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AI DRIVEN IMAGE BASED DIGITAL TWIN ROCK PROPERTIES- FAST, CONSISTENT, AND COST EFFECTIVE

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ABSTRACT

Rock properties derived from core analysis have been used as references for formation evaluation and integrated reservoir studies for decades. Some of the challenges in obtaining core data are that it is time consuming to perform measurements, results may not be consistent from one laboratory to another, and it can be costly to acquire cores and if many analyses are required. The main objective of this study is to test a new innovative method of extracting probability-based analog rock properties, the digital twin (DT), from high-resolution images (HRI) of thin sections (TS) by leveraging the power of artificial intelligence (AI).

The method is based on a proprietary AI technology, Advanced Rock Typing, which includes two components. The first is to create a database, consisting of the measured rock properties of multiple rock types, each of which has been thoroughly quality controlled, and an associated TS HRI. Such a database, which can be comprised of samples from multiple fields and/or formations, forms the foundation of this technology. The second part of the process is to develop an image recognition AI model comprised of the TS HRI and associated rock properties from component one.

Once created and validated, such an AI model can be used, in instances where conventional cores are unavailable, to analyze HRI sourced from alternative formation-representative samples such as oddly shaped rotary sidewall cores or even drill cuttings. In these situations, TS HRI is prepared and compared, through the AI model, to images in the database. If a match is obtained, the rock properties associated with the matched image in the database, which can be thought of as its pore geometry DT, would be retrieved and serve as probability-based analog data for that sample. This unique combination of a conventional core database and image recognition technology is at the core of this analytical process. The above methodology was applied to a database of selected 100 core samples of core analysis data with associated TS HRI, and a customized AI model was developed, tested, and verified with satisfactory results.

In addition, we are pushing the envelope of further developing this technology by extending it to drill cuttings and studying the effect of cutting sizes and rock heterogeneity on the performance of the AI model built using data generated from core plugs. Twenty sets of synthetic cuttings in 5 mm, 4 mm, and 2 mm size fractions, created from core plugs which had previously been used in the creation of the AI model, were prepared. A TS of each cutting size fraction was scanned, and each scan was then submitted to the AI model for analysis and analog matches were identified. Preliminary results demonstrate potential of applying this technology to estimate rock properties as part of advanced mud logging, thus expanding the capabilities of mud logging to estimate rock petrophysical properties from TS HRI analysis in near real-time while drilling.

INTRODUCTION

It would be ideal and desirable if formation rock properties could be obtained in situ at reservoir conditions and reservoir scale (Kuchuck et al., 2010; Li et al., 2014; Zhang et al., 2018 and 2020), but as extensively discussed in the Special Session 08 titled The Future of Core Analysis at the 2022 SPE ATCE in Houston, technical challenges still prevent those developed methods from practical applications. Consequently, until today, rock properties are still routinely derived from laboratory core analysis and used as references or calibrations for formation evaluation and integrated reservoir studies (Ma, et al., 2002 and 2006). In obtaining core data, however, some of the challenges are that it could be expensive to acquire cores, time consuming to perform laboratory measurements, results may not be consistent from one laboratory to another and may not even be representative (Ma and Amabeoku, 2015), and can be costly if many analyses are required. In cases where measured core data are unavailable, analog core data are often used in reservoir characterization projects.

Analogs provide a probabilistic alternative and are a valuable tool for geological and engineering studies. The basic input in any petrophysical analog selection process is the rock type, either derived from drainage capillary pressure measurements (Ma and Morrow, 1993) or more commonly estimated visually from rock samples (conventional cores, sidewall cores or even drill cuttings) under microscope (Ehrlich et al., 1984; Cather et al., 1991; Hume et al., 2018). A comprehensive review on conventional methods of pore structure characterization can be found from Anovtz and Cole (2015).

