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Reservoir Rock Type Characterization and Prediction of the Lower Trias Argillaceous - Sandstone Reservoirs (Trias Argileux Greseux Inferieur: TAGI): Case Study of the Algerian Hassi Berkine Oil Fields

Option: **Reservoir Engineering**

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Abstract

Reservoir characterization is a set of parameters that describe the behaviour of the solid in relation to the porous medium. In the oil and gas industry, accurate reservoir characterization is a critical aspect of reservoir development and management. A strong understanding of reservoir characteristics should be required. Rock typing and petrophysical property prediction in uncored boreholes are two important reservoir characterization processes. Uncertainties in determining these characteristics can affect the expectations in different topics: well performance, reservoir potential, and reservoir behaviour. Overall, it has an impact on the quality of studies presented for field development and optimization, as well as increasing technical and economic risks.

The aim of the endorsed research, for the case study, is focusing on improving the characterization of the Lower Triassic argillaceous sandstone reservoirs (TAGI). The investigation focuses mainly on the application of different approaches to rock typing for the determination of the optimal number of reservoir rock types (RRT). The concerned method was based on determining lithofacies and petrofacies. Among logging tools, the gamma-ray logging device was utilized. Its role was to identify and classify lithofacies based on core descriptions and cuttings. As outcomes, four lithofacies have been identified: shale (argillaceous), shaly sandstone, sandstone, and clean sandstone. The petrofacies were determined using a variety of approaches, including the flow zone indicator (FZI), discrete rock type (DRT), pore throat radius (R35), discrete pore throat (DRT-R35), and global hydraulic element (GHE) methods. The FZI approach has been revealed to be the most effective and reliable mode for determining reservoir rock types in TAGI formations. Capillary pressure profiles (Pc), relative permeability curves (Kr), and water saturation (Sw) profiles have constituted a particulair and further classification methodologies for this investigation. These techniques yielded the same categorization results as the FZI-applied method. Depending on the simulation objectives, the DRT method was chosen to have a minimum number of reservoir rock types. RRT in the TAGI formation for the Hassi Berkine oil field has been classified into four lithofacies and eight petrofacies, with no compatibility between lithofacies and petrofacies.

Therefore, the development of a mathematical model has become more than necessary to find out a technique permitting the determination of petrophysical properties in non-core zones. The main rock properties are porosity, permeability, and water saturation. The use of conventional well logs can be an efficient tool for porosity and permeability expectations. While, the use of deep and shallow resistivity logs combined with porosity logs, may be more suitable for water saturation prediction. The porosity is computed using a variety of approaches, including conventional methods, regression methods, and neural network techniques. Regression and machine learning approaches are also being developed with the intent to describe the relationship between FZI and conventional well logs. The radial basis neural network was found to be the best solution for predicting porosity and FZI and, consequently, the permeability of TAGI sandstone formations. Therefore, and additionally and as a result, this procedure can be extended to predict water saturation.

الملخص

توصيف المكمن عبارة عن مجموعة من الخصائص التي تصف سلوك المادة الصلبة فيما يتعلق بالوسط المسامي. في صناعة النفط والغاز، يعد الوصف الدقيق للمكامن جانبًا هامًا من جوانب تطوير المكامن وإدارتها. يجب أن تكون هناك حاجة إلى فهم قوي لخصائص المكمن. يعد تعريف انواع الصخور والتنبؤ بخصائصها البتروفيزيائية في الآبار غير المختبرة عمليتين مهمتين في توصيف المكامن. يمكن أن تؤثر حالات عدم اليقين في تحديد هذه الخصائص على التوقعات في موضوعات مختلفة: أداء البئر ، وإمكانات المكمن وسلوكه. بشكل عام, لها تأثير على جودة الدراسات المقدمة لتطوير الحقول وتحسينها ، فضلا عن زيادة المخاطر التقنية والاقتصادية.

يهدف هذا البحث الى تحسين توصيف مكمن الحجر الرملي الطيني السفلي (TAGI) لحوض حاسي بركين. يركز البحث بشكل أساسي على تطبيق الأساليب المختلفة لتعريف الصخور لتحديد العدد الأمثل لأنواع صخور المكمنRRT. اعتمدت هذه الطريقة على تحديد الليثوفاسيات و البتروفاسيات. يمكن استخدام العديد من أدوات التسجيل من بينها استخدام أشعة جاما التي تعتمد وظيفتها على وصف العينات و القطع الصخرية. نتيجة لذلك ، تم تحديد أربعة انواع من الصخور: الصخر الطيني ، الحجر الرملي الطيني ، الحجر الرملي ، والحجر الرملي النقي. أما بالنسبة للبتروفاسيات, فقد تم تحديدها باستخدام طرق مختلفة من بينها: مؤشر منطقة التدفق (FZI) ، نوع الصخور المنفصلة (DRT) ، نصف قطرالمسام (R_{35}) ، القطر المسامي المنفصل (DRT_R35), والوحدة الهيدروليكية العامة (GHE). تم الكشف أن نهج FZI هو الطريقة الأكثر فعالية وموثوقية لتحديد أنواع صخور المكمن في تكوينات TAGI. يمكن اعتبار ملامح الضغط الشعري (Pc) ، منحنيات النفاذية النسبية (Kr)، وملامح تشبع الماء (Sw) كمنهجيات تصنيف اضافية لكونها تعطي نفس نتائج طريقة FZI المطبقة.

اعتمادًا على أهداف المحاكاة، تم اختيار طريقة DRT للحصول على الحد الأدنى من أنواع صخور المكمن. تم تصنيف RRT في حقل حاسي بركين إلى أربعة ليثوفاسيات وثمانية بتروفاسيات ، مع عدم وجود توافق بين الليثوفاسيات والبتروفاسيات. لذلك صار لزاما تطوير نموذج رياضي لإيجاد تقنية تسمح بتحديد الخصائص البتروفيزيائية في المناطق الغير المستكشفة. تعتبر المسامية والنفاذية وتشبع الماء هي الخصائص الرئيسية للصخور. يمكن أن يكون استخدام سجلات الآبار التقليدية أداة قوية لتقدير المسامية والنفاذية، في حين أن استخدام سجلات المقاومة العميقة والقريبة جنبًا إلى جنب مع سجلات المسامية قد يكون أكثر ملاءمة للتنبؤ بالتشبع بالمياه. تم حساب المسامية باستخدام مجموعة من الطرق من بينها: الطرق التقليدية وطرق رياضية وتقنيات الشبكة العصبية. يليها تطوير نماذج رياضية والتعلم الآلي لوصف العلاقة بين FZI وسجلات الآبار التقليدية. أثبتت الشبكة العصبية ذات الأساس الشعاعي أنها الحل الأفضل للتنبؤ بالمسامية و FZI ، وبالتالي النفاذية في تكوينات الحجر الرملي. لذلك يمكن استخدام هذه الطريقة للتنبؤ بتشبع الماء في المناطق الغير المستكشفة.

