SPE-211066-MS

Foundational Study of Artificial Intelligence Reservoir Simulation by Integrating Digital Core Technology and Logging Data to Optimise Recovery

Alberto Lener, University of Aberdeen Graduate

This paper was prepared for presentation at the ADIPEC held in Abu Dhabi, UAE, 31 October – 3 November 2022.

Abstract

In strategising development of hydrocarbon reservoirs, substantial uncertainty in recovery potential is often attributed to subsurface heterogeneity. Challenged **reservoir characterisation** is proposed to be directly due to the inability of correlating spatial scales: core analyses to well logging data. This study's central goal is to propose a '**Multiscale link**' by challenging empirical correlations of multiphase displacement and 'upscaling' processes of reservoir characterisation by exploiting Artificial Intelligence and **'Digital Rock Technology'**, aiming at **minimising geological risk**.

By exploiting 40 years of a North Sea field's appraisal and production and formulating an AI-compatible 'multiscale' data set, petrophysical correlations have integrated a further innovative concept: **borehole image processing** to characterise geological features and oil potential. In binding the 'Multiscale', fundamental multiphase dynamics at pore-scale have been critically associated to most affine reservoir modelling 'deep learning' frameworks, leading to ideating an AI workflow linking field-scale rates, well logs and core analyses to the continuously-reconstructed pore network, whilst extracting invaluable multiphase dependencies.

The preliminary results implementing selected Machine Learning algorithms, coupled with advanced digital technologies in reservoir simulation, have been showcased in proposing a solution to the 'Multiscale link' in reservoir characterisation, providing the groundworks for its programming realisation. Importantly, it was concluded that the layers of complexity within learning algorithms, which constrained its execution within this project, undoubtedly require multidisciplinary approach. By conceiving a physically and coding-robust workflow for advanced reservoir characterisation and modelling permitting 'multiscale' representative multiphase simulations, identification of optimal EOR becomes attainable.

This leading edge represents potential to minimise geological risk, thus de-risking reservoir management (in turn FDP) of mature and live fields; but also expected to set a starting point for further developments of Artificial Intelligence in the oil and gas industry.

Introduction

In exploiting hydrocarbon reservoirs, characterising subsurface dynamic dependencies is key. It is indeed the degree of heterogeneity within these to determine the uncertainty in identifying volumes and importantly in planning effective recovery. Existing empirical models, imbedded with assumptions to upscale localised measured properties allow marginal reduction of this uncertainty, due to their limited representation of physical phenomena at the pore scale. Technologies allowing a detailed analysis of dynamic and static properties of the pore scale have been developed, as well as data-driven reservoir modelling by 'artificial intelligence'; whereas, the workflow integrating the two scales to attain true representativity of multiphase physics, is missing.

The logic of the study which directly forged the methodology to design of the AI workflow as solution to the binding the 'multiscale' have revolved around: identifying the challenges of production within the test field-scale data (Guillemot), assessing these in function of well-scale petrophysical data and untapped potential of its interpretations, combining the invaluable pore-scale data accessible by technological advancements of digital rock technology and ultimately practically relate potential within fundamentals of multiphase flow and conducted research on artificial intelligence (AI) and machine learning (ML) applications (laid in the following chapter), into formulating a physically (and programming) sound workflow. The latter with the addition of another discipline of great potential, image processing.

Albeit essential in developing a physically representative reservoir model, the sole petroleum engineering background is deemed limiting to the complete realisation of the proposed coding-intensive analytical approach. The following ought to be the consolidating fundamentals of a greater resourced and involved research, for an already funded PhD project.

For the scope of this knowledge sharing publication, the in-depth analysis conducted has been skimmed retaining essential engineering method, although the full research paper is available.

Fundamental background

Multiphase flow at pore-scale

An accurate reservoir model of the field under analysis by the envisioned multiscale approach integrating static and dynamic parameters, may only be funded on representative pore scale features to yield correct physics. In fact, the governing concept lies in the hydrocarbon-rock system dynamic dependencies. With the goal of surpassing empirical correlations funded at the field scale, a theoretical base of the physics characterising fluid displacement at porous media is the key to identifying the pore scale features and binding multiphase–oil, water, gas–flow phenomena, which are implicitly responsible for the overall hydrocarbon recovery (Blunt, 2017).

Pore geometry and connectivity. Interest of the physics at pore scale of geological systems is heavily characterised by the geometry of the matrix through which fluid flows. Focus begins at the interstices between single solid grains, their shape and volume (Blunt, 2017) making up cross section to flow, are determinant of the forces involved at every time step of hydrocarbon displacement. Enhancing the focus, singular shape and roughness of surface of the rock grains, delineating the boundaries to flow, also have their impact in the dynamic behaviour of multiphase fluid flow. Effectively, this geometrical dependency is attributed to the sedimentary and diagenetic history of the reservoir formation (Blunt, 2017), together with the type and sorting of grains making up the rock matrix, highlighting the extent of heterogeneity as the dominating concept. Whereas, the network of connected pores within the rock matrix is the dominating factor in determining productivity of a reservoir (Ganat, 2019). Recognizing that averaging–by 'upscaling'– these geometric pore features likely yields approximated representation of the reservoir's flow potential; but also, that mapping the reservoir's porous media to such extent is impracticable (Blunt, 2017), opportunity lies in developing a new approach to classify pore geometry features at fine scale, whist maintaining high degree of accuracy. As proven by the work of Chen and Zhou (2017), high degree of interpretation to predict displacement is attainable by seizing the essential pore space geometry and respective dynamic dependencies of multiphase flow.

Wettability, relative permeability and capillary pressure. Upon understanding the hydrocarbon distribution dominating the porous system, the dynamic multiphase nature of hydrocarbon reservoirs must be integrated. Particularly, one of the essential rock properties affecting recovery–due to displacement efficiency–is the determination of the preferential phase residing on the rock surface, thus wettability. This qualitative feature consisting in: the wetting phase to be retained in the corners and roughness close to surface–where it can maximise its contact with the rock–while the non-wetting resides in the centre of the pore void (Blunt, 2017), is a result of interfacial tensions equilibrium between the pore bound non-wetting (σ_{nws}) and wetting (σ_{ws}) phases, and the rock matrix itself (portrayed by Figure 1 and equation 2.1).

$$\cos\theta = \frac{\sigma_{nws} - \sigma_{ws}}{\sigma} \tag{2.1}$$

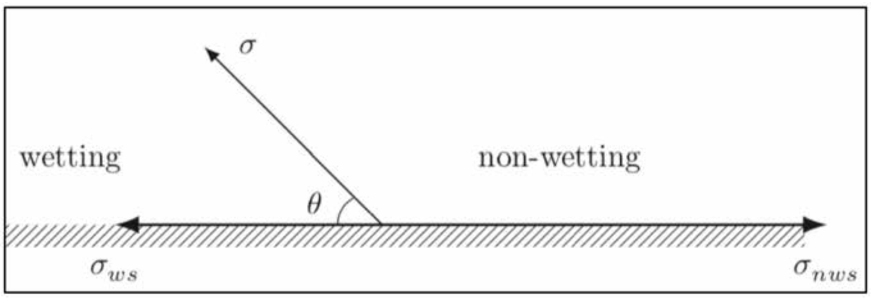

Figure 1—Interfacial tension equilibrium leading to fluid-fluid interface (σ), physically quantifiable by contact angle, as described below; taken from Blunt (2017).

In computing multiphase displacement processes, accuracy of the dynamic rock-fluid interaction, as described by contact angle, is the limiting factor in populating the reservoir model with superficially more accurate representation of static parameters of pore geometry or connectivity (Blunt, 2017).

Flow dependency, leads to the concept of relative permeability: ability of one phase to flow in presence of another (Chierici, 1994), in turn dependent on the wetting phase and its saturation. The latter multiphase phenomenon is characterised by the contact angle (θ) with the reservoir rock surface (Figure 2), measured through the denser phase (Blunt, 2017); in situ, thus accounting for surface roughness, another important static property influencing interfacial tension (Chierici, 1994).

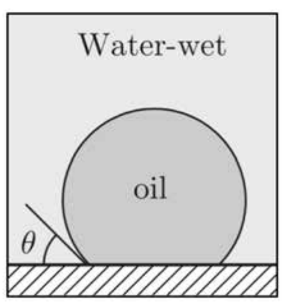

Figure 2—Contact angle measurement in water-wet rock system: from rock surface, through denser phase being reservoir water/brine, to fluid interface; taken from Blunt (2017).