Visual rock typing has historically been a manual, time consuming, and subjective process based on a limited number of observed parameters (Pattnaik et al., 2020). In sandstones for instance, the visually estimated parameters may include

1. Porosity,
2. Grain size,
3. Sorting,
4. Degree of consolidation,
5. Argillaceous content, and
6. Cements.

Once rock typing for a sample is complete, the estimated rock type parameters are used to find matching parameters in an established database. When a match is found, the associated rock properties represent the digital twin rock properties. The main objective of this study is to test a new, innovative, rapid, and objective artificial intelligence (AI) based method of extracting probability-based analog rock properties, the digital twin, from high-resolution images (HRI) of thin sections (TS).

METHODOLOGY

The method of AI driven image based digital twin rock properties is innovative, and yet straightforward (Britton, 2021; Cox, 2022). As outlined in Fig. 1, it consists of the following steps;

1. **Database**- build a rock property database covering a wide variety of rock types and associated TS HRI.
    a. Collecting data consists of various conventional and special core analysis rock properties, derived from a variety of rock types, combined with representative and standardized TS scanned in transmitted and polarized light at a resolution of 0.44 microns/pixel to produce the HRI.
    b. Clean and quality control the collected data using conventional methods (Ma and Amabeoku, 2015) or data analytics methods (Li et al., 2022).
2. **AI model**- build an AI model with image recognition linking the TS HRI and associated rock properties.
    a. As routinely done in machine learning (Xu et al, 2019), divide the database into two sets; one for model building and testing and another for model validation.
    b. Once the model is established using the model building dataset, the testing data set is used to test the robustness of the model and further any fine tuning. The remaining data would be used to validate the robustness of the built model.
3. **DT** (digital twin) rock properties
    a. Once the AI model is built, it may be used to estimate rock properties in situations where a TS is made and imaged (similar as those used in constructing the database), but rock properties are not measurable or not available, due to reasons such as
        i. Certain rock properties, such as some special core analysis properties, are not measured
        ii. Irregular rock samples, such as mis-shaped sidewall cores
        iii. Limited rock material, such as wells with only drill cuttings.
    b. The newly acquired TS HRIs would be matched by the AI model with TS HRI in the database. Note that pattern recognition probabilistic based image matching and the mathematical criteria used to determine image similarities are at the core of the technology presented in this study and will be detailed later in this paper.
    c. Once a match is found, the associated rock properties would be, by definition, the DT rock properties of the new sample.
    d. On the other hand, if no match is found, it merely indicates that the rock type is not covered in the database; information important for future improvement of the database and then enhancement of the AI model.

It should be noted that since this methodology is image based, pore structure and matrix sensitive rock properties may be estimated, such as

1. Porosity
2. Permeability
3. Mineralogy
4. Archie cementation exponent m, and
5. Drainage capillary pressure.

On the other hand, pore surface roughness (Singer et al., 2022) and degrees of pore surface properties alteration due to changes in wettability (Ma et al, 1996 and 1999) may be difficult to be observed and examined under a normal microscope. The end user should be cautious when using this type of technology to estimate rock pore surface roughness and wettability sensitive properties, unless special images such as surface property sensitive images of environmental scanning electron microscope (Kowalewski et al., 2003) are used in construction of the AI model for potential wettability related studies.