Résumé

La caractérisation du réservoir se base sur en ensemble de paramètres décrivant le comportement de la fraction solide par rapport au volume poreux. Dans le domaine des hydrocarbures (H – C), la caractérisation d'un réservoir consiste en l'aspect aspect du développement et de la gestion des réservoirs considérés. Une compréhension consistante des caractéristiques du réservoir devrait être requise. Le Rock Typing et la prédiction des propriétés pétrophysiques dans les puits non carottés peuvent être deux processus importants de caractérisation des réservoirs. Les incertitudes dans la détermination de ces propriétés peuvent influencer les prévisions d'une évaluation du réservoir et ce selon plusieurs domaines : performances des puits, potentiel du réservoir et comportement du réservoir. L'impact important dans cette considération est la qualité des études présentées pour le développement et l'optimisation du champ. Un important focus et non négligeable s'oriente sur les risques techniques et économiques.

L'objectif de cette recherche se focalise sur l'amélioration de la caractérisation du réservoir Trias Argileux Gréseux Inférieur (TAGI) de la plateforme Saharienne (champ de Hassi Berkine). L'investigation menée se concentre principalement sur l'application de différentes approches de Rock Typing pour la détermination du nombre optimal de types de roches réservoirs (RRT). La méthode en vue était basée sur la détermination des lithofaciès et pétrofaciès. Plusieurs outils de diagraphies peuvent être utilises, parmi lesquels, il y a l'utilisation de l'outil Gamma Ray. Sa fonction était d'identifier et de classer les lithofaciès à partir de la description des carottes et des déblais de forage. L'application a mené à la détermination de quatre lithofaciès : argile, argile-gréseux, grès et grès propre. Quant aux petrofacies, elles ont été déterminés à l'aide de diverses approches, notamment l'indicateur de zone d'écoulement (FZI), le type de roche discrète (DRT), le rayon de gorge de pore (R_{35}), la gorge de pore discrète (DRT_R_{35}) et l'élément hydraulique globale (GHE). L'approche FZI s'est avérée être la méthode la plus efficace et la plus fiable pour déterminer les types de roches réservoirs du Trias Argileux Gréseux Inférieur (TAGI). Les profils de pression capillaire (Pc), les courbes de perméabilité relative (Kr) et les profils de saturation en eau (Sw) ont constitué des procédés de classification spécifiques et complémentaires pour mener cette étude. Ces techniques ont donné les mêmes résultats de catégorisation que la méthode FZI.

En fonction des objectifs de simulation, la méthode DRT a été choisie pour avoir un nombre minimum de types de roches réservoirs. Les RRT dans la formation Trias Argileux Gréseux Inférieur (TAGI) pour le champ de Hassi Berkine ont été classée en quatre lithofaciès et huit pétrofaciès, sans aucune compatibilité entre lithofaciès et pétrofaciès. Pour une manière cohérente et harmonieuse, le développement d'un modèle mathématique est devenu plus que nécessaire. Ce modèle suggéré a pour but de trouver une technique permettant de déterminer les propriétés pétrophysiques particulièrement dans les zones non carottées. Il est connu que les principales propriétés des roches sont la porosité, la perméabilité et la saturation en eau. L'utilisation de diagraphies de puits conventionnelles peut être un outil puissant pour estimer la porosité et la perméabilité. Bien que l'utilisation de diagraphies de résistivité d'investigation peu profondes et profondes combinées aux diagraphies de porosité puisse d'être plus appropriée surtout pour prédire de la saturation en eau. La porosité est calculée à l'aide de plusieurs approches, y compris des méthodes conventionnelles, des méthodes de régression et des techniques de réseau neurones. Les approches de régression et d'apprentissage automatique sont également développées pour décrire la relation entre le FZI et les diagraphies conventionnelles. Le réseau de neurones à base radiale s'est avéré être la meilleure solution pour prédire la porosité et le FZI, et par conséquent, la perméabilité des formations gréseuses. De ce fait, cette méthode additionnelle peut être étendue pour prédire notamment la saturation en eau.

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Introduction

Reservoir characterisation is an important phase in reservoir development, monitoring, and management, as well as production optimization. To gain a solid understanding of the reservoir properties, all information from various sources, including seismic, logging, core data, well testing, wire-line formation tests, and production data, must be collected. The best model is one that provides quantitative reservoir properties, which is often difficult to produce. The development of a reservoir model involves various steps that are dependent on the applied conceptual studies. Each of these studies has an impact on the modelling process in some way, as seen by issues with numerical model stability, convergence, and efficiency.

For that purpose, particular studies have been established with the goal of having a more solid, consistent, and coherent model, as well as to promote flexibility in the intelligent mixing of diverse modelling approaches. Among these topics are the conceptual processes utilized in reservoir characterization, such as seismic, sedimentological, and logging interpretations, core analysis, rock typing, and dynamic modelling procedures such as reservoir fluid characterization, rock-fluid model specification, and initial condition identification. Reservoir characterization, with its three modules of seismic interpretation, rock type, and petrophysical property prediction, and geostatistical study, is the most important parameter in the context of a technically probabilistic function that provides a larger source of uncertainty.

The primary parameters, determining rock typing uncertainty in this investigation, are rock solids textural and fractional composition. Additionally, fluid-flow filling of the porous medium and its characteristics are likely a part of contribution. These all factors may have a significant impact on the assessment of the original oil in place, distribution of oil saturation, reservoir potential and behaviour, and well performance. The latter's determination becomes the focus of this research. Therefore, the following figured out steps may constitute the tasks intended for being approached during our investigation. These considered outcomes may dispel results with various uncertainties:

- Data gathering and quality control.
- Rock type identification based on the integration, analysis, and synthesis of data from logs and core analysis. Three major steps will be followed to identify and assign reservoir rock types (RRT).
    - Lithofacies determination based on shale volume calculation from gamma rays (GR),
    - Petrofacies determination based on a comparative analysis of several rock type classification methodologies such as flow zone indictors (FZI), discrete rock typing (D.R.T), pore throats (R_{35}), discrete pore throats (DRT_R_{35}), global hydraulic element (GHE), capillary pressure (Pc), saturation height function above free water level (HFWL) and relative permeability (Kr). In that concern, the optimal approach will be related to the best permeability evaluation.
    - Rock type assignment, based on the compatibility between lithofacies and petrofacies is another step to be considered.