Relative permeability, as mentioned, characterises the ease of one phase to flow in presence of another as a function of the saturation of that fluid (Ganat, 2019); as a result of microscale pore physics.

$$k_{ro} = \frac{k_o}{k} = f(S_o) \tag{2.2}$$

As portrayed by equation 2.2, relative permeability to oil (k_{ro}) is defined as the ratio of effective-oil to absolute permeabilities $\frac{k_o}{k}$ (Chierici, 1994). Recognising that it solely depends on an assigned scalar saturation of the respective phase –$f(S_o)$– rather than its distribution within porous matrix described (Chierici, 1994), this resulting parameter omits the physical interaction between viscous, gravity and capillary forces relative to direction of flow. Indeed, heterogeneity in pore features–geometry, connectivity and wetting properties–, along with fluid saturation distribution and history, represent the pore scale dependencies (Golparvar *et al*., 2018). Thus, relative permeability is better described as a tensor and as such should surpass the correlation based on imbibition and drainage scenario-based empirical curves, considered method of choice for nearly 100 years (Chierici, 1994).

In understanding the physical effects of multiphase spreading behaviour at pore scale flow, the balance of interfacial forces, directly related to wettability, finds a practical quantification in capillary pressure (Blunt, 2017). Essentially due to the microscale geometry to flow of porous matrix, gravitational and importantly capillary forces are indeed dominant in multiphase displacement–compared to viscous forces (Chierici, 1994)– due to their significance in maintaining the phases in a local energy balance (Blunt, 2017). Thus, it is evident that the saturation change of the wetting phase is proportional to the capillary pressure. Also for this dynamic parameter, pore scale heterogeneity in radial flow geometry is responsible for its spatial variation (Zhao *et al*., 2019) and consequently also of the preferential pathways taken by hydrocarbons–order of phase replacement.

Upon evaluation of modelling such property, surpassing Navier Stokes' approach, the empirical equation maintaining high details of the multiphase pore-scale and deemed of practicable integration into a multiscale model is the Young Laplace equation. This empirical statement–illustrated in equation 3.3 (Blunt, 2017)– funded on local energy balance, accounting for wettability in terms of interfacial tension (σ) equilibria, thus contact angle (θ) –between the solid and fluids and at the multiphase interface–as well as pore geometry controlled by pore radius (r), is able to yield a pore-by-pore capillary pressure (P_c) estimation, which makes qualitative physical sense (Blunt, 2017). Essential research by Liu and Cao (2016) also provides attainable approaches in validating this equation at realistic pore scale. Importantly, the Young Laplace empirical correlation makes use of pore scale parameters which are practicably accessible in a reservoir static model, especially populated by the envisioned method, at pore scale detail.

$$P_c = \frac{2\sigma \cos\theta}{r} \tag{3.3}$$

Pore scale modelling and Digital Rock Technology. The full study has attributed complete focus to successful methods developed for state-of-the-art geometric reconstruction of porous media, particularly towards the degree of physically plausible multiphase flow behaviour on the simplified pore space (Golparvar *et al*., 2018).

Computational power and imaging technologies have opened boundless opportunities to discover and understand the physical dependencies of multiphase flow in various hydrocarbon-rock systems (Chen and Zhou, 2017). It is indeed well established in industry that rock cores, albeit essential for formation evaluation (Berg, Lopez and Berland, 2017) permitting distribution of rock and fluid properties, require expensive–also timewise–analyses; whilst coming with substantial degree of uncertainty to reach field scale characterisation (Blunt, 2017). Providing the lacking resolution of rock microstructure modelling to extract equivalent field scale physical and transport properties–without the need of resourceful physical core experiments (Chen and Zhou, 2017)– 'digital rock technology', has stirred exponential interest within research and industry (Zhu *et al*., 2018). Rewards of its implementation range from targeting most productive rock to planning more effective completions as well as decreasing development time of ad-hoc EOR techniques (Rassenfoss, 2011).

Pore network construction. Upon the wide spectrum in literature, the reconstruction of porous network, thus precise geometry of flow boundaries, is essential to modelling capabilities and corresponds to the initial focus of this technology (Zhang *et al*., 2015). Essentially permitting to surpass the mere statistical recreation of porous media built by distribution of morphological parameters (Golparvar *et al*., 2018). The construction of last generation digital cores begins with high resolution 3D X-ray computed tomography images, rather than the pioneering method of re-constructing 3D structures from 2D electron microscopy scans (Dong and Blunt, 2009). In fact, the second displays a net advantage in integrating pore distribution in all 3 dimensions (Chen and Zhou, 2017). Micro–scale–computed tomography (mCT), being non-destructive and non-invasive in acquiring detailed imaging of reservoir rock cross-sectional internal flow paths (Zhang *et al*., 2015), is the most practical and high-resolution technique for pore network construction available at advanced stage of implementation (Zhu *et al*., 2018).

Upon virtual recognition and classification–along quantification–of structural characteristics of rock core's internal structure, the porous medium is discretised, thus reconstructed, in such way that flow can be simulated on it; known as 'pore architecture models'–such as the one illustrated in Figure 3– and advantageous for being computationally efficient (Dong and Blunt, 2009). 'Maximal inscribed sphere' (MIS) (Silin, Jin and Patzek, 2003) and 'medial axis' as most common morphology-based algorithms have been analysed for their effectiveness in pore description, thus capillary equilibrium and entry pressures.

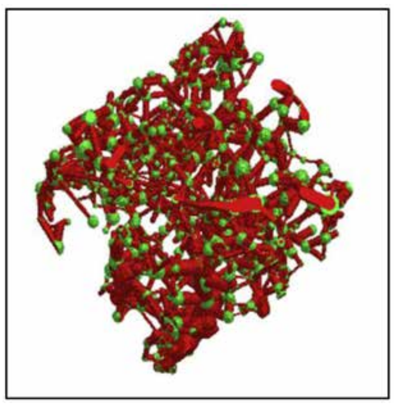

Figure 3—Digitally extracted 3D pore network displaying pores (green) and throats (red); taken from An *et al*., (2016).

Importantly, network parameters extracted by the digital rock model as true representation of the porous medium are determinant in evaluating absolute and relative permeabilities, along with capillary entry pressures (An *et al*., 2016). In cases in which 'conventional' and 'special' core analyses (CCA and SCAL) data is already available, integration into the digital pore network is effective for validation, but also completing population of the model (Berg, Lopez and Berland, 2017). As such, the consequent simulations onto the 3D rock model–since highly representative–permit identification and quantification of rock and multiphase properties. Effectively serving as common denominator to geological and petrophysical interpretations, as well as reservoir simulations (Berg, Lopez and Berland, 2017).

Artificial Intelligence

The multidisciplinary approach, known as 'artificial intelligence' refers to all 'intelligent' agents–since mimic the brain's cognitive/logical approach to tackling problems– (Mohmad *et al*., 2020); and encompasses many facets in data analytics, for which its valued applications in sciences have also received great attention by reservoir engineering (Zhang *et al*., 2018). As outlined in the previous sections, physical phenomena at pore scale are extremely complex due to scale of medium, but also multiphase and fluid-rock dependencies. And albeit decades of research, which arrived at meticulous results, the limiting factor remains modelling uncertainty in degree of complexity of relationships between pore scale tensors and scalars responsible for the behaviour of dynamic phenomena (Mohaghegh, 2011). This is indeed where artificial intelligence–encompassing 'machine learning'–coupled with 'digital rock technology' offers great potential in deriving robust evidence based models, whilst staying true to physics governing pore scale dynamics (Mohmad *et al*., 2020). Thus, incorporating these physically binding principles explicitly to reservoir scale applications, as permitted by AI (Mohaghegh, 2011) –instead of relying on approximative empirical correlations–is the key to reaching quantitative characterisation of multiscale phenomena and heterogeneity.

Reservoir Modelling. Conventionally, in numeric reservoir simulations, the functional relationships, such as Darcy's law or conservation of mass are taken as deterministic and importantly unchangeable (Mohaghegh, 2011). This being the innovation of this approach, by which these empirical relationships are permitted to change during dynamic modelling, thus replaced by formulated ad-hoc dependencies, enabling higher degree of complexity in modelling the reservoir; ranging from geo-mechanical considerations to multiphase flow and dual porosity systems (Gaskari, Mohaghegh and Jalali, 2007). Until reaching matching multi-functional dependencies, this process is assisted by subject matter experts (Mohaghegh, 2011); as reality check to remain true to physics.

