectively.

6.4 References

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Digital Rock Typing

In previous Chapters, we detailed determining the most critical properties in performing Reservoir Characterization. While in this chapter, we will deliver the wrapping piece of Reservoir Characterization, that is, Rock Typing. We show a novel wrapping aided by the digital world capabilities, combined with Machine Learning and Image Processing, MLIP, to produce a new concept in modern Reservoir Characterization, Digital Rock Typing. After having the power of digital systems demonstrated in previous chapters, emphasizing the importance of prior Chapters methods and algorithms, we realized it is the right time to launch the DRT (Digital Rock Typing) for the first time. This DRT concept is essential for all the subsurface scientific and industrial communities because this concept can deliver more data, higher quality, and faster.

Moreover, DRT cannot be initiated or proposed without the work established in Chapters (1, 2, 3, 4, 5 & 6). Every other geoscience discipline will need appropriate Rock Types to use them and build on top of them further petrophysical properties (static and dynamic). Any work that involves dynamic properties determination remains incomplete without proper rock classification. If no rock typing is in place, it is almost impossible to know to which rock type a specific dynamic property belongs and why it behaves in a certain way. Without rock typing, running flow simulation is practically impossible unless every cell is represented discretely as a different rock type or class.

7.1 The beginning of Rock Typing

In the '50s of the last century (Archie – 1950) [1], he developed his famous rock typing flow diagram that remained the primary rock typing reference for almost half a century as the first scientific reference. In Figure 7.1, we showed the exact original version that Archie built.

Figure 7. 1. Type of Rock (reproduction from Archie -1950) [1]

After exactly 59 years from this first Rock Typing, a new Rock Typing concept was built by (Al-Farisi – 2009) [2], which we will discuss in the next section. We detailed our novel Digital Rock Typing DRT Flow Diagram in this Chapter; porosity (in Archie's rock typing) does not easily fit with carbonate. We have also discussed in Chapter 3 porosity aids permeability determination and even rock typing but not as the main driver in carbonate. In other words, it is one of the sub-features (or properties) that support the main property of interest in Carbonate, which is Permeability. Therefore, we subsequently describe the efforts after Archie to develop the Carbonate Rock Typing.

7.2 The Carbonate Rock Typing After Archie

7.2.1 The Dunham Carbonate Rock Typing - 1961

After 11 years of Archie's Rock Typing (Dunham – 1961) [3], depositional texture-based rock typing emerged. This work identifies the percentage ranges of grain size in the rock to define its type. The classes are:

- 1- Mudstone
- 2- Wackestone
- 3- Packstone
- 4- Grainstone
- 5- Bondstone

These classes are in Figure 7.2, showing the original classification reproduced from (Dunham – 1961) [3].

DEPOSITIONAL TEXTURE RECOGNIZABLE					DEPOSITIONAL TEXTURE NOT RECOGNIZABLE
Original Components Not Bound Together During Deposition				Original components were bound together during deposition... as shown by intergrown skeletal matter, lamination contrary to gravity, or sediment-floored cavities that are roofed over by organic or questionably organic matter and are too large to be interstices.	<u>Crystalline Carbonate</u> (Subdivide according to classifications designed to bear on physical texture or diagenesis.)
Contains mud (particles of clay and fine silt size)		Lacks mud and is grain-supported			
Mud-supported			Grain-supported		
Less than 10 percent grains	More than 10 percent grains				
<u>Mudstone</u>	<u>Wackestone</u>				

Figure 7. 2. Deposition Based Carbonate Rock Classification (reproduction from Dunham – 1961) [3].

Diagenesis has not been in the description nor the classification; however, the word Diagenesis appears in Figure 7.2 as the last word, leading to the need for further research in Diagenesis. As described in the next section, the lack of Diagenesis consideration in Dunham's work opened the door for further study.

7.2.2 The Lucia Carbonate Rock Typing – 1995

After 45 years of Archie's Rock Typing (Lucia – 1995) [4], we consider Lucia the father of Carbonate Rock Typing. In this work, Lucia refers to his earlier work in 1983, which included diagenesis. The main driver for rock typing was the interparticle porosity relationship to Permeability, Figure 7.3, which is a reproduction from the original (Lucia – 1995) [4] paper. This interparticle porosity has one major drawback. Figure 7.3 shows that porosity cannot describe permeability in carbonate rather than the pore throat size. Lucia (Lucia – 1995) [4] has mentioned in the paper that he used a similar concept to (Archie -1950) [1].