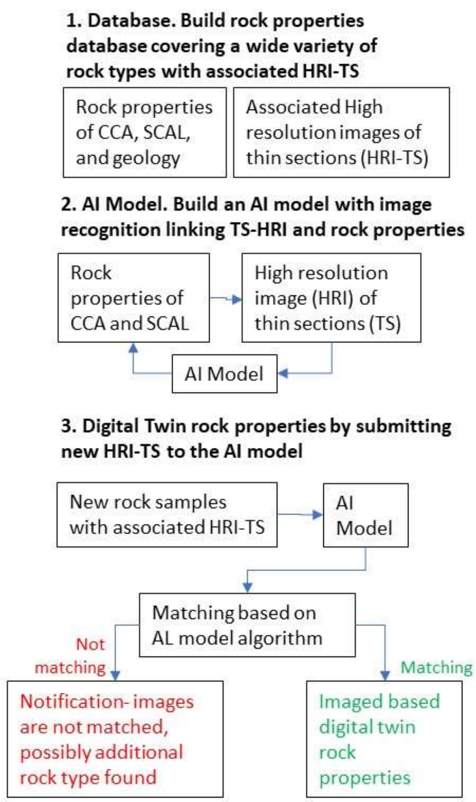

Fig. 1 Workflow of estimating AI driven image based digital twin rock properties

RESULTS AND DISCUSSIONS

The Database

To evaluate the methodology of Fig. 1, a feasibility study was conducted where a database of 100 core samples were selected with rock properties (such as Fig. 2) and associated TS HRI (Fig. 3) of various lithologies of

1. Sandstone
2. Siltstone
3. Limestone
4. Dolostone
5. Mudstone
6. Anhydrite

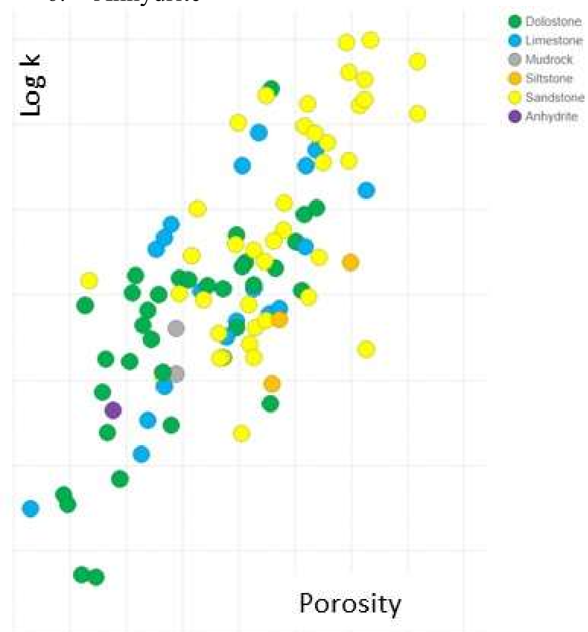

Fig. 2 Example of data used to evaluate the AI driven image-based DT rock properties methodology of Fig. 1.

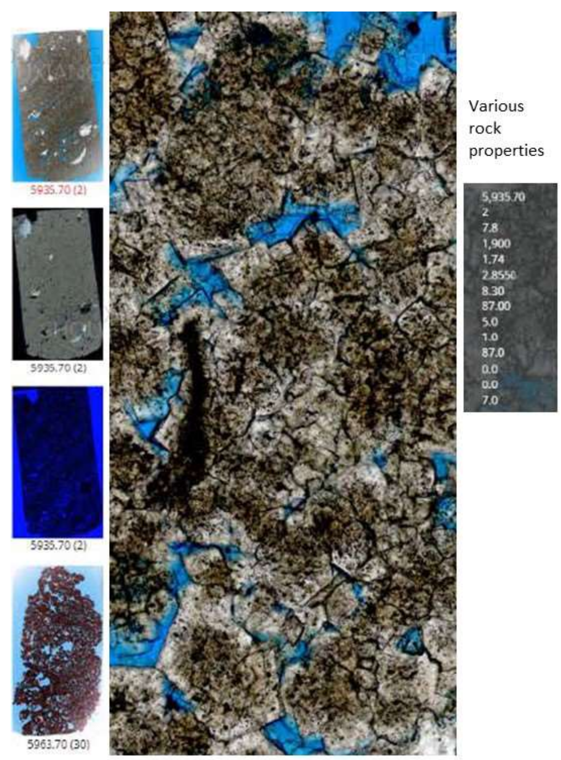

Fig. 3 Example of thin section (TS) high-resolution image (HRI) and associated rock properties.