Thoroughly evaluating successes in integrated modelling, the 'top-down model' (TDM) has inspired this project's envisioned multiscale AI integration reservoir modelling. Developed by Mohaghegh (2011), the workflow outperforms conventional numerical models, by cost and time of development; along with the ability quantify uncertainties associated with static model (Kalantari-Dahaghi, Mohaghegh and Khazaeni, 2010).

Machine learning agents. Recognising that the latter workflow in developing a reservoir model is greatly consolidated within research, the turnkey between the models lies in the AI algorithms applied to field data for extracting physical patterns; its understanding is therefore deemed essential in proposing a novelty approach. These machine learning algorithms–as branch of AI–consist in multi-layered progressive processing units, referred to as 'artificial neural network' (ANN), capable of acquiring experience from varied data inputs, without explicit programming (Mohmad *et al*., 2020). As illustrated in Figure 4 below, in the learning process, specific 'agents' make use of hidden neural layers adapting to reach the pursued output (Mohmad *et al*., 2020). As data-driven approach, pattern recognition is achieved by: training the ANN 'agent' with a partitioned set of data, which as basis, correspond to the majority (Ian Goodfellow, Yoshua Bengio, 2016); then cyclic calibration, by use of a randomly selected blind–output retained–dataset; finalised by a validation dataset, again blind and uninfluenced by the previous steps (Mohmad *et al*., 2020). Specifically, the training step adjusts the 'weight' of the activation function iteratively, by a pattern fitting algorithm, until optimum to accomplish the function obtaining minimised error (Mohmad *et al*., 2020). Following, the calibration data induces the training process by examining patterns achieved and preventing ANN over-training to minimise the error gap between training and testing data, known as 'overfitting', thus also unnecessary pattern memorisation (Ian Goodfellow, Yoshua Bengio, 2016). As means to validate the agent's predictive abilities outside of the training model, the validation set is tested, for robustness of the patterns extracted (Ian Goodfellow, Yoshua Bengio, 2016).

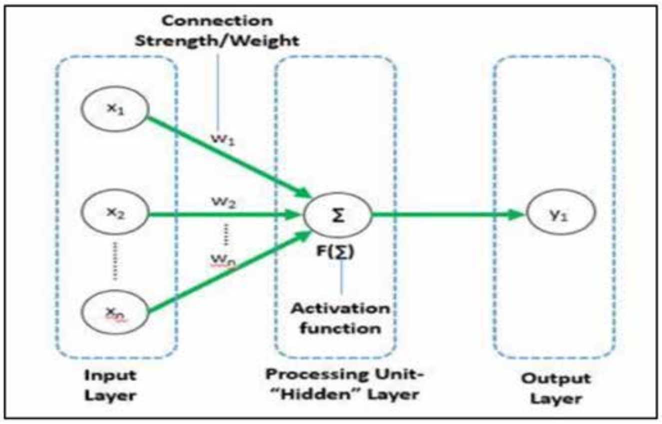

Figure 4—Illustration of simple ANN, displaying activation function and respective 'weight' from input layer; taken from Mohmad *et al*. (2020).

Upon passing the latter standard machine learning process, as for the effective top-down reservoir modelling, the agent undergoes further affinity by accustoming the algorithm to real field data on different time scales, as well as potential flow rates: history matching–critical to attain predictive reliability on dynamic model (Mohmad *et al*., 2020). Although in Mohaghegh's (2011) validated TDM, the pattern fitting algorithm corresponds to back error propagation, competitive machine learning algorithms have been investigated for their potential implementation into a model integrating wider types and scales of field data. Narrowing down the analysis to the algorithms conventionally employed in AI based reservoir modelling, 'backpropagation' (*BP*), 'support vector regression' (*SVR*) and 'long short-term memory' (*LSTM*) have obtained attention from research (Mohmad *et al*., 2020). Surpassing these algorithms' analytical analysis (in full paper), *LSTM* outperforms other machine learning algorithms in accuracy, sequential predictive ability and computing speed, also in varied input flow regimes and time scale of prediction (Mohmad *et al*., 2020).

Major constraint of this technology lie in the requirement of continuous field data to permit effective predictive learning (Mohmad *et al*., 2020); thus shall aim at achieving this when implementing a consolidated agent, without risking a disruptive learning sequence and inaccurate predictions. The latter would in fact be encompassed in the principle common to all data driven approaches: 'garbage in and garbage out', meaning that key success factor for accurate machine learning and history matching lies in quality of field data, but also quantity (Ian Goodfellow, Yoshua Bengio, 2016), all with the exclusive supervision of a reservoir engineer, as subject matter expert.

Consolidated applications

Recognising potential of 'artificial intelligence' to reduce complexity in modelling subsurface physical dependencies, interdisciplinary research in the field of reservoir engineering has achieved and validated 'artificial neural networks' capable of evaluating essential petrophysical properties, lithology and classifying rock heterogeneity. The methods yielded permit not only cost savings from eliminating core sample extraction and expensive laboratory measurements, but also reliable computation of these properties at reservoir scale (Ba alawi, Gharbi and Mahmoud, 2020), thus populating the static model without relying on stochastic averages.

Another frontier reached by AI is image processing by machine learning, representing indefinite potential in reservoir characterisation by borehole images and core sample scans. 'Machine learning assisted image recognition' (MLIR) improved by 'difference of gaussian random forest' algorithm is the successful approach developed by Al-Farisi *et al*. (2019) to accurately –97%– measure porosity and digitally classifying rock heterogeneity and lithology from 3D mCT image; with essential role of subject matter experts' labelling the desired features for the algorithm to learn under supervision. Upon resolving the great challenge of low-resolution–pore size being smaller than pixel–by AI automated filters, improved segmentation could be attained (Al-Farisi *et al*., 2019).

Recognizing that features and colour of the rock portray mineral content, depositional processes, sedimentary environment, and chemical composition (Ran *et al*., 2019), the potential of borehole core images stimulated novel AI milestones in high precision rock characterisation. Particularly, solving the inability of existing machine learning methods to correctly classify untrained lithotypes (Baraboshkin, 2018), due to weathering, lighting and artificial selection of features (Ran *et al*., 2019) 'convolutional neural networks' (CNN) allowed improved classification and accuracy (Ran *et al*., 2019); with the ability to automatically extract and learn key features for classification and training. Consisting in ANN, with a special layer performing arithmetic convolution on a series of expert-selected filters, –allowing rock image feature extraction by cross correlation–these predictive models reach high performance by being topped up with a statistical function quantifying certainty of prediction (Baraboshkin *et al*., 2019).

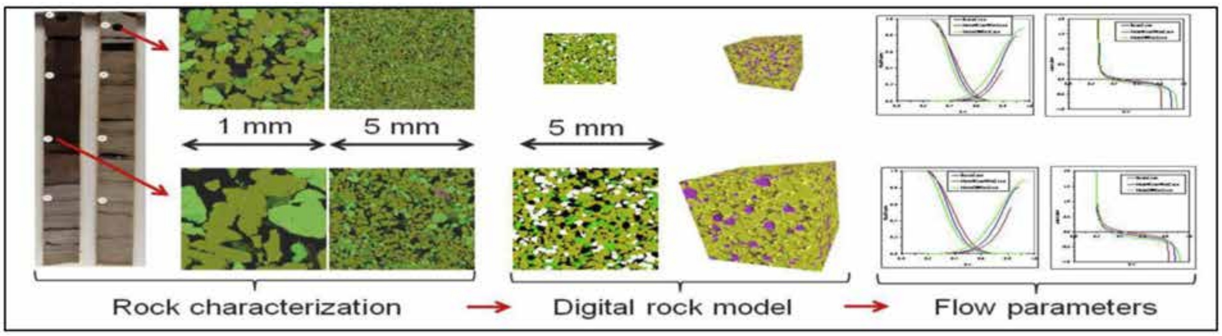

Figure 5—Workflow of simulating flow parameters by digital rock modeling; taken from Berg, Lopez and Berland (2017). Specifically, relative permeability and capillary pressure–as essential dynamic parameters–are simulated on virtual rock model extracted directly from AI-driven image processing functions developed for recognition and segmentation of lithology.

Methodology to design

Based on the latter consolidated fundamentals, to attain robust representability of the underlying physics, the validated design concepts of the envisioned AI-workflow are described in the most logical sequence; proposed as preliminary work for future realisation and representing a key deliverable of this integrated study. In formulating this novel approach characterising reservoir heterogeneity at multiscale, data from the Guillemot field has permitted a reality check of its applicability in realistic industry applications.