Figure 7. 3. Rock Typing based on Interparticle Porosity (reproduction from Lucia – 1995) [4].

Lucia introduced the effect of Diagenesis, where he described vug types. However, the direct link to permeability was to interparticle porosity only, causing rock typing hard to perform for honoring dynamic reservoir properties in most carbonate cases. Besides, Lucia (Lucia – 1995) [4] has introduced the link between P_c and rock types of the

unimodal and bimodal pore system. However, the distinction between the two P_c curves that honor unimodal and bimodal did not show where the main change happened. This lack of clear differentiation is due to displaying two changes simultaneously. These two changes are;

- 1- Pore throat size for the two different rocks has two distinctive peaks.
- 2- One plug is unimodal, and the other plug is bimodal.

Lucia's work has two interlinked difficulties. One is due to using porosity instead of the pore throat size. The second is that the P_c curve of Lucia represents more than one rock type. Two simultaneous unsolved points make it hard to perform rock typing in carbonate beyond 1995. However, this opened the door for further research in 2009 by Al-Farisi (Al-Farisi – 2009) [2], to solve one of these unsolved points (the use of pore throat size rather than porosity). Later, Al-Farisi (Al-Farisi – 2013) [5] solved the second by making one change at the time, rather than two changes, which we explain further in this Chapter.

7.2.3 The Al-Farisi Carbonate Rock Typing - 2009

After 59 years of Archie's Rock Typing (Al-Farisi – 2009) [2], the research continued to solve the difficulty in Lucia. Al-Farisi introduced a new concept in work typing to solve the considerable overlap between classes and the overlap in petrophysical properties with Conjunction of Rock Petrophysical Properties in Carbonate, "CROPC," as the bases of carbonate classification, as shown in Figure 7.4, which is a reproduction from (Al-Farisi – 2009) [2] paper.

Figure 7. 4. Carbonate Rock Typing based on Petrophysical Properties Conjunction
(reproduction from Al-Farisi – 2009) [2].

In CROPC, the rock type definition is four words; rock type is rocks with similar properties. This Conjunction of properties prevented the significant overlap of Lucia from producing segregated properties with minimal overlap. Figure 7.5 shows the CROPC summary flow diagram reproduced from (Al-Farisi – 2013) [5].

Figure 7. 5. Rock Typing Conjunction of Properties “CROPC” (reproduction from Al-Farisi – 2013) [5].

CROPC offered a great advantage as a static properties classifier for dynamic flow simulation, especially for no permeability overlap between different rocks. However, rock classification links to unimodal and bimodal were not part of the CROPC scope, making it hard for the geologist to interpolate data between wells in the geological Model. Therefore, further research is needed to resolve this difficulty, which we will explain in the next section.

7.2.4 The Al-Farisi Carbonate Rock Typing - 2013

After 63 years of Archie’s Rock Typing (Al-Farisi – 2013) [5], Al-Farisi worked to resolve for including the unimodal and bimodal in the Classification. In Table 7.1, the pore models classification comes first based on Singular (unimodal), Dual (bimodal), and Triple (trimodal) pore systems. Then the second round established the link between permeability and P_c using two points in the P_c curve, as described earlier in Chapter 5.

While Table 7.2, which is a reproduction from (Al-Farisi – 2013) [5] paper, shows the results of the rock typing catalog, where the range of P_c , Permeability, and S_{wi} were defined.

Table 7. 1. Rock typing method on Uni-Bi-Tri “RocMat” pore system and the “CROPC” (reproduction from Al-Farisi – 2013) [5].

	Micro	Meso	Macro	%	%	%
Triple	O	O	O	20-50-30	20-30-50	
Dual	O		O	25-75	50-50	75-25
Dual	O	O		25-75	50-50	75-25
Dual		O	O	25-75	50-50	75-25
Singular	O			100		
Singular		O			100	
Singular			O			100

Table 7. 2. Carbonate Rock Typing Catalogue based on “RocMat” (reproduction from Al-Farisi – 2013) [5].