Probabilistic Based Analog Match

In conventional TS image analysis, rock typing variables that can be characterized may include

1. Grain size,
2. Sorting,
3. Cements,
4. Texture, and
5. Visible porosity

The method presented in this study is AI based using image recognition technologies to evaluate pore geometry heterogeneity inherent in each TS image submitted for analysis and find probabilistic-based analog matches to that range of heterogeneity in the database of rock types. Matching parameters in this probabilistic way is mathematically based and thus there can be much more parameters evaluated as compared to the five variables noted above. Fig. 4 illustrates the matching concept. With modern computing power, this matching process can be completed rapidly in such as seconds.

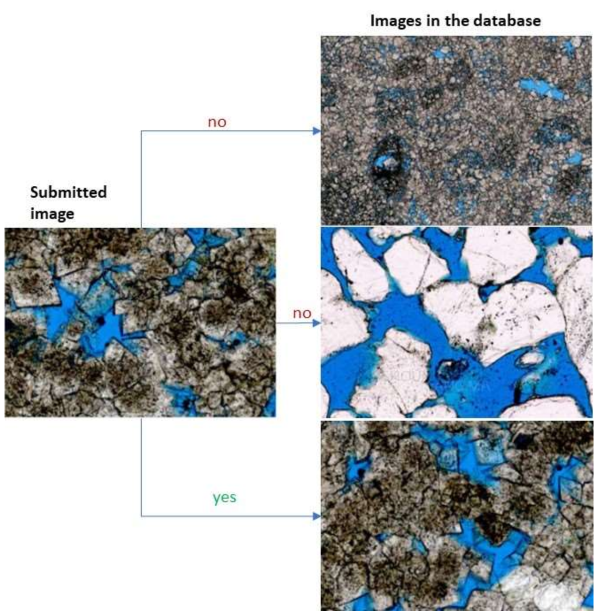

Fig. 4 Illustration of probabilistic match with image recognition.

Factors affecting image matching may include the number of rock types contained in the database used to build the AI model and how well the rock types in the model represent the pore geometry variability of the formation modeled. Having a wide range of core-based rock types in the model allows for a more robust AI interpretation of the formation being evaluated.

Note that in the probabilistic approach to validation, while the image of a child will have similarities with an image of its parent and thus a probabilistic 'match', it may not be an exact match. Likewise, matches based on rock images with varying cements, grain shapes and sizes will never be an exact match, even though their petrophysical attributes are very similar.

Results and DT Rock Properties

Results of this study show that the model was 99% accurate in verifying the training set used to create the model, i.e., 99 out of the 100 model samples matched based on image recognition parameters during model validation, demonstrating the robustness of the built model for practical applications. The one sample that did not match itself found a similar sample with similar properties within the same well (Fig. 5).

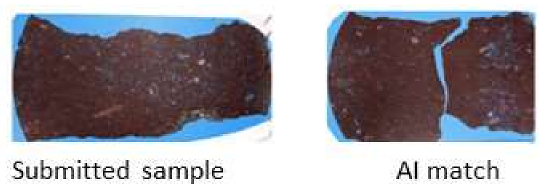

Fig. 5 Example of the one model validation sample that did not match.

Results of the built AI model to predict various digital twin rock properties is illustrated in Fig. 6 for porosity, grain density, permeability, and Archie porosity exponent 'm'. The robustness of its performance will be further tested with a much larger database.

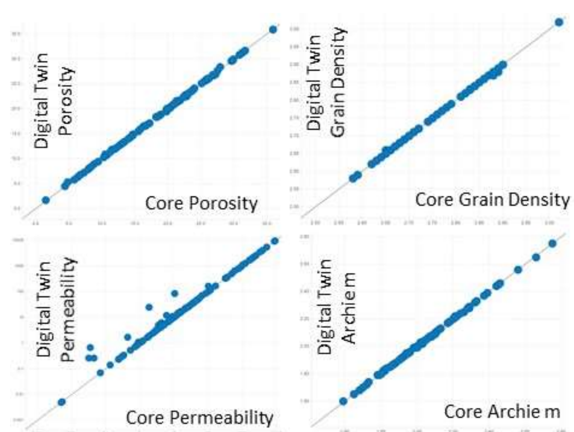

Fig. 6 Results of the predicted digital twin properties (porosity, grain density, permeability, and Archie porosity exponent 'm') vs. measured core data.