- Interest will focus on the prediction of porosity using conventional methods, regression methodologies, and radial neural network techniques.
- Attentiveness is to: predict the flow zone indicator (FZI) from conventional well logs (gamma ray, neutron porosity, density log, and sonic) using regression methods and radial neural network techniques.
- Prediction of well log permeability based on the rock type categorization method.
- Prediction of water saturation using a radial neural network with porosity and resistivity records.

Document Organization

The work is structured as follows: It begins with a general introduction that presents the problem, the purpose, and the plan, followed by a bibliographical investigation that traces the history of the development of the various reservoir characterization methodologies. The first chapter addressed the theoretical aspects of static and dynamic modelling, as well as the data sources used in the modelling and procedure for building the reservoir model. The second chapter covers the fundamental concept of rock typing, the data required, and the techniques that can be used for reservoir rock type determination. It closes with the incorporation of machine learning techniques for reservoir characterisation, rock type determination, and prediction.

The third chapter is devoted to the characterisation of reservoir rock types for our case study. The various characterisation procedures are detailed in-depth, including lithofacies identification, petrofacies determination, and rock typing assignment. Several rock-type techniques have been investigated in order to select the optimum number of rock types for which the estimated permeability fully converges to the core permeability.

The fourth chapter is assigned to determining porosity using conventional methods, the regression approach, and the radial basis neural network, followed by the permeability prediction. The latter is based, firstly and essentially, on the calculation of the flow zone indicator (FZI) from standard well logs (gamma ray, neutron, density, and sonic) using the regression approach and a radial basis neural network. These approaches were tested to determine the optimal alternative for porosity and FZI prediction. Once the function is defined, the permeability is calculated using the rock typing approach. As a radial basis, the neural network is the best solution for porosity and FZI determination. This method has been applied to predict water saturation by the use of porosity and resistivity well logs. Finally, a general conclusion will be coating the overall concerned research.

Research History

The development of an oil field is a set of activities that includes research on exploration, development, and exploitation of hydrocarbons (Dada, M. A. et al., 2020). These activities began with the exploration and analysis of deep sedimentary basins in order to characterize these basins and develop an integrated model to better seize opportunities for better planning and prediction of the most efficient and appropriate mechanisms for future project application (Guido, L., Carpio, T. and Margu, M. V., 2007). In this regard, a study of all possible concepts for the field's development will be conducted in order to identify the spatial and temporal characteristics from which guidelines for the technical-economic context can be developed (Santos, S. M. G., et Al., 2018). This necessitates comprehensive research of the reservoir geology, reservoir type, fluid type, and the plant's constraints.

To respond to the most diverse technical constraints of the project development, it was necessary to reduce the degree of uncertainty that resulted from different steps; data collection, reservoir modelling and characterisation, field development, and a forecasting study (Ian Lerche, and James A. MacKay, 1999). One of the phases with a high degree of uncertainty is reservoir modelling and characterization (Y. Zee Ma, 2011). For this purpose, several authors have worked on that topic to improve reservoir characterisation and modelling, thereby reducing the uncertainties (Bryant, I. D. & Flint, S. S., 1992), (Haldorsen, H. H. and Damsleth, E,, 1993) and (John Archer, 1998).

Petroleum system characterization is given by understanding, defining, determining, modelling, and specifying all physical, mechanical, and chemical properties in order to cover all assumptions related to the objectives, reflect the evolution of best practices, and better understand the strengths and limitations of the root data (Amaral, J. et Al., 2003). Indeed, reservoir characterization is the process of specifying the physical and chemical properties of the fluid-rock system, which includes the entire chain of exploration, development, and production and allows for a more robust model centered on oil field development studies (Homuth, S. et Al., 2015). These characteristics facilitate the determination of the key points and limits of the data used for reservoir studies. Generally, these studies are based on various scientific approaches to information meaning, comprehension, and application. Indeed, each domain has its own understanding and appreciation of physical phenomena, which can lead to differences in explanation and interpretation.

Several authors have addressed the processes involved in the characterization of a porous medium, as well as its comprehension and quality (Guerreiro, L. et Al., 2000), (Arnold, A. et Al., 2013), and (Anifowose, F., et Al., 2014). The evaluation of the reservoir quality beyond the areas covered by the boreholes is one of the critical aspects of evaluating the prospect of an identified field or its development. The latter's quality assessment is effectively based on the search for logical relationships between data from various sources (Kupecz, J. A., et Al., 1997). Several studies on this effect have been conducted due to the large amount of data sources such as; geology, geophysics, sedimentology, petrophysics, fluid, and rock - fluid relationship (Oliver, Ds, 1994), (Nikravesh, M., and Aminzadeh, F., 2001), and (MacGregor, L., and

Andreis, D., 2012). These studies enable the identification of the various processes involved in the reservoir characterization.

Recent reservoir characterization studies have used seismic data to systematically identify structural traps likely to accumulate hydrocarbons, as well as logging data to calibrate the petro-physical well models and validate the geostatistical model used (Oldenziel, A. et Al., 2001). Seismic inversion can also be used to provide a geometric description of the reservoir's structural and stratigraphic features (Ameloko, A. A. and Omali, A. O., 2013). Furthermore, according to Torres, A., and Reverón, J., (2014), the combination of rock physics and geostatistical methods with seismic inversion results allowed for the generation of lithological discrimination, which allows for preliminary interpretations of the depositional environment as well as the determination of relationships between lithologic facies and reservoir elastic properties (Torres, A., and Reverón, J., 2014). Therefore, acoustic impedance can be used to determine lithology, porosity, and even the presence of hydrocarbons. Thus, it can also be used for qualitative and quantitative reservoir analysis (Koesoemadinata, A. et Al., 2008).

An in-depth study of the logs was conducted by Wong, K. W. et Al., (2005) in order to provide an accurate picture of the petrophysical properties. This survey provided answers to questions about petrophysical properties and the parameters that control them, such as lithology, clay volume, texture, compaction, and saturation, as well as a diagram of the liquid-solid relationship (Wong, K. W. et Al., 2005). For better subsequent interpretations and conclusions, log interpretations should be calibrated using source data (Al-Baldawi, B. A., 2016). This data is critical for delimiting reservoir units, estimating useful thickness, and determining a hydrocarbon deposit's production potential (Wong, K. W. et Al., 2005). To link permeability to rocks with similar depositional environments, geological information from core descriptions such as lithology, including diagenetic, petrographic, sedimentological, and even geomechanical information, is essential (Al-Amri, M. et Al., 2017).