Lim Rock	New RT L # # # Lim Perm Pc Swi	Perm Range	PC shape	Swi
1	L111	>60	note2&3 (<400,<100psi)	note 4 &5 (7-13%)
2	L121	>60	note2&3 (>400, <100psi)	note 4 &5 (7-13%)
3	L231	7<K<60	Note 6 & 7 (<700, >80psi)	Note 8&9 (7-13%)
4	L241	7<K<60	Note 6 & 7 (>700,<30psi)	Note 8&9 (7-13%)
5	L242	7<K<60	Note 6 & 7 (>700,<30psi)	Note 8&9 (14-20%)
6	L351	1<K<7	Note 10&11 (<1100,<100psi)	Note 12&13 (7-13%)
7	L352	1<K<7	Note 10&11 (<1100,<100psi)	Note 12&13 (14-20%)
8	L361	1<K<7	Note 10&11 (<1400, >250psi)	Note 12&13 (7-13%)
9	L372	1<K<7	Note 10&11 (>1400, >100psi)	Note 12&13 (14-20%)
10	L373	1<K<7	Note 10&11 (>1400, >100psi)	Note 12&13 (21-27%)
11	L374	1<K<7	Note 10&11 (>1400, >100psi)	Note 12&13 (28-34%)
12	L382	1<K<7	Note 10&11 (>1400, >100psi)	Note 12&13 (14-20%)
13	L461	0.1<K<1	{P(<1000, <400)}	P (7-13%)
14	L492	0.1<K<1	{Q(<1200, <600)}	Q (14-20%)
20	LD5	<0.1		

While in Figure 7.6, we can see how the different pore systems (Single, Dual, Triple) links Permeability to porosity, this Figure is a reproduction from (Al-Farisi – 2009 & 2013) [2] [5].

Figure 7. 6. The pore system links permeability and porosity (reproduction from Al-Farisi – 2013) [5].

With all these advances in solving last century rock typing challenges, as demonstrated in (Al-Farisi – 2009 & 2013) [2] [5], what was still missing is machine learning utilization. Previous chapters showed Machine Learning algorithms' ability to recognize the rock and classify the different zones within the rock to define the Singular, Dual, and Triple pore systems. Then we reconstruct the rock to produce the petrophysical property of interest, Permeability, and then P_c . The research results we reported in Chapters 1 to 5 show the modern age framework for Digital Rock Typing (DRT).

7.2.5 Digital Rock Typing (DRT) - 2019

After 69 years of Archie's Rock Typing, we introduced Digital Rock Typing (DRT).

We explained the DRT path in Chapters 1, 2, 3, 4, 5 & 6. Where Figure 7.7 shows the final DRT algorithm for rock typing. With the digital aid, we provided a framework to scale up the identification of each rock CMV to produce its properties and deliver the rock type classification. We labeled rock morphology features (i.e., The Rhombohedral Configuration, Intragranular Vugs Connectivity, and Cementation).

DRT produces, for the first time, a Machine Learning Image Processing aided Pore Throat Network Segmentation based Rock Types. Then, we created the digital rock type identifier chart, Figure 7.8, the Carbonate Morphology (CAMO) chart. This chart ensured porosity-permeability-morphology relation classifying the connected, non-connected, and micropore morphology.

Figure 7. 7. Digital Rock Typing DRT path.

Figure 7. 8. CAMO Chart is an upgrade for the Permeability (mD) - Porosity (fraction) chart of [5] with these research findings.

The DRT flow diagram that we introduced in Figure 7.7 works for both log and core domains. This relation was the drive to patent the Permeability logging tool. DRT contribution, on top of the previous wisdom, is that the machine classifies the rock properties of and determine the rock type, as summarized below:

- 1- The porosity determination is achievable by the machine with two methods:
 - a. Image analysis that uses the IROGA algorithm.
 - b. Machine learning that uses the MLDGRF algorithm.
- 2- The permeability determination is achievable by the machine in two steps:
 - a. Calibrate PorTS with image intensity.

- b. Machine learning uses the MLDGRF algorithm to classify Singular, Dual, and Triple pore systems.
- 3- The P_c determination is achievable by the machine in two steps:
 - a. The machine calculates P_{cd} from permeability.
 - b. The machine used P_{cd} and P_{cu} points to calculate the P_c curve in a power function.
- 4- The machine uses our research-built Carbonate Morphology (CAMO) chart, shown in Figure 7.8, to determine the rock type.

DRT is a digital door opener for determining electrical properties, relative permeabilities, wettability ranges, and alteration effects.

7.3 References

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CHAPTER 8

Conclusions and Future Work Recommendations

In this chapter, we conclude the main results and findings, and then we end this chapter with recommendations for future research work.