EXTENSION TO DRILL CUTTINGS

Cutting Data Sets

With the core plug based DT rock property model tested and established, its application is naturally extended to drill cuttings with the ultimate goal of deriving rock petrophysical properties as part of advanced mud logging (Singer et al., 2021; Kesserwan et al., 2023). To realize that ambitious Archie's dream of Loermans et al. (2005), the effects of sample heterogeneity and cutting size on the performance of the plug-based DT rock property model needed to be evaluated, thus the following feasibility study was conducted;

1. 20 sets of synthetic cuttings were created from conventional core plugs which had previously been used in the creation of the model.
2. A TS of each cutting sample was scanned,
3. Each scan was submitted to the core plug DT rock property model for analysis and analog match determination.

The 20 sets of cuttings were selected to cover a range of geological and petrophysical properties including porosity, permeability, and lithology of:

1. Clastics
    a. Siltstone
    b. Argillaceous sandy siltstone
    c. Sandstone
    d. Argillaceous sandstone
    e. Argillaceous dolomitic sandstone
    f. Organic argillaceous sandstone
2. Carbonates
    a. Limestone
    b. Dolomitic limestone
    c. Dolostone
    d. Calcareous dolostone
    e. Celestine dolostone
    f. Bituminous dolostone

Synthetic cuttings from each selected sample were created by carefully disaggregating each core plug and sieving the resulting size fractions into three size classes of diameters of 5 mm, 4 mm, and down to 2 mm, i.e., a total of 60 samples. A TS of each cutting sample was created and subsequently scanned in transmitted light and polarized light at 0.44 microns/pixel (Fig. 7), same as that of core plug TS HRI..

Fig. 7. An example of thin section (TS) high resolution image (HRI) of synthetic cutting sample.

Child-Parent Matching

Matching results indicate that 60% of the cutting images match their analog parent (Fig. 8), while the remaining 40% match a non-parent analog sample better (Fig. 9). Further examination reveals that the primary reason for the non-matching was due to pore geometry heterogeneity, which is especially prevalent among the carbonate samples analyzed. In some cases, the level of heterogeneity was reduced as the sample size becomes smaller, i.e., macro porosity in the parent TS disappeared in the analyzed cuttings TS. To comprehensively address these effects of sample size and heterogeneity on model performance, a larger data set covering a wide range of geological and petrophysical properties would be required to have better understanding of the issue, statistically.

Fig. 8 Example of a good match between cutting image and its parent plug image.

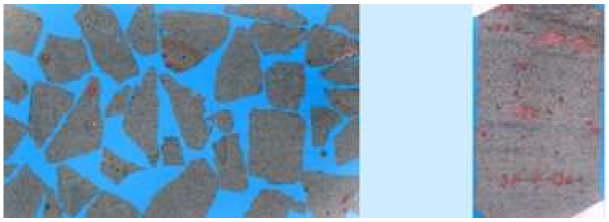

Fig. 9 Example of a mismatch between cutting image and its parent plug image.

Child-Parent Matching Comparison

Identification of rock properties associated with each analog match from the established AI model allows comparison of the measured parent core plug properties with analog properties of child cutting samples, after proper averaging. Fig. 10 shows examples of permeability and porosity comparisons in the clastic samples; in the case where multiple analogs are returned by the AI model, analog cutting permeability and analog cutting porosity values are weight averaged based on each analogs' areal match percentage in the thin section image that was analyzed. Results of carbonate samples are shown in Fig. 11. Visually, it can be seen that the performance of the core plug based AI model in predicting rock properties of rock cuttings is better for clastic samples compared to that of carbonate samples, most likely due to the carbonate samples exhibiting more heterogeneity than clastic samples, as explained above. Fig. 12 is a combination of both clastic (Fig. 10) and carbonate samples (Fig. 11).