Multiscale data integration

To set context to the data being analysed, the reservoir formations being exploited and respective key characteristics served as preface for integrating field data in a critical manner. Production performance and remaining hydrocarbons potential, being already assessed by geological and dynamic models, have provided valuable insights for laying an improved approach (Spaak *et al*., 1999). Acquired core analyses, reports and research on facies characterisation, depositional stratigraphy and depositional models of the main reservoir formations (Akpokodje *et al*., 2018) have been a valid way to acquire know-how on setting up analysis centred on borehole core images. On top of the latter, data screening has evolved around spatial collocation of geological boundaries, pore bound fluid properties and non-trivially, 'digital rock technology' pore scale imaging.

Critical phase to design to reflect logic of design (learning and aggregation) of the envisioned AI workflow lies in compiling a compatible database integrating multiscale, static and dynamic properties. Funded on consolidated learnings from AI data structure requisites, a depth based spreadsheet would permit highest degree of consistency, effectiveness and operator flexibility.

Well logging data

Providing central field scale and properties to this study, selection of well logs and signal interpretation prioritised consistent inclusion of multiscale data envisioned for machine learning. Physical signals required reservoir interpretation prior to being segregated per depth scale and discretised (per amplitude). This last being essential for classifying heterogeneity by permitting recognition of unapparent relationships between the physical signal's amplitude and corresponding evaluated rock properties.

Digital Core Technology Implementation

Upholding the relevance of pore scale's static and dynamic properties into sequent reservoir modelling, the procedure for attaining virtual pore space has been established in line with its application within the workflow, as basis of representative multiphase flow simulations. As detailed in complete research, this phase has been specifically designed to achieve most accurate quantitative representation of pore space and qualitative classification of throats, whilst being computationally efficient.

Essentially, for enhanced algorithm learning, core specimens to undergo lithology-calibrated 'micro-computed tomography' (mCT) X-ray scanning shall preferably correspond to distinct petrophysical interpretations of reservoir interval. To attain representative reservoir wettability, 'native-state' or restored cores shall be prioritised (Anderson, 1987). On top of pre-processing the tomographic slices, a further image-processing process, through a selected algorithm sequence, has been developed for fine tuning of: captured pore elements, phase distribution and contact angle scanning; translating to representative dynamic modelling (Chen and Zhou, 2017).

The construction of pore network by initial cross-sectional discretisation, morphology modelling (Dong and Blunt, 2009), is then to be completed by 'Maxim-inscribed-ball' 3D computational algorithm. Technology extracting microscale characteristics, yielding quantification of effective porosity, connectivity and absolute permeability (Chen and Zhou, 2017). Pore size distribution would be cross-evaluated by complementary SEM high resolution imaging. Pore-bound saturation and contact angle distribution of distinct fluids phases, to be integrated into the capillary pressure behaviour computation by Young Laplace equation–fined tuned with dynamic core analyses. An algorithm characterising microscale heterogeneity in wettability–undoubtedly greatest dependency of dynamic properties at this scale (Hamon, 2000)– would be implemented to attain accurate derivation of relative permeability by dynamic simulations of the multiphase displacement; thus portraying effective remaining oil potential at pore scale.

Borehole core images integration

In exploring the implementation of machine learning within the field data available, have inspired significant potential to enhance the. Albeit image processing being a discipline to itself, integration of which has represented a substantial sink of project's resources, the innovation for developing a graphically-backed physical correlation has inspired its integration within the ML scheme. Indeed, significant potential to enhance classification of heterogeneity in both properties and remaining oil within the predictive model (Al-Farisi *et al*., 2019) lies in the extended intervals (100's ft) of borehole photographs, providing geological and petrophysical description of lithology. From field data, three wells–most data-intense–have contributed 432 ft of core images to designing ad-hoc sound processing workflow (detailed in full paper), funded on literature and Python libraries, whilst cross-referencing to stratigraphic reports and well logs. Pre-processing essentially consisted in 0.5 ft–corresponding to dataset cells–intervals' extraction, re-sizing and de-noising.

Based on well log computed water saturation range, borehole images corresponding to depths of relative high, low and medium oil saturation have been selected and juxtaposed, investigating potential correlations of oil presence. Image processing functions have been coded to enhance a certain rock feature (texture, staining and veins); separately analysed and assessed for validity of implementation into automated ML pattern recognition.

Similarly, pixel-processing algorithms, aimed at distinguishing visual rock features have been analysed for potential of linking pore scale mCT properties to graphically-recognised geological features. In essence, roughness has been deemed most significant rock characteristic for stratigraphic classification, then to be extracted associated to corresponding mCT microstructure properties by deploying Python's *Keras* deep learning library–selected for its computational and programming efficiency (Singh, 2019).

Setting aside visual correlations, rock features have been quantified by exploiting discretised pixel colour model of the borehole images. Extracting 'red-blue-green-alpha' intensities, on an absolute scale of 0 to 255 ('alpha' specifying opacity), a 160 pixel matrix–sized to maintain computing efficiency of the model (Singh, 2019) – has been created for sequential linking to geological features' pattern recognition. Latter upon validation of physical robustness by hard-coding an *if* function, on relating ranges of oil saturation to respective depth's pixel intensity.

Artificial Intelligence modelling

On the basis of the integrated wells database–developed for 3 wells of Guillemot field's interbedded reservoirs–, *XGBoost* machine learning algorithm (open-source) –chosen for its versatility in application and precision based efficiency (Singh, 2019)– would be implemented to model complex multiscale dependencies and populate the unmeasured petrophysical properties and dynamic behaviour by well depth, on MS Excel cell's basis. As research-validated correlation (Ba alawi, Gharbi and Mahmoud, 2020), the latter process shall include aimed capillary pressure modelling, thus prediction, from well logging resistivity measurements. In turn, relative permeability–even more relevant dynamic multiphase property– would be computed by matching Corey and Brooks qualitative attributes (Ba alawi, Gharbi and Mahmoud, 2020), extracted by core analyses. Distinct pore and field scale imbedded heterogeneity characterisation shall be programmed within the algorithm's functional fields. Importantly, to yield representative and physically abiding predictions, algorithm 'training' shall be performed on distributed and most completely characterised set (rows, thus depth), whilst adjusting (Gaskari, Mohaghegh and Jalali, 2007) Young Laplace empirical pore scale dependency. 'Validation' of matured algorithm predictive ability shall be funded on 'digital rock technology' findings, thus prior withholding of respective depths analysed. Latter step is particularly crucial for progressing onto populating the acquired geological model, as part of an integrated process, deploying concurrent AI agents. In fact, to achieve ad-hoc modelling of complex physical relationships between geological features (scalars) and multiphase saturation dependent properties (tensors), *LSTM* algorithm shall be implemented for reservoir scale dynamic simulation; for its enhanced predictive concept of ANN (Zhang *et al*., 2018).

Inspired by TDM research validated approach and realistic algorithm abilities, AI-controlled 'history matching' of production flow–at stabilised pressure drop interval–would characterise effective pore scale properties governing flow (Mohaghegh, 2011). To attain such, *LSTM* shall be programmed to simultaneously fine-tune Darcy's Law modified for multiphase flow and previously evaluated dynamic pore scale model, funded on Young Laplace; whilst integrating PVT behaviour and porous media static properties consolidated on the well basis. Essential step lies in reservoir engineer's physical validation of the formulated multi-functional relationships. Within this simulation to be run on the geological static model, macro grid-cell multiphase displacement programmed would integrate the predictive ability satisfying the reservoir scale and in turn pore scale phenomena, as acquired from the well –'line source' analogue–across the entire reservoir grid cells. Running iterations of this concurrent integrated AI dynamic modelling, would fine-tune the predictive algorithm (Zhang *et al*., 2018), achieving a model of record resolution and especially portrayal of reservoir multiphase behaviour.

Evaluating EOR potential

Realisation of the representative AI reservoir model accounting for pore scale multiphase phenomena at multiscale and diagnosed heterogeneity would permit grid-based simulations of each phase's saturation distribution within the reservoir. Essentially, upon simulation of primary and secondary recovery, residual oil would be delineated at pore scale microstructure–achieved reservoir wide, by 'multiscale link'–along with classifying 'unswept' regions at field scale, thus remaining oil. Prior to computing volumes, the algorithm shall characterise localised flow dominating petrophysical and fluid properties (Chen and Zhou, 2017). Particular weight shall be assigned to capillary pressure–thus interfacial tension–and viscosity (Ahmed, 2010), from reservoir-accustomed Young Laplace and multiphase Darcy's Law respectively. Indeed, rock-multiphase dependencies evaluated as critical to displacement shall be integrated into an iterative function feeding into 'history matched' dynamic reservoir to yield effective remaining oil potential.