Outcrop samples can be a valuable source of data for reservoir studies involving observations of sedimentary structures and changes in lateral facies. These can also be used to predict the porosity and permeability of subsurface reservoirs by understanding the history of burial and the roles of various diagenetic processes on reservoir properties. Outcrop analogue studies allow for the prediction of reservoir properties by determining and correlating physical and petrophysical parameters related to lithofacies and their behaviour in relation to various subsurface changes (Al-Laboun, A. et Al., 2013). Another classification based on the thermal formations of the carbonate formations can be made to determine heterogeneities and production areas. Describing the texture in combination with the rock content is another scheme for producing rock types of similar reservoir quality (Homuth, S. et Al., 2015).

However, complications can arise when evaluating reservoir parameters, particularly in non-core areas where one of the basic records is missing. This can make predicting petrophysical properties more difficult. To this purpose, a synthetic model has been developed by Artun, E. et Al., (2005) based on the application of neural networks to predict the missing logs. This led approach has been implemented in Buffalo Valley Field to predict neutron porosity and density logs using seismic and recorded well logs (Artun, E. et Al., 2005). Parallel to the porosity

determination, where the density and neutron logs are indispensable, permeability can be calculated primarily by the application of porosity-permeability correlations inferred from core data. The addition of useful saturations can also be another factor for the permeability prediction log (Schlumberger, 1986).

According to that, Archie (1950) proposed a new approach based on the grouping of rocks of the same facies, with similar diagenesis and nearly identical petrophysical characteristics in the same rock type. These classes are assumed to have the same electrical properties, mineralogy, radioactive and nuclear properties, and fluid behaviour vis-à-vis the rocks, as well as their interaction (Archie, G. E., 1942). This method is most likely used to forecast permeability and water saturation.

Due to the importance of understanding rock properties at the pore scale, the modified Kozni-Karman equation (1996) was the most commonly used technique to model permeability. However, this technique can underestimate permeability in good-quality sands and overestimate it in poor-quality sands, leading to the development of other models based on reservoir rock and fluid properties and their interactions (Bagheri, A.M. and Biranvand, B., 2006). Several studies have been conducted on this basis to determine the rock properties, classify them, and determine their effect on permeability. Reservoir rock types are conceptually defined by depositional facies sequences, diagenetic overprint, and petrophysical properties such as pore size distribution, porosity, and permeability (Silva, F. P.T., et Al., 2002). On this substance, a new science known as "rock typing" has emerged, which is based on connecting conclusions from all disciplines, including geology, petrophysics, and reservoir engineering (Gomaa, N. M. et Al., 2006). Due to the standards followed in each specialty, the conclusions are frequently different. A geologist, for example, uses basic description and analysis in cored wells to classify rock types based on similar depositional and diagenetic settings and labels them as lithofacies. While petrophysicists divide rocks into electrofacies based on comparable responses from well logging measurements, each of the latter is given a number that indicates an electrical unit of the rock (Woan Jing Teh et Al., 2012). The reservoir engineer, on the other hand, uses pore size distribution, capillary pressure, relative permeability curves, and wettability to distinguish between rock types (Asgari, A. A. and Sobhi, G. A., 2006).

According to J.A. Rushing et al., the identification, comparison, and combination of these three rock types is fundamental to the entire rock typing process (Rushing, J. A. et Al., 2008). These rock types are as follows:

- Lithofacies are defined as mappable stratigraphic units that can be differentiated laterally from adjacent intervals based on lithological characteristics such as mineralogical, petrographic, and paleontological signatures associated with rock appearance, texture, or composition. Facies, or geological facies, are terminology that defines comparable rock types (Lee, J., 2018).
- Electrofacies are defined as a similar set of differentiated log responses that can be discriminated and adapted to rock classification based on the electrical properties, thereby characterizing a specific rock type and helping to distinguish it from others (John C. Davis, 2018). Electrofacies are clearly influenced by geology and can often be

ascribed to either lithofacies, despite the fact that the correlation is not always uniform (Edyta Puskarczyk, 2019).

- Petrofacies are defined as rock intervals with similar mean pore radius and thus fluid dynamic behaviours. All definitions of rock types focused on attempting to establish the link between: pore structure (dimension, geometry, size, distribution, etc.) and petrophysical properties such as effective porosity and absolute permeability, with each rock category having the same pore edifice and dynamic behaviour (Al Ameri, M. B. and Shebl, H., 2011).

Diverse data sources and data types, such as logging, routine core analysis (CCAL), and special core analysis (SCAL), must be integrated into the rock typing process. Furthermore, the link between the type of rock defined at the well levels and the type of deposit medium is an important task for having a better facies distribution in the reservoir model (Gomes, J. S. et Al., 2008). Rock type distribution maps can be used as devices to identify areas with reference to the quality reservoirs. Established maps, with the facies distribution sourced from the sedimentological, petrographic approaches, core analysis, seismic, and logging outcomes may enable the probable identification of reservoir limits and potential drilling locations. In numerical reservoir modelling, grouping similar rock types has proven to be an excellent method for defining the number of simulation layers (Porras, J. C. et Al., 2001).

According to the literature, the rock typing process started with determining sedimentary and diagenetic rock types through petrographic studies of thin sections prepared from cores and cuttings, followed by determining electrofacies based on rock classification (Benzagouta M.S , 1991), and (Benzagouta M. S., et Al., 2001). Responses should be logged using an appropriate classification algorithm (Turkey, S. et Al., 2012). Porosity logs (NPHI, DT, and RHOB), litho - density logs (PEF), and gamma ray logs are used to determine electrofacies. The overall process leads to the determination of hydraulic units in addition to the pore size distribution analysis. Accurate pore size estimation improves reservoir simulation, process evaluation, and subsequent reservoir behaviour prediction (Tonietto, S. N. et Al., 2014).

In recent years, several methods and technologies have been introduced in the petroleum geosciences to predict the permeability from open well logs using source data; Devices such as wire-line formation tests (MDT/RFT/XPT/RDT/RCI), and well testing, in that topic, are anticipated to ensure suitable reservoir management, define a well completion strategy and improve the forecasting (Kharrat, R. et Al., 2009), (Belhouchet, H. E. et Al., 2021). The main issue, discovered during the reservoir characterization process, is the degree of uncertainty in determining permeability (Ghafoori, M. et Al., 2008). To reduce these uncertainties, several studies based on the rock typing process have been conducted to develop mathematical models that can predict permeability in non-cored zones using data from cores, well logs, and, in some cases, seismic data (Kadkhodaie, A. and Kadkhodaie, R., 2018). This procedure is primarily concerned with the classification of reservoir rock types, each of the preceding cited focuses is represented by a mathematical model. The number of rock types may have a significant impact on permeability prediction, and can be related to reservoir complexity settings. In addition, to deal with increasing geological complexity and understand the property distribution in

heterogeneous reservoirs, a rock-typing concept has been developed by (Fernando P.T. Silva et Al., 2002). In that concept, a typical reservoir model necessitates accurate characterization in terms of lithology, porosity, and permeability, beside hydrocarbon saturation.