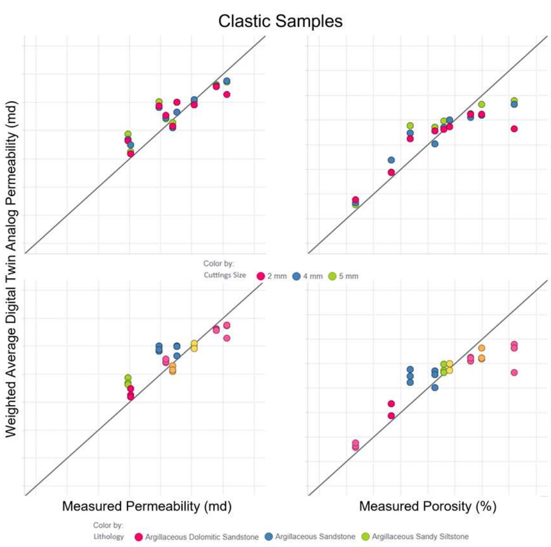

Fig. 10 Comparison between digital twin and measured rock properties, clastic samples.

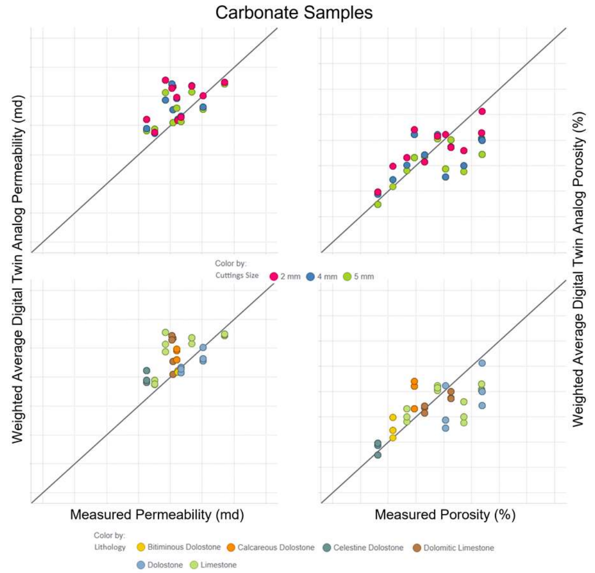

Fig. 11 Comparison between digital twin and measured rock properties, carbonate samples.

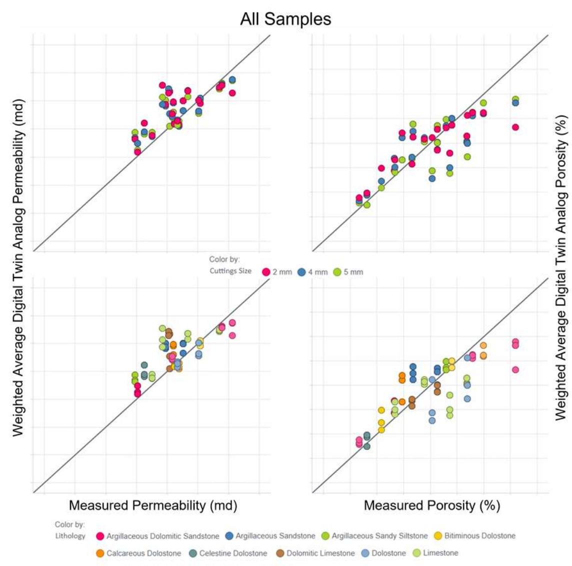

Fig. 12 Comparison between digital twin and measured rock properties, all samples.