Results and Discussion

Integrated Database

Solution to the challenge of producing highly heterogenous formations, driver of this study, and portrayed by the Guillemot field, was realistically formulated by application of its mature data. An initial geological and petrophysical interpretation of reservoir quality, zonal isolation and layering has set a stance for relating model validation and data check for effective representativity; and is part of the full paper.

Specifically, realisation of a discretised MS Excel spreadsheet has proven practicability and efficient integration of multiscale resources. Compiled as in Figure 6, achieved design confirmed compatible logic for *XGBoost* algorithm classification of heterogeneity, characterisation of specific reservoir physical dependencies, but also validated AI sequential requirements for predictive population.

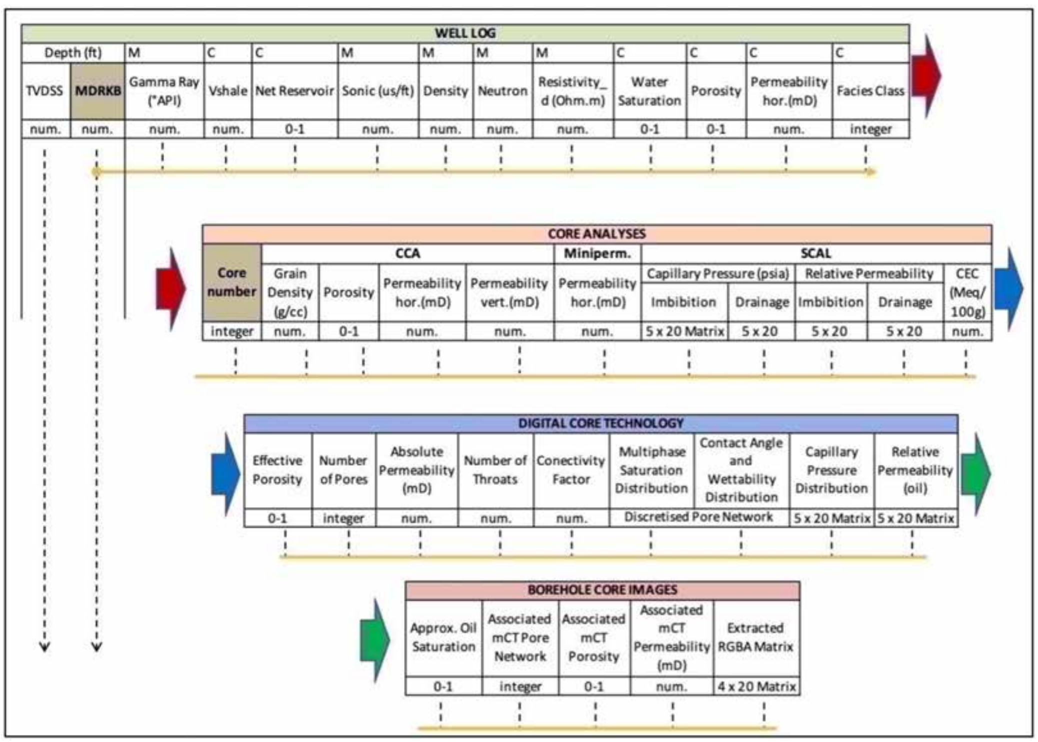

Figure 6—Formulated database for machine learning, as MS Excel spreadsheet, compiling the integrated data set, in terms of well log 'measured' depth–MDRKB. The bold arrows portray continuity across the multiscale data sets, in terms of rows, which correspond to a single depth, as illustrated by the yellow line. The data type within the column is specified as either general numerical value, integer, fraction (0-1) or imbedded matrices by size (including discretised pore network) as extracted from selected cores. Distinction between empirically computed (C) and measured (M) well log discretised signal included for prioritising objective pattern recognition.

Having assessed machine learning requirements for multi-variable pattern recognition for accurate heterogeneity characterisation (training, testing and validation sets), has accentuated the limited data of the established database; thus minimal size of populated database has been deemed to require a whole 2 orders of magnitude greater (Ran *et al*., 2019) than the representative wells (3) compiled for this study. A fundamental limit, which has been designed by planning single well, localised, multi-variable 'machine learning' and population prior to iterating over the well set and sequent field scale.

Borehole core graphical correlations

Integrating borehole images as innovative element to characterise the reservoir, within the study of AI implementation, has yielded conception of a novel approach and scale of analysis: pixels. Gaining a geological appreciation of the interdependence between these rock features–preceding recognition by 'machine learning'–has permitted distinct pattern objectives in image processing (Al-Farisi *et al*., 2019).

Oil saturation. Potentially most crucial graphical correlation to be investigated for evaluating remaining oil potential, emerging oil presence by processing borehole core images found endorsement in macro geological features, such as apparent oil-imbibed veins and staining. Advancements on linking texture and veins have been confirmed by 'unsharp' blurring and 'clahe' paraboloid smoothing applications as illustrated in Figure 7. Original images confirmed geological reports of characteristic oil staining as apparent tie to oil saturation, specifically from intensity of shading. By successfully displaying intensity of texture, blurring mask has yielded moderate potential to link oil saturation. Rather, for mildly oil stained sandstone, better purpose in 'machine learning' may be to associate emphasized veins to potential residual oil saturation. Similarly, application of 'smoothing' function resulted ineffective as direct link to oil, whereas advantageous for extracting peculiar lithological features.

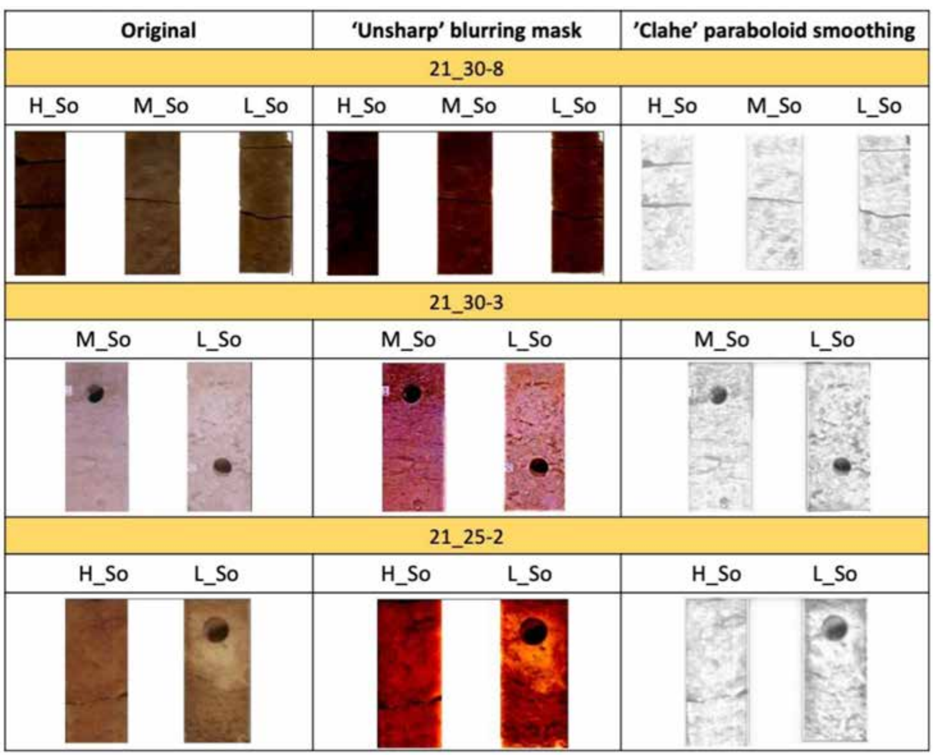

Figure 7—Processed borehole core images for 3 representative wells, featuring texture and veins by specified filters for selected oil saturations (So) –relative high (H), medium (M) and low (L)– investigating potential petrophysical validity of correlations.

The partial link of rock shading acuteness was pursued by function of selected colour maps, then by pixel intensity–RGBA. The first approach, as displayed in Figure 8, has been optimal for emerging graphical intensity, although not for reaching a naked-eye distinction between oil saturations, thus direct correlation, on any colour map. Having achieved considerable contrast of dark shadings on rock surface–regarded key to linking oil saturation by core geological description–validity of this approach shall be settled upon implementation of machine learning pattern recognition, by *Keras* algorithm–on direct images or extracted RGBA pixel intensity.