In clastic reservoirs, the heterogeneity of sandstone is strongly affected by the depositional environment and the diagenetic processes that govern rock texture, such as grain size and shape, pores interconnection, grain contact, compaction, and sorting. The mineral contents, including clay content and mode of occurrence, are part of the effect on the shape, size, and pore interconnectivity. Understanding the geometry and structure of pores is essential to manage reservoir heterogeneity (Musu, J. T. et Al., 2007). Thus, a detailed sedimentary description of the deposition environment as well as a petrographic analysis are essential topics (Turkey, S. et Al., 2012). Multi-scale imaging can provide rapid complementary resources to characterize the distribution and nature of different types of pores and matrix components (Benzagouta M.S , 1991**),** and (Benzagouta M. S., et Al., 2001). Moreover, obtained results can improve the understanding of physical lithology, fracturing, and multiphase flow in atypical reservoirs (low porosity and permeability) (Benzagouta M.S & Amro M, 2007), and (Knackstedt, M. et Al., 2012). These petrophysical properties are closely related to pore geometry and are determined by both the Leveret function (the J function) and the Thomeer G factor (Xu, C. and Torres-Verdin, C., 2012).

In 1941, Levrette introduced the notion of J-function to group rocks with the same normalized capillary pressure in the same set (Fournier, F., et Al., 2013). This function is inversely proportional to the reservoir rock tortuosity. This relationship can be interpreted as an indicator of the similarity of tortuosity for a number of capillary pressure rock samples that can be represented by a single J function curve (Musu, J. T. et Al., 2007). According to that, the J function can be related to the capillary pressure, the rock quality index (RQI), and the mean pore radius. Rock quality index (RQI) and flow zone indicator (FZI) are implemented to characterize pore geometry and structure in correlation with microscopic geological features (Musu, J. T. et Al., 2007). In addition, the pore geometry factor (Thomeer factor G) can also be used to quantify the quality of the reservoir in terms of pore geometry (Xu, C. and Torres-Verdin, C., 2012).

Pore characteristics play an important role in controlling the initial and residual hydrocarbon distributions. Thus, pore structure scrutiny refers to its geometry, size, distribution and its interconnected relationship to rock bulk pores, mineralogy, and rock texture (Yan, Z. et Al., 2015). Thus, pore structure characterization parameters are associated with porosity, pore size distribution, and pore characteristics of the rock (Benzagouta, M.S., 2015). In this regard, several methods have been developed to characterize rock pore structure using data obtained from mercury injection tests (Nabawy, B. S. et Al., 2009) and (Al-Khidir, K. E. et Al., 2011).

In 1970, Winland developed an empirical relation between porosity and air permeability, which makes it possible to calculate the pore radius corresponding to a non-wetting phase with mercury injection. In that regard, a mixed set of sandstones and carbonates, with more than 312 samples was used. Multiple regression analyses for other mercury saturation values (10% 20%, 30%, and up to 90%), were performed. The best correlation corresponding to the pore size of

these samples is that of 35% mercury saturation. This correlation is chosen based on the highest correlation coefficient. This correlation is therefore two-way: calculation of pore radius, and determination of hydraulic units (Lafage, Stephanie Isabelle, 2008).

A similar approach was developed by Amaefule et al. (1993) for the determination of hydraulic units (HFU), using a flow zone indicator (FZI). This method consists of plotting the RQI as a function of $\emptyset_z$ on a logarithmic scale. All boards with the same FZI will be on the same linear slope straight line. The intersection of unit slope linen with $\emptyset_z = 1$ determines the FZI value of each group. Boards that have the same FZI have the same hydraulic unit (Amaefule, J. O. et al., 1993). For determining the optimal number of hydraulic units, a set of mathematical tools can be implemented, including histogram analysis, a normal probability plot, and the least squares regression method. According to Mahjour et al., (2015), and Hesham Abdulelah et al., March (2018), flow zone indicator (FZI) histogram analysis can be a quick method for determining the number of hydraulic flow units (Mahjour, S. K. et Al., 2015) and (Abdulelah, H., et Al., 2018). This number can be corresponded to the number of normal distributions in the histogram plot of log(FZI). For further investigation, the probability method can be applied. This approach is based on the plot of log FZI against the cumulative FZI. The number of significant lines observed in the normal probability curves can be represented by the number of hydraulic flow units (Mahjour, S. K. et Al., 2015).

Several restatements of the linear regression analysis between the rock quality index (RQI) and the normalized porosity ($\emptyset_z$) were approximated in order to optimize the number of HFUs. Correlation coefficients (R^2) can also be used to determine the optimal number of HFUs (Abdulelah, H., et Al., 2018). Furthermore, Corbett, P. W. M. and Potter, D. K. , (2004) propose another petrotype approach for determining the number of rock types required for reservoir description and which can be used for permeability prediction. This method is based on determining global hydraulic elements (GHE) by using specific FZI values as boundaries between grain size classes, similar to how certain ranges of median grain sizes are used to define grain size classes in sedimentology (Corbett, P. W. M. and Potter, D. K. , 2004). In numerical simulation models and in order to have the minimum number of rock types, Shamsuddin H. Shenawi et al. (2007) and E. Tillero (2012) converted the continuous values of the zone flow index (FZI) and the mean pore radius calculated from Winland's method into discrete values (Genliang Guo, et Al., 2007), (Shamsuddin H. Shenawi, et Al., 2007) and (Tillero, E., 2012).

The identification of reservoir rock types and their most significant vertical and horizontal heterogeneities is a critical step in the reservoir characterization process. It is one of the main input parameters in geological and flow simulation models (Bagheri A.M. et Biranvand B. , 2006). Vertical changes in rock types are ascertained by depositional facies, whereas downstream lateral variations in structure within the same lithofacies unit are primarily determined by diagenesis (Fernando P.T. Silva et Al., 2002). The impact of diagenesis on the pore system is evaluated by examining pore types, cement textures, dissolution characteristics, and dolomitization (Tonietto, S. N. et Al., 2014) and (Amro, M. and Benzagouta, M.S., 2009). For this purpose, Lucia (2003) developed a new method of rock typing for carbonate reservoirs

based on the porous space, which consists in classifying rocks with the same rock fabric number (RFN) in the same rock type (Palabiran, M. et Al., 2016). Therefore, the pore geometry, which represents the hydraulic unit, and the pore structure of the rocks, which represents the hydraulic conductivity, have a strong influence on the rock quality. Depending on the relationship between these two parameters, Wibowo and Permadi (2013) developed a Pore Geometry Structure (PGS) approach which is effectively based on the generation of typical curves (Wibowo, A.S. and Permadi, P., 2013). These curves are derived from rocks with similar geometry and porous structure that are classified as belonging to the same rock type interval (Palabiran, M. et Al., 2016), (Prakoso, S. and Winardhi, S., 2017) and (Haikel, S., Rosid, M. S. and Haidar, M. W. , 2018).