From the results of this feasibility study as demonstrated in Figs. 10, 11, and 12, the AI model shows very promising results in predicting well cutting rock properties. This is especially useful for qualitative applications such as use of drill cutting analysis as part of mud logging for geo-steering and well placement, in challenging environments such as that in slimhole underbalanced coil tubing drilling with limited logs available for geo-steering.

SUMMARY AND CONCLUSIONS

A study specific AI driven image based digital twin rock property model was established. This model can be used to estimate rock properties of core samples which have high resolution thin section images, but where rock properties have not been acquired.

The above core plug-based model was extended to drill cuttings, and a feasibility study indicates that the rock cutting properties may be estimated from its higher resolution images for homogeneous rocks.

While scale dependent rock heterogeneity may limit the extension of a core plug-based model to drill cuttings, further research is required to make the AI driven image-based digital twin rock property technology a deliverable for advanced mud logging.

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NOMENCLATURE

AI:	Artificial intelligence
DT:	Digital twin
HRI:	High resolution image
K:	Permeability
TS:	Thin section
ϕ:	Porosity

REFERENCES

L. Anovitz and D. Cole: "Characterization and analysis of porosity and pore structures," Reviews in Mineralogy and Geochemistry, 80(1): 61-164, 2015.

A.W. Britton: "An Artificial Intelligence Approach to Finding Core-Based Petrophysical Analogs," September 16, 2021 – London Petrophysical Society.

M. Cather, N. Morrow, and I. Klich: "Characterization of porosity & pore quality in sedimentary rocks," Studies in Surface Science & Catalysis, v62, 1991, p727-36.

K. Cox: "Advanced Rock Typing—An Artificial Intelligence Approach to Find Petrophysical Analogs," March 23-25, 2022 – Society of Applied Geoscientists & Engineers, Lafayette, Louisiana, USA.

R. Ehrlich, S. Kennedy, S. Crabtree, and R. Cannon: "Petrographic image analysis. I. Analysis of reservoir pore complexes," J Sed Petrol 54(4), Dec 1984, 1365-78.

D. Hume, A. Britton, and D. Brown: "Analysis of High-Resolution Digital Thin Section Images – Applications for Rock-Typing," May 7-8, 2018 – AAPG Middle East GTW, Digital Subsurface Transformation, Dubai, UAE.

H. Kesserwan, G. Jin, & S. Ma: "Integrating Petrophysical & Geochemical Measurements of Drill Cuttings for Enhanced Formation Evaluation," SPE 213,217, MEOS GEO, 19-21 Feb 2023, Bahrain.

E. Kowalewski, T. Boassen, and O. Torsaeter: "Wettability alterations due to aging in crude oil; wettability and cryo-ESEM analysis," J of Pet Sci and Eng, 39(3-4), Sept, 377-88.

F. Kuchuck, L. Zhan, S. Ma, A. Shahri, T. Ramakrishnan, B. Altundas, M. Zeybek, R. Loubens, and N. Chugunov: "Determination of in situ two phase flow properties through downhole fluid movement monitoring," SPE 116068, 2008 ATCE. *SPEREE*, Aug 2010, pp.575-87.

K. Li, M. Shapiro, R. Horne, S. Ma, A. Hajari, & M. Mudhhi: "In situ estimation of relative permeability from resistivity measurements," SPE 129627, 2010 Int'l O&G., Beijing, China. *J of Petr Geoscience,* V20, no1, Feb 2014, pp.143-51.

Y. Li, S. Ma, M. Luo, P. Lu, & C. Ayadiuno: "Quality control for geoscience data using machine learning," patent application PCT/CN2022/139904, 19 Dec 2022.

T. Loermans, M. Kanj, and C. Bradford: "Advanced mud logging: from Archie's dream to reality," SPE 106,324, 14 May 2005.

S. Ma & N. Morrow: "Similarity of pore structure and the selection of core samples for tests of scaling," Proc. 9th Wyoming EOR Symposium, May 12-13, 1993, Casper, Wyoming.