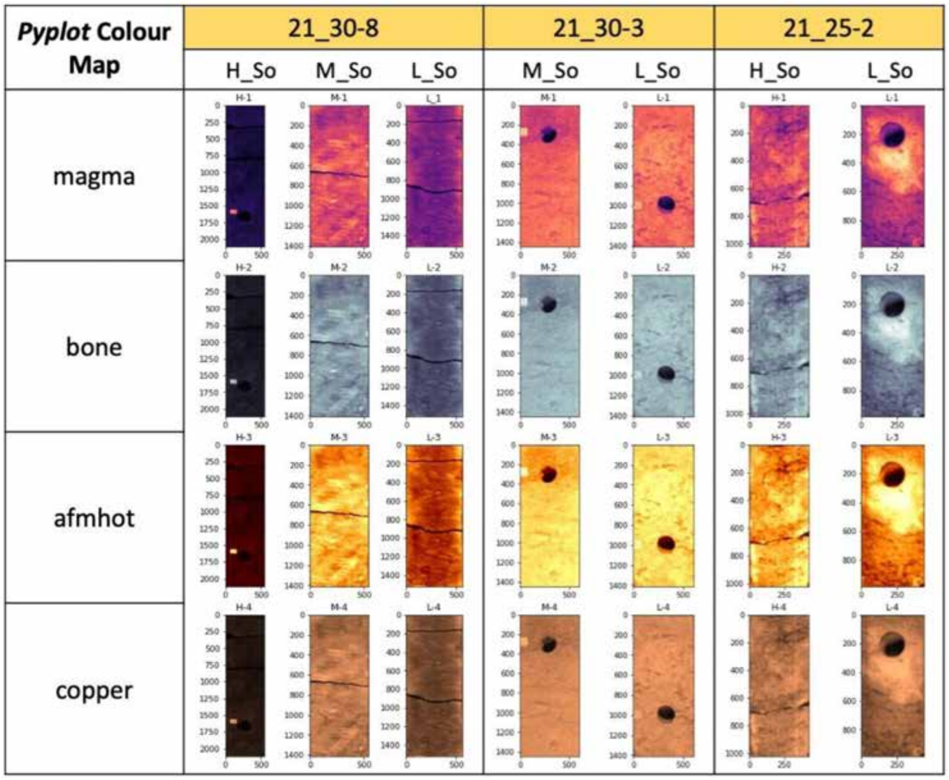

Figure 8—Processed borehole core images for 3 representative wells, by applying selected *Pyplot* colour maps, classified (1-4) in order of effectiveness in featuring distinct shading intensities for selected oil saturations (So) –relative high (H), medium (M) and low (L)– investigating potential petrophysical validity of correlations.

Association of mCT cores' pore structure. The design principle of corresponding pore scale–in terms of mCT extracted pore network–to cores, based on recognition of distinct geological features, has proven to be a robust machine learning objective to be implemented directly on images by *Keras* algorithm; having validated the correlation potential from extracting texture, veins, roughness and sedimentology directly. As displayed in Figure 9, image processing algorithms exalting the latter rock features have been validated along naked-eye detection of analogies; achieved between porosity and roughness, as well as permeability and texture. Namely, the greater the roughness–picked up edges and coupled 'clahe' features–the greater the porosity; physically motivated by grain size distribution proportionality with void space (Chierici, 1994). Whereas, permeability relatively to incongruous texture –'BGlense' coupled 'clahe' features–associated to throat size distribution (Blunt, 2017). Correlation to a degree may lie within sedimentology and permeability, emerging between cores 44 and 77 from lithological strata deposition (Chierici, 1994), presented by practically distinguished shades of grey.

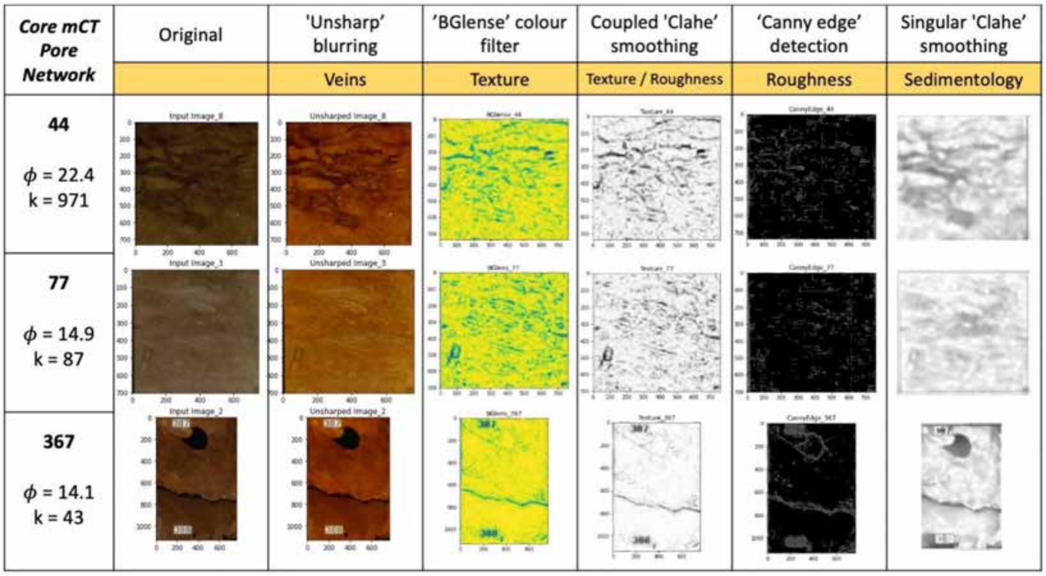

Figure 9—Processed borehole images of 3 cores corresponding to mCT extracted properties–distinct specified, i.e. connectivity similar for all–, by applying processing functions selected for emerging geological features in yellow cells.

Discretised borehole images: RGBA extraction. Being an integral element of the developed multiscale database, for each cell, borehole core image discretisation has been implemented as 4 by 20 matrix – RGBA values per each of the 20 depth layers–to attain computational efficiency, whilst scale accuracy. Significantly, the assembled RGBA extraction would permit pattern recognition with properties at well scale; enhanced by parallel machine learning implementation, extracting pixel intensities from purpose-processed mCT core images.

Formulated AI reservoir modelling workflow

Within the integrated data-driven learning, borehole images' novel exploitation and virtual pore models have been deemed to contribute robust representability of reservoir; as parallel process to improve predictive ability of modelling static properties and ad-hoc flow equations at the multiscale. In fact, calibration of machine learning at pore scale resolution shall result in robust modelling of wettability and phases' saturation (Mohmad *et al*., 2020), thus relative permeability and capillary pressure, importantly modelled as tensors.

For the scope and realisable depth of the study, the developed solution to the 'multiscale link' has been presented in the form of a flow diagram, inherent of physical and practical robustness attributes.

Ability to conduct physically abiding simulations onto the achieved dynamic reservoir model would allow design of EOR technologies attaining optimal recovery, on the basis of targeting porous properties directly associated with evaluated remaining–include residual–oil potential.