Chapter 1: Reservoir Characterization and Modelling: General view

1-1 Introduction

Reservoir modelling is a process of understanding, characterizing, and constructing the reservoir through the integration of all available, reliable, and appropriate data from different sources into 3D geocellular and numerical models (Ma, Y. Z., 2019), (Rusty, J. G. et Al., 2004). Reservoir data can be classified into two categories, static and dynamic data according to the type, origin and behaviour of these data. Data originated from geology, logs, core descriptions, and 2D/3D seismic can be considered static data, whereas information derived from well testing, special core analysis, 4D seismic, and reservoir production data can be considered dynamic data (Landa, J. L. et Al., 1996). The use of all this information is becoming necessary in the oil and gas industry to construct a reservoir model that reflects geological understanding, simulates dynamic behaviour, and predicts optimum operating conditions for oil recovery (Knut Bjorlykke, 2015). The main objective of this chapter is to provide a general review of the reservoir characterization and modelling, present the necessary input data, define the quality control and quality check tasks, and illustrate geological and dynamic modelling workflows.

1-2 Input Data and Databases

Several types of data can be used and incorporated for the reservoir characterization, including seismic data, outcrop data, core data, well logs, PVT data, and well testing (Figure 1-1). These data can be represented according to the source by different scales. In the reservoir modelling process, information at different scales must be brought to a reference scale so that the data is consistent. In order to ensure the consistency and representativeness of the reservoir model, it is also necessary to verify the quality of the data. In addition, the integration of dynamic data with static data can improve the quality of the reservoir model (Cunha, L. B., 2004). There are numerous data sources that can be utilised for reservoir modelling such as:

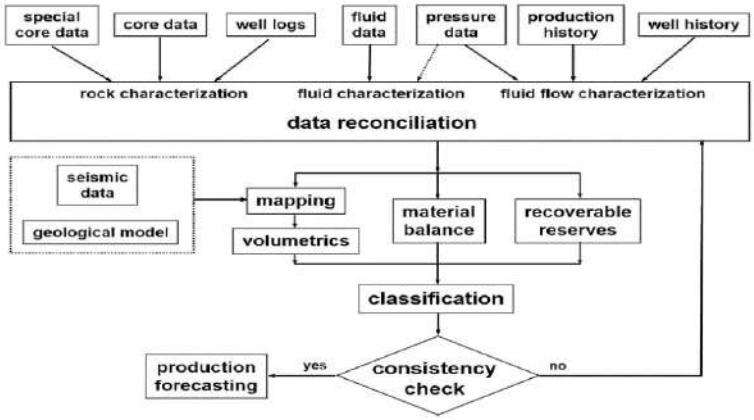

Figure 1-1: Components involved in the reservoir characterization process **(Baker, R. O. et Al. , 2015)**.

1-2-1 Seismic Data

Seismic data is a set of measurements for the wave signals that emanate from a source on the surface and they are reflected by the subsurface layers and there are recorded again by the receivers on the surface (Dean S. Oliver et Al., 2008). Seismic data are necessary for reservoir characterization and modelling because the interpretation of these allows to build the structural and stratigraphic models, providing global information on the formation thickness, defining the depositional environment, and defining the location of faults (Roger M. Slatt, 2013). For mature oil fields, an advanced seismic survey allows an exploration of undrained hydrocarbon areas and therefore provides suggestions for zones where new wells may be drilled. In addition, 4D seismic data can provide additional information on reservoir behaviour during production (Knut Bjorlykke, 2015).

1-2-2 Outcrops and Basin Studies

An outcrop is a set of rocks not separated from the subsoil being exposed by a set of factors such as hydraulic erosion, glacial, marine, or human activity without being masked by surface formations such as soil, scree, alluvium, wind, or glacial deposits (Pyrcz, M. J. and Deutsch, C. V., 2014). Outcrops can provide a unique opportunity to observe rock on the surface and take samples to get an accurate representation of the stratigraphic sequence that has been difficult to obtain in the subsurface (Lucia, F. J. , 2002). Reservoir rock outcrops can be used to provide complementary information on the geometry and texture of sedimentary bodies and their internal heterogeneity, as well as to detect minor faults (Merchán, S. A. et Al., 2002). The description of outcrops and cores in combination with textural and mineral analyses of the rock can be used for the interpretation of the diagenetic reactions that occur during the progressive burial in a sedimentary basin (Knut Bjorlykke, 2015).

1-2-3 Well Data

Well data is defined by the information that are related directly or indirectly to the well characteristics that could be extracted from different physical aspects such as; wellbore path, well logs, core description, core photographs, core plug data, reservoir zonation, and pressure data (Steve Cannon, 2018). The necessary well data needed for reservoir characterisation and modelling can be defined as follows:

1-2-3-1 Wellbore path

The well path is defined by the location of the well (x, y, z) in the surface area in the desired exploration block, the depth, the azimuth, and the angle from the vertical (Figure 1-2), to have a real localisation of the well in the reservoir (Wise, J. et Al., 2020).

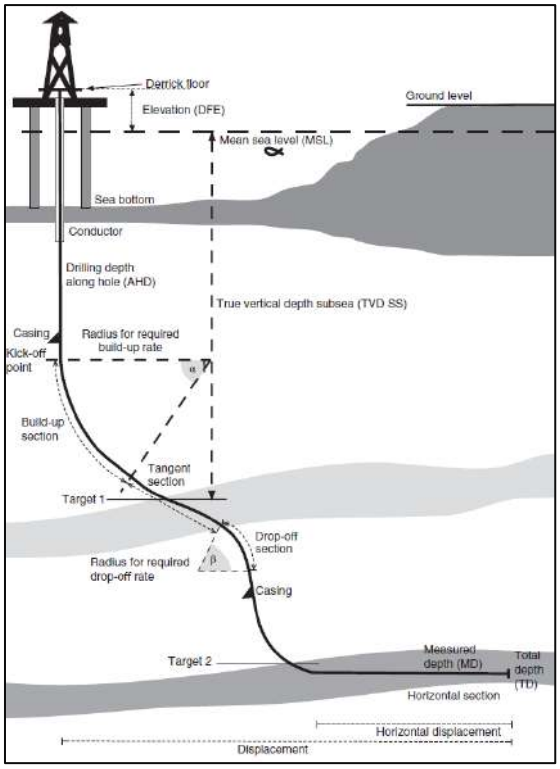

Figure 1-2: Depth measurement and well path trajectory **(Steve Cannon, 2018)**

1-2-3-2 Well logs

Logging is a geophysical technique based on the continuous recording of the physical parameters of the different geological formations in the borehole as a function of the depth (Roger M. Slatt, 2013). This technique is applied regularly in the oil and gas industry for formation reservoir evaluation, and integration with other sources such as core data and seismic data to generate specific profiles that can contribute to reservoir characterization and modelling (Steve Cannon, 2018). The main logs used in this context are; gamma ray (GR), density (RHOB), sonic (DT), neutron (NPHI), resistivity (Rt), and nuclear magnetic resonance (NMR) logs. These well logs are interpreted and analysed to provide facies, porosity, permeability, and saturation profiles (Ma, Y. Z., 2019).