8.1 Conclusions

The principal aim of this research was to deliver a pioneering framework for what we called Digital Rock Typing for the first time worldwide. Throughout this effort, we concluded some critical points that induce a change in the oil industry upstream sector, these are:

- 1- Machine learning can assist in identifying rock features from images (MRI and μ CT).
- 2- Image processing can also perform the same role as machine learning in identifying rock features; however, the accuracy, efficiency, and quality are higher when using machine learning-aided image processing.
- 3- A human domain expert (i.e., Petrophysicist and Geologist) is required to identify the essential features in rock images before machine learning image processing. However, automated feature extraction can also aid the geoscientists before performing the supervised prediction. The role of a Petrophysicist in machine learning image processing will be to label the good

places in the image. However, the Petrophysicist role is not limited to labeling in reservoir characterization research, but to ensure delivering and linking the proper geometry and the right property for the CMV.

- 4- Grain size plays a vital role in flow dynamics — the larger the grain, the better the rock quality.
- 5- Grain size alone is insufficient to determine carbonate's petrophysical properties and rock types. Diagenesis induced intraparticle porosity (e.g., connected and non-connected vugs) influences $PorThN$, permeability, P_c , and relative permeability. Even wettability can be affected by diagenesis when dolomitization happens or crystallization.
- 6- Porosity cannot play a primary role in carbonate rock typing.
- 7- Permeability and porosity are proportionally undirectly linked, based on pore throat network $PorThN$.
- 8- Pore throat size directly links two main parameters; grain size and grain sorting.
- 9- Pore throat size plays the center role in identifying permeability value. In this research, we established two new relations:
 - a. Permeability and throat size.
 - b. Permeability and grain size.
- 10- Grain size determines permeability in homogenous rock, but this is not true for heterogeneous rock types.
- 11- Permeability identifies three points in the P_c curve.
- 12- A Power function and two P_c endpoints can generate the P_c curve.
- 13- MRI is the primary tool for grain size determination, while μCT is the primary tool to identify the geometry of CMV.

- 14- The coupling between MRI and μ CT is vital for permeability determination. However, MRI can alone determine permeability if we can enhance the MRI resolution.
- 15- The two new concepts introduced in this research are Pore Throat Network (PorThN) and Digital Rock Typing (DRT) frameworks.
- 16- Digital Rock Typing reflects the modern rock typing trend that harnesses artificial intelligence as a natural growth to the changes happening in the digital world. DRT is inevitable. Therefore, we took the initiative to build the first complete framework. Starting from Porosity, then to Pore Throat Size, then to rock Texture feature identification, then to Permeability, then to Capillary Pressure, then to CAMO chart to produce digital rock typing.

8.2 Recommendations for Future Work

In this research, we concluded a DRT framework to open new doors for further study, and we recommend the following future research work:

- 1- Relative Permeability is also a viable research topic for DRT, which we touched base on in this research. We have developed the governing equation, as shown in Figure 8.1.
- 2- Wettability can be another target that we did not detail in this research; however, we have submitted three patents related to visualizing a water droplet inside crude oil for the first time, as shown in Figure 8.2. Also, we measured the contact angle at the absorption condition for the first time.
- 3- Higher-resolution machinery like MRI will deliver much more insight into the fluid distribution and flow behavior extraction.

- 4- Calibrating MRI images with different fluid types and rock textures helps build a calibrating catalog.
- 5- Enhancing image processing automation with more image templates (labeled features) drives efficiency further.

Figure 8. 1. Our new Relative Permeability Equations and MRI images of flooding experiment.

Figure 8. 2. Illumination of a water droplet on carbonate rock in dark fluid (crude oil) for measuring wettability contact angle – Patentability Review is positive.

List of initiated Publication & Patent during Ph.D. Study

Patents IP Filing:

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Abbreviations

k_{HeC}	Heterogeneous Carbonate Permeability.
PorThN	Pore Throat Network.
MRII	MRI Image Intensity.
CMV	Controllable Measurable Volume.
DuphE	Dual Physics Enclosure.
MorSE	Morphological Similarity Enveloping.
DHZ	Differentiating Heterogeneity Zones.
MLIP	Machine Learning Image Processing.
MRI	Magnetic Resonance Imaging.
μ CT	Micro Computed (x-ray) Tomography.
3DMM	3D Micro Model.
DRT	Digital Rock Typing.
MLIP	Machine Learning Image Processing.
IROGA	Image Resolution Enhancement Optimized Gaussian Algorithm.
IRE	Image Resolution Enhancement.
3DFUB	3D Flow Upscale Basis.
PorTh	Pore Throat.
P_{cd}	Displacement Pressure.
P_{cu}	Ultimate Capillary Pressure.
r_{PorTh}	Radius of Pore Throat.
r_g	Radius of Grain.