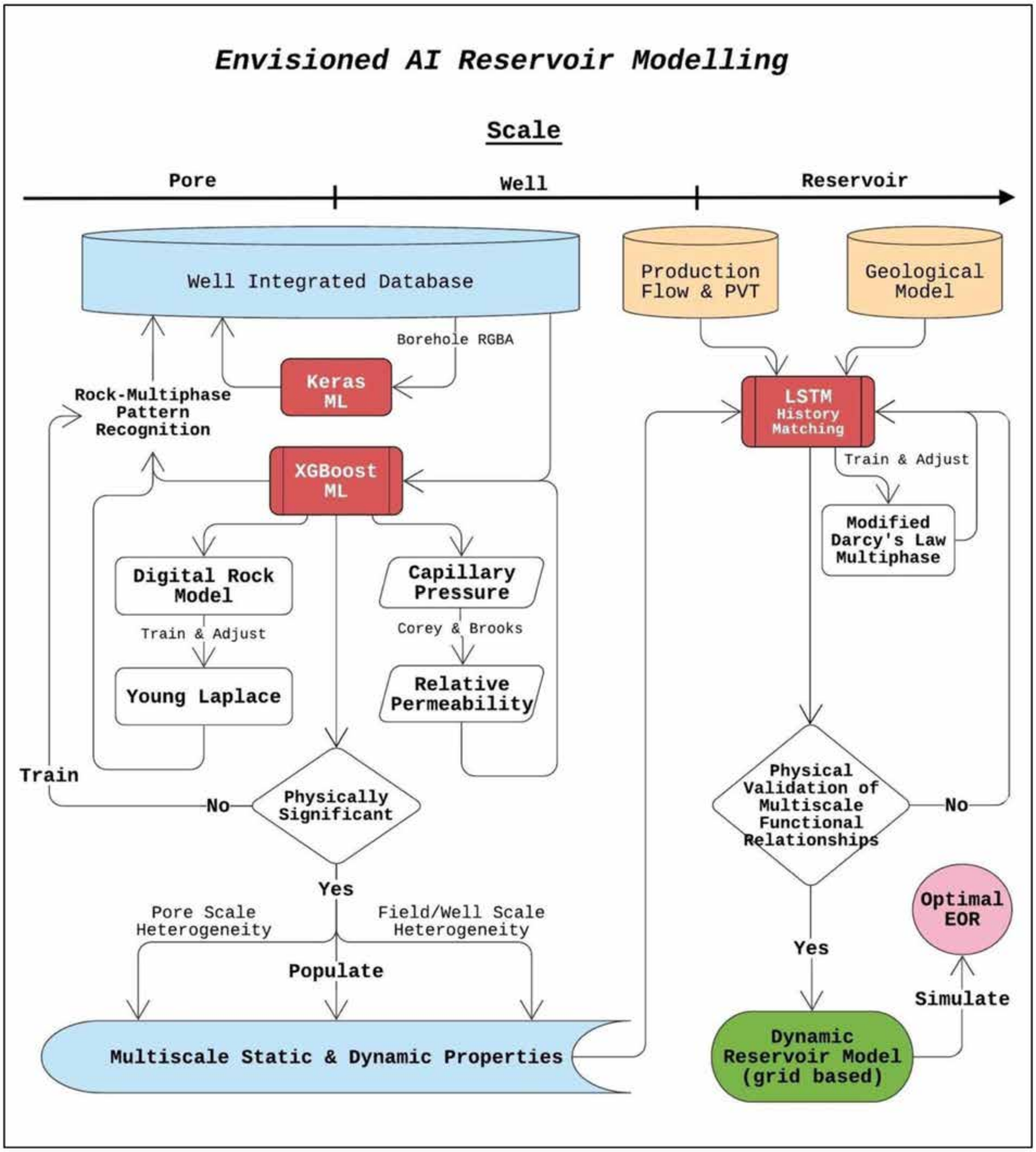

Figure 10—Flow diagram of developed 'artificial intelligence' workflow integrating multiscale field data to achieve enhanced-representability dynamic reservoir modelling and sequent simulation for selection of optimal EOR technology; indeed representing main deliverable of study. Following the philosophy of its fundamental background, the workflow is ordered in terms of spatial scale of data, as illustrated by the overlying horizontal axis. Initiating from the 'well integrated database', iterations controlled by *XGBoost* machine learning algorithm would allow enhanced rock-multiphase pattern recognition. Latter encompassing parallel learning processes, designed for solving 'multiscale link' (static & dynamic) and *Keras* borehole images driven property matching and population of database. The achieved multiscale properties intermediate dataset precedes physical robustness validation by operator, on top of separate scale classification of heterogeneity. This dataset is then conceived to be integrated to reservoir scale databases for *LSTM* 'history matching' critical dynamic process, prior to validation and conception of dynamic reservoir model to simulate and select optimal EOR technologies.

Conclusions

Appreciating the important impact of subsurface heterogeneity on oil recovery processes, the shortcoming of the tie between length scales of its characterisation has been aspired to be resolved. Indeed, including the latter in reservoir modelling has the potential to mitigate adverse impacts on production strategy, by representing effective complexity of multiphase flow interaction within porous media. Since these microscale phenomena have direct repercussions on field scale flow, the opportunity to reach physically representative reservoir modelling, encompassing the formulation of a field-exclusive link binding these apparently separated scales, has motivated the efforts of this AI study.

Unconventionally, focus was given to AI algorithms for their potential in surpassing mere scale-associated analyses–characterising dynamic and static reservoir heterogeneities separately–by integration of these into a multiscale model and understand ad-hoc relationships. As physical foundations to the envisioned approach, a critical investigation of pore scale properties, directly concerned in multiphase flow, has confirmed the importance of modelling phase saturation-dependant parameters as tensors, rather than scalars –'upscalable' to a certain degree. Distinguished impact of wettability and relative permeability in recovery efficiency has been consolidated by literature, as well as directly from mCT extracted pore network models; part of 'digital rock technology' research. In fact, on top of invaluable rock-multiphase phenomena, directly from advanced resolution of rock microstructure, its integration is highly regarded to portray the most accurate phase distribution and medium to flow. Funded on Young Laplace equation, this spectrum has been centrally regarded in generating ad-hoc dynamic dependencies, by means of conceived machine learning driven simulations; thus contributing to classification of remaining oil potential.

By conducting geological and petrophysical evaluations on the acquired Guillemot field data, the field scale heterogeneity has been approximated at the level permitting physically coherent integration with pore scale–nearly 10 orders of magnitude smaller (Golparvar *et al*., 2018). Within the latter field data, borehole images have inspired innovative image processing correlations to petrophysical properties by association of reservoir lithology as well as machine learning by pixel extraction. Particularly, extending correlations to oil saturation and 'digital rock technology' to the integrated database have proven high potential in the model's full implementation.

As binding element, functional application of 'artificial intelligence' in reservoir modelling has been reviewed and evaluated for its potential in solving the 'multiscale link', whilst attaining computational efficiency. The latter has reflected the logic of compiling the spatially integrated database with discretised data, along with formulation of algorithm learning and predictive processes. As a result, *Keras* and *XGBoost* 'machine learning' algorithms have been selected for their specific pattern recognition and predictive abilities. Whereas more involved LSTM algorithm has been validated from associated research to perform history matching phase of the envisioned workflow.

Invaluable contribution to industry consists in the petrophysical rationale, bridging subsurface physics and artificial intelligence. Untapped potential results from set methodology fundamentals and programming implications for simulating reservoir flow based on pore scale dynamic dependencies. From optimal selection of EOR technology and precise production strategy to kick-off similar integrated AI modelling, the groundworks to the 'multiscale link' are deemed crucial in efficiently attaining maximised oil recovery, thus unlocking energy assets.

Bibliography

Ahmed, T. (2010) *Reservoir Engineering Handbook, Reservoir Engineering Handbook*.

Akpokodje, M. et al. (2018) 'Regional study of controls on reservoir quality in the Triassic Skagerrak Formation of the Central North Sea', Petroleum Geology Conference Proceedings, pp. 125–136. doi: 10.1144/PGC8.29.

Al-Farisi, O. et al. (2019) 'Machine learning for 3D image recognition to determine porosity and lithology of heterogeneous carbonate rock', Society of Petroleum Engineers - SPE Reservoir Characterisation and Simulation Conference and Exhibition 2019, RCSC 2019, pp. 1–19. doi: 10.2118/196657-ms.

Amirmasoud Kalantari, D. and Shahab, D. M. (2009) 'Intelligent Top-Down Reservoir Modeling of New Albany Shale', in SPE Eastern Regional Meeting, pp. 282–287.

An, S. et al. (2016) 'Influence of pore structure parameters on flow characteristics based on a digital rock and the pore network model', *Journal of Natural Gas Science and Engineering*, **31**, pp. 156–163. doi: 10.1016/j.jngse.2016.03.009.

Anderson, W. G. (1987) 'Wettability Literature Survey-Part 5', *Journal of Petroleum Technology*, pp. 1453; 1454; 1466.

Baalawi, M., Gharbi, S. and Mahmoud, M. (2020) 'Modeling and prediction of resistivity, capillary pressure and relative permeability using artificial neural network', International Petroleum Technology Conference 2020, IPTC 2020, pp. 1-9; 20; 26. doi: 10.2523/iptc-19854-ms.

Balhoff, M. T. and Wheeler, M. F. (2009) 'A predictive pore-scale model for non-Darcy flow in porous media', *SPE Journal*, pp. 579–583. doi: 10.2118/110838-PA.

Baraboshkin, E. E. et al. (2019) 'Deep convolutions for in-depth automated rock typing', *arXiv*, pp. 1–24. doi: 10.1016/j.cageo.2019.104330.

Baraboshkin, E. E. et al. (2018) 'Core photos lithological interpretation using neural networks', in 20th International Sedimentological Congress, pp. 1–5.