1-2-3-3 Core data

Core data is defined as the information extracted from plugs taken from a certain depth in a well in order to define reservoir characteristics that cannot be addressed from other data sources (Vahid Tavakoli, 2018). The integration of these data with field and production data, well logging, well testing, and seismic data is indispensable to minimize the uncertainties related to reservoir characterization (Islam, M.R. and Khan, M.I., 2013). The main characteristics defined from core analysis at laboratories are; rock porosity, matrix permeability, fluid saturation, grain density, kerogen, lithology, capillary pressure, wettability, electrical and acoustical properties, cation exchange capacity, relative permeability, capillary pressure, petrographic properties, and pore fluid properties. Also, core data can provide information on the depositional environment and its diagenetic (Murphy, D. P. et Al., 1996).

1-2-3-4 Borehole imaging

Borehole imaging is one of the logging and data processing techniques used to capture images inside the borehole wall for the purpose of analysing small-scale sedimentological features, identifying fractures, specifying their nature, and determining the fracture orientations (Roger M. Slatt, 2013).

1-2-3-5 Pressure gradients data

Formation pressures and fluid samples are obtained from the reservoir at selected points using wireline formation tester tools (WFT). Pressure gradients can be defined using a graphical analysis of the pressures recorded in the borehole as a function of depth (James Howes, 1999). These pressure gradients can be used to determine fluid contacts, reservoir heterogeneities, and permeability barriers. The use of these pressure gradients aims to study the communication between boreholes and provide information on the reservoir behaviour when a new well is drilled after a certain production time (Bo Cribbs, 2009).

At the initial conditions, the vertical pressure profile reflects the distribution of fluids in the reservoir and indicates the reservoir compartmentalization resulting from fluid flow barriers. Reservoir compartmentalization identification and initial properties determination are key factors for reservoir characterisation and field development plans. These characteristics are largely used to describe the type and number of reservoir fluid settings (Belhouchet, H. E. et Al., 2021).

1-2-3-6 Well test data

The transient pressure test is the method used to obtain information about the reservoir behaviour around the well. It is based on measuring the pressure evolution at the bottom hole of the well as a function of time and flow (Fanchi, J. R. and Christiansen, R. L., 2017). These pressure measurements are plotted with their derivative in the same plot to determine the reservoir permeability along with the porosity, reservoir shape, average reservoir pressure, static pressures, and the location of the reservoir boundaries, such as sealing faults, in the vicinity of the well (Djebbar, Tiab and Erle, C. Donaldson, 2016).

Transient well testing is one of the practical and indirect techniques used for reservoir characterization, especially in the areas around wells where the estimation of reservoir properties can help to improve the understanding of the reservoir behaviour, and thus define the preferential paths of fluids which are related to the type of the depositional environment and the distribution of petrophysical properties (Aidan, A. and Kennedy, G., 2017). Therefore, integration of these informations from transient pressure testing with data from other sources might be necessary for improving the reservoir characterization.

1-2-4 Fluid Properties data

In the petroleum industry, the identification of reservoir fluid properties is essential for studying reservoir fluid behaviour at initial conditions and during field exploitation, choosing

the type of well completion, and designing the surface facilities (Steve Cannon, 2018). These properties may vary depending on the type of reservoir fluid. For example in oil deposits, the main properties include the oil density, bubble point pressure, formation volumetric factor, gas oil ratio, and oil viscosity, and for the gas deposit, the properties necessary to define are density, gas composition, compressibility factor, viscosity, and dew point pressure (Knut Bjorlykke, 2015).

The vertical and spatial variation in the fluid properties measured in the boreholes must be integrated into the characterization and modelling of the reservoir in order to determine the potential zones, and estimate the hydrocarbon volumes in place (Nnaemeka Ezekwe, 2011), (Belhouchet, H. E. et Al., 2021).

1-2-5 Reservoir Performance Data

Reservoir performance data includes all production, injection, and pressure data measured during reservoir exploitation. These include well flow data, dynamic and static downhole pressures, production logging tools (PLT) data, and well testing data. These data are compiled and compared to the assumptions applied during the construction of the geological model and the characterization of the reservoir (Nnaemeka Ezekwe, 2011).

The reservoir performance data could be considered as an experimental observation used to deduce the uncertain parameters of the geological model such as porosity, permeability, and transmissibility, and this by applying the principle of the inverse problem which is based on the illustration of the reservoir behaviour during its exploitation, and export the main parameters that can improve the response of the reservoir model (Landa, J. L. and Horne, R. N. , 1997).

1-3 Data quality control and Quality Assurance (QC/QA)

Data quality control and quality assurance are the processes or series of procedures intended to verify the type, quality, quantity and the size of data adequate for the objective application. Data quality control and quality assurance (QC/QA) are essential for any scheduled execution either for geological modelling and reservoir characterization or any of the steps introduced in the modelling process (Wikipedia, 2020).

Before beginning any reservoir study, all data acquired or collected related to all stages of exploration, appraisal, development, and production should be evaluated, and any discrepancies and/or deficiencies in the data must be identified (Sylvester, O. et Al., 2015). The data required must be consistent with the objectives of the study (Nnaemeka Ezekwe, 2011). One of the longest and most expensive parts of a project is controlling the quality of the input data used in geocellular modelling, and for this purpose, this step is essential to ensure the quality of the data used and minimize the uncertainties associated with the input data (Steve Cannon, 2018).

1-4 Reservoir characterization and modelling workflow

Geological modelling is the process of constructing and specifying a structural and stratigraphic model of a reservoir using all the information coming from seismic analyses and interpretations, well data, core data, fluid properties, production data, etc., taking into account the geological understanding of the basin's sedimentology and outcrop studies of similar formations (Nnaemeka Ezekwe, 2011). Depending on the types of data included and the logic applied in this context, geological modelling actually takes place in two stages, it begins with the establishment of a structural model expressed as a 3D model, followed by the filling of this model with rock properties. The filling of the model by the different petrophysical properties of the rock can be closely related to the reservoir characterization, which can be considered the key point for obtaining the best representation close to the reality of the reservoir (Al Hamami, M. T. M. N., et Al., 2012). The general recommended procedure for geological modelling and reservoir characterization is presented according to the following processes:

1-4-1 Conceptual Model

Conceptual modelling is the process of developing a graphical representation based on reservoir understanding. The conceptual model can be defined as a synthesis of our understanding of the reservoir targeted for modelling, based on all available input data from all subsurface disciplines. In many cases, it will also be crucial to include additional information, such as data from neighbouring fields, regional models, an understanding, and experience of analogue production fields, and/or outcrop data (Knut Bjorlykke, 2015). The conceptual geological model is the integration of the discussed physical processes, local information, and available analogues into one or more consistent qualitative models of the reservoir (Pyrcz, M. J. and Deutsch, C. V., 2014). The conceptual model may represent the field structure, stratigraphic sequence, depositional environment, petrophysical properties, fluid distribution, or a combination of all of these (Steve Cannon, 2018). Typically, the conceptual model can be summarized with several drawings and qualitative descriptions prior to the modelling (Knut Bjorlykke, 2015).

1-4-2 Structural Modelling

Structural modelling is defined as the design and the definition of the characteristics of the geological skeleton of the reservoir. Structural modelling consists of reporting all the structural events (anticline or syncline, folds, faults, etc.) obtained by the different sources of the data cited above on an imaginary model (skeleton), taking into account the geological chronology of the events and the tectonics of the study area (Roger M. Slatt, 2013). Building the structural model is the first step in the workflow for geological modelling and possibly the most crucial in terms of representing the large-scale geology of the field (Steve Cannon, 2018). According to (Nnaemeka Ezekwe, 2011), structural modelling typically includes modelling of the reservoir skeleton, faults and geological structural features that can be interpreted from seismic data, well logging data, and performance data, with the aim of constructing a consistent reservoir framework that can be gridded for a 3D geological and dynamic simulation. This

model aims to capture large-scale heterogeneities that can affect the fluid flow in the porous medium (Steve Cannon, 2018). Structural modelling is mainly defined by the following steps:

1-4-2-1 Seismic interpretation

The structural analysis is effectively based on 2D and 3D seismic interpretation to define the top and the base of the reservoir, and to identify the faults that are interpreted from discontinuities in the seismic reflectors (Steve Cannon, 2018). Depending on the seismic resolution limitation to a few horizons in the reservoir, additional zones may be added based on the well correlations supported by the conceptual model. The resulting mix of interpreted seismic surfaces, faults, and intermediate horizons calculated from the well correlation can represent the geological framework needed for building the reservoir skeleton and seismic framework (Knut Bjorlykke, 2015).

Seismic is an extremely powerful tool used in the exploration of oil fields. Its purpose is the detection of oil-bearing traps and folds, thus it makes it possible to locate faults with all their properties (the length of the fault, its width, and its rejection), so it represents an essential part of the structural modelling (Figure 1-3). The surface seismic interpretation combined with the well seismic helps to select the geological horizons, identify the type of facies, and build the sedimentological model, the seismic also enters into the stratigraphic modelling.

1-4-2-2 Fault modelling

Faults are defined as structural events in which geological surfaces and horizons are discontinuous, and these could be selected by seismic reflectors. The search for faults in subsurface formations is necessary because it presents a suitable environment for the storage of hydrocarbons. The determination of fault characteristics such as size, number, type, quantity, geometry, and orientation becomes essential to obtaining information on the heterogeneity of the reservoirs (Ma, Y. Z., 2019).

For reservoir modelling and characterization, fault modelling is one of the primary tasks used in structural modelling, due to its aid in understanding the connectivity of reservoirs in different parts of the field, improving the model stratigraphic and understanding of trapping potential. Modelling is actually based on mapping the faults in 3D with their characteristics in the reservoir in order to improve the schema of the reservoir's global structure. (Nnaemeka Ezekwe, 2011).

1-4-2-3 Horizon modelling

Geological horizons are defined by surfaces that can be mapped from seismic data, well logs, or used together, with the objective to capture the large-scale of the geological form, the basis of a sequence, an erosion event, and a discontinuous surface (Steve Cannon, 2018). The number of geological surfaces generated depends closely on the complexity of the structure. In simple structures, two geological surfaces may be sufficient to represent the top and the bottom of the structure. In contrast, in complex geologic structures, additional surfaces should be added to

capture geologic features such as faults, permeability barriers, unconformities, truncations, etc. (Nnaemeka Ezekwe, 2011).

In reservoir characterization, the top and the bottom surfaces of the regional anticline are indispensable for accurate estimations of hydrocarbon volumes, because they impact the gross rock volume that is hydrocarbon-bearing. Moreover, the local structures, such as the local anticlines and synclines can affect both hydrocarbon volumetric and fluid flow (Ma, Y. Z., 2019).

1-4-3 Stratigraphic modelling

Stratigraphic modelling is a process that serves to identify stratigraphic units based on seismic and well-log interpretation (Nnaemeka Ezekwe, 2011). This process aims to merge the stratigraphic levels represented by seismically interpreted horizons and events with the geologically significant surfaces identified in boreholes to determine stratigraphic zones. Stratigraphy involves the study, division, and documentation of sedimentary successions to explain the geological history they represent (Knut Bjorlykke, 2015). Geological zones should be separated by geologically significant bands, such as correlated shale intervals. The stratigraphic process could be subdivided into:

1-4-3-1 Zones Determination

The stratigraphic zones in the 3D model are defined on the basis of objective criteria including the relative homogeneities of facies, rock types, petrophysical properties, and depositional sequence (Ma, Y. Z., 2019). Reservoir zonation can reveal the lateral and vertical distribution of reservoir and non-reservoir zones from the borehole to the regional scale. To improve the understanding of reservoir zonation, large analytical datasets such as porosity, permeability, clay content, and hydrocarbon saturation of cores should be used to calibrate log data. Integration of these data with the interpreted stratigraphic sequence is required to identify stratigraphic units of the field (Jakobsen, F. et Al., 2003). A reservoir zonation is a term referring to a statistical process applied for a given reservoir to slice and discriminate, based on its oil potentiality evaluated from its measured and calculated petrophysical data (Nabawy, B. S. & Al-Azazi, N.A. S. A. , 2015).

Sequential correlation begins by identifying the sequence and parasequence boundaries within the reservoir section. Since these are timelines, they coincide with seismic markers, and as such should be coherent with seismic interpretations (Figure 1-3). The reservoir units are a composite of two or more zones that represent variable degrees of heterogeneity in the form of lamination, bedding, or flasers (Jakobsen, F. et Al., 2003). Subdividing a reservoir into flow units provides a convenient way to stratify the reservoir by