S. Ma, G. Mason, & N. Morrow: "Effect of contact angle on drainage and imbibition in regular polygonal tubes," *Colloids & Surfaces, A: Physicochemical and Engineering Aspect*, v.117, pp.273, 1996.

S. Ma, N. Morrow, X. Zhou, & X. Zhang: "Characterization of wettability from spontaneous imbibition measurements," *JCPT*, v.38, no.13, 1999.

S. Ma, A. Al-Muthana, & R. Dennis: "Use of core data in log lithology calibration: Arab-D reservoir, Abqaiq and Ghawar fields," SPE 77778, SPE ATCE, San Antonio, TX, Oct., 2002.

S. Ma, A. Al-Hajari, D. Kersey, J. Funk, K. Holmes, & G. Potter: "Enhanced petrophysics: integration of core & log data for improved reservoir saturation monitoring," SPE 106350, 2006 SPEKSA Technical Symposium.

S. Ma & M. Amabeoku: "Core analysis with emphasis on carbonate rocks- quality assurance and control for accuracy & representativeness," *Journal of Interpretation*, SEG, Feb 2015, pp.91-106.

Pattnaik, S., Chen, S., Helba, A., and Ma, S: "Automatic carbonate rock facies identification with deep learning," SPE 201673, SPE ATCE, 27-29 Oct 2020.

G. Singer, M. Flaum, S. Chen, S. Ma: "NMR drill cutting analysis: methodology evaluation & operational best practices," paper SPWLA-2021-0095, SPWLA 62nd Annual Symposium, 17-20 May 2021.

G. Singer, S. Ma, S. Chen, and M. Eid: "2D surface roughness quantification for enhanced petrophysical applications," *SPE Journal*, 6 Jan 2023 (SPE 210178, SPE ATCE, 3-5 Oct 2022, Houston, TX, USA).

C. Xu, S. Misra, P. Srinivasan, & S. Ma: "When petrophysics meets big data: what can machine do?" SPE 195068, 2019 MEOS, 18-21 March 2019.

P. Zhang, W. Abdallah, S. Ma, & CB Liu: "Extracting rock cation exchange capacity from EM measurements," SPWLA-2018-QQ, London, June 2018.

P. Zhang, W. Abdallah, S. Ma, & CB Liu: "Clay typing from downhole array electromagnetic measurements," IPTC-19816, 2020 IPTC in Dhahran Saudi Arabia, 13-15 Jan 2020.

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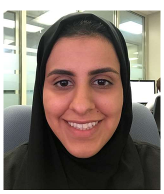

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Katrina Cox is a senior geologist and technical advisor with 15+ years of experience in oil, gas, and environmental industries. Her experience includes working at a major Oil & Gas Company in exploration, development, and research and currently at Core Laboratories focused on petrography, rock typing, integration, and reservoir quality. Katrina has probably looked at over 20K thin sections from all over the world. Recently she joined the Digital Innovation Group at Core Laboratories to use her experience and knowledge to develop analytical programs and products. She is using her petrologic knowledge to advise and advance artificial intelligence applications to address challenging and routine samples.

Allen Britton is responsible for International Business Development of Core Laboratories' Digital Innovation Group. He has 40+ years of experience at Core Laboratories in a wide variety of positions. His current responsibilities include development of AI technologies (Advanced Rock Typing), marketing of Joint Industry Projects as well as Data Management services (RAPID database, Relative Permeability Toolkit and RAPID Analytics). Formerly, he was the Manager of Core Laboratories' Coastal Regions, which included the U.S. West Coast and Gulf Coast Petroleum Services operations. He is a graduate of New Mexico Tech (B.S. Geology). For 25+ years he was a guest lecturer at Stanford University on petrophysical applications to log analysis in reservoir evaluation. He is a member of AAPG (Past-President and Honorary Lifetime Member of the Pacific Section AAPG).