Berg, C. F., Lopez, O. and Berland, H. (2017) 'Industrial applications of digital rock technology', *Journal of Petroleum Science and Engineering*, **157**(June), pp. 131–147. doi: 10.1016/j.petrol.2017.06.074.

Blunt, M. J. (2017) Multiphase Flow in Permeable Media, Multiphase Flow in Permeable Media. doi: 10.1017/9781316145098.

Buckley, J. S. and Liu, Y. (1998) 'Some mechanisms of crude oil/brine/solid interactions', *Journal of Petroleum Science and Engineering*, pp. 155–160. doi: 10.1016/S0920-4105(98)00015-1.

C. Soulaine; J. Maes; S. Roman (2021) 'Computational Microfluidics for Geosciences', *Frontiers in Water*, **3**, pp. 1–11. doi: 10.3389.

Chen, X. and Zhou, Y. (2017) 'Applications of digital core analysis and hydraulic flow units in petrophysical characterization', *Advances in Geo-Energy Research*, **1**(1), pp. 18–30. doi: 10.26804/ager.2017.01.02.

Chierici, G. L. (1994) Principles of Petroleum Reservoir Engineering, Principles of Petroleum Reservoir Engineering. doi: 10.1007/978-3-662-02964-0.

Dong, H. and Blunt, M. J. (2009) 'Pore-network extraction from micro-computerized-tomography images', *Physical Review E - Statistical, Nonlinear, and Soft Matter Physics*, pp. 1–11. doi: 10.1103/PhysRevE.80.036307.

Ganat, T. A. A. O. (2019) Fundamentals of reservoir rock properties, Fundamentals of Reservoir Rock Properties. doi: 10.1007/978-3-030-28140-3.

Gaskari, R., Mohaghegh, S. D. and Jalali, J. (2007) 'An integrated technique for production data analysis (PDA) with application to mature fields', *SPE Production and Operations*, **22**(4), pp. 403–416. doi: 10.2118/100562-pa.

Golparvar, A. et al. (2018) 'A comprehensive review of pore scale modeling methodologies for multiphase flow in porous media', *Advances in Geo-Energy Research*, **2**(4), pp. 418–440. doi: 10.26804/ager.2018.04.07.

Gomez, Y. et al. (2009) 'Top-Down Intelligent Reservoir Modeling (TDIRM)', in Proceedings - SPE Annual Technical Conference and Exhibition, pp. 1321–1331.

Hamon, G. (2000) 'Field-wide variations of wettability', in *SPE Reservoir Engineering (Society of Petroleum Engineers)*, pp. 1–6. doi: 10.2523/63144-ms.

Hey, T. (2012) 'The Fourth Paradigm – Data-Intensive Scientific Discovery', in *E-Science and Information Management*, pp. 3–8. doi: 10.1007/978-3-642-33299-9_1.

Hui, M. H. and Blunt, M. J. (2000) 'Effects of wettability on three-phase flow in porous media', *Journal of Physical Chemistry B*, **104**(16), pp. 3833–3845. doi: 10.1021/jp9933222.

Ian Goodfellow, Yoshua Bengio, A. C. (2016) Deep Learning - Ian Goodfellow, Yoshua Bengio, Aaron Courville - Google Books, MIT Press.

Iassonov, P., Gebrenegus, T. and Tuller, M. (2009) 'Segmentation of X-ray computed tomography images of porous materials: A crucial step for characterization and quantitative analysis of pore structures', *Water Resources Research*, **45**(9). doi: 10.1029/2009WR008087.

Jackson, M. D., Butler, A. P. and Vinogradov, J. (2012) 'Measurements of spontaneous potential in chalk with application to aquifer characterization in the southern UK', *Quarterly Journal of Engineering Geology and Hydrogeology*, **45**(4), pp. 457–459. doi: 10.1144/qjegh2011-021.

Kalantari-Dahaghi, A., Mohaghegh, S. D. and Khazaeni, Y. (2010) 'New insight into integrated reservoir management using Top-Down, Intelligent Reservoir Modeling technique; application to a giant and Complex Oil Field In The Middle East', in Society of Petroleum Engineers Western North American Regional Meeting 2010 - In Collaboration with the Joint Meetings of the Pacific Section AAPG and Cordilleran Section GSA, pp. 63–64. doi: 10.2523/132621-ms.

Lin, W. et al. (2017) 'Construction of Dual Pore 3-D Digital Cores with a Hybrid Method Combined with Physical Experiment Method and Numerical Reconstruction Method', *Transport in Porous Media*, **120**(1), pp. 227–235. doi: 10.1007/s11242-017-0917-x.

Liu, H. and Cao, G. (2016) 'Effectiveness of the Young-Laplace equation at nanoscale', *Scientific Reports*, (6), pp. 1–4. doi: 10.1038/srep23936.

Mohaghegh, S. D. (2011) 'Reservoir simulation and modeling based on artificial intelligence and data mining (AI&DM)', *Journal of Natural Gas Science and Engineering*, **3**(6), pp. 697–705. doi: 10.1016/j.jngse.2011.08.003.

Mohmad, N. I. et al. (2020) 'History matching of production performance for highly faulted, multi layered, clastic oil reservoirs using artificial intelligence and data analytics: A novel approach', in Society of Petroleum Engineers - SPE Asia Pacific Oil and Gas Conference and Exhibition 2020, APOG 2020, pp. 1–18. doi: 10.2118/202460-ms.

Piri, M. and Blunt, M. J. (2005) 'Three-dimensional mixed-wet random pore-scale network modeling of two- And three-phase flow in porous media. I. Model description', *Physical Review E - Statistical, Nonlinear, and Soft Matter Physics*, **71**(2). doi: 10.1103/PhysRevE.71.026301.

Ran, X. et al. (2019) 'Rock classification from field image patches analyzed using a deep convolutional neural network', *Mathematics*. doi: 10.3390/math7080755.

Rassenfoss, S. (2011) 'Digital rocks out to become a core technology', *JPT, Journal of Petroleum Technology*, **63**(5), pp. 36–41. doi: 10.2118/0511-0036-JPT.

Saxena, N. et al. (2019) 'Rock properties from micro-CT images: Digital rock transforms for resolution, pore volume, and field of view', *Advances in Water Resources*, **134**. doi: 10.1016/j.advwatres.2019.103419.

Silin, D. B., Jin, G. and Patzek, T. W. (2003) 'Robust Determination of the Pore Space Morphology in Sedimentary Rocks', in Proceedings - SPE Annual Technical Conference and Exhibition, pp. 2135–2136. doi: 10.2118/84296-ms.

Singh, H. (2019) Practical Machine Learning and Image Processing, Practical Machine Learning and Image Processing. doi: 10.1007/978-1-4842-4149-3.

Spaak, P. et al. (1999) 'Fulmar: A mature field revisited', *Petroleum Geology Conference Proceedings*, **5**, pp. 1089–1100. doi: 10.1144/0051089.

Yin, X., Zheng, Y. and Zong, Z. (2017) 'Research on the equivalence between digital core and rock physics models', *Journal of Geophysics and Engineering*, **14**(3), pp. 666–674. doi: 10.1088/1742-2140/aa6650.

Zhang, D. et al. (2018) 'Modeling and simulating of reservoir operation using the artificial neural network, support vector regression, deep learning algorithm', *Journal of Hydrology*, **565**(May), pp. 720–736. doi: 10.1016/j.jhydrol.2018.08.050.

Zhang, L. et al. (2015) 'Pore scale simulation of liquid and gas two-phase flow based on digital core technology', *Science China Technological Sciences*, **58**(8), pp. 1375–1384. doi: 10.1007/s11431-015-5842-z.

Zhao, B. et al. (2019) 'Comprehensive comparison of pore-scale models for multiphase flow in porous media', *Proceedings of the National Academy of Sciences of the United States of America*, **116**(28). doi: 10.1073/pnas.1901619116.

Zhou, Y., Hatzignatiou, D. G. and Helland, J. O. (2017) 'On the estimation of CO2 capillary entry pressure: Implications on geological CO2 storage', *International Journal of Greenhouse Gas Control*, **63**, pp. 26–28. doi: 10.1016/j.ijggc.2017.04.013.

Zhu, H. L. et al. (2018) 'Study of the numerical simulation of tight sandstone gas molecular diffusion based on digital core technology', *Petroleum Science*, **15**(1), pp. 68–76. doi: 10.1007/s12182-017-0210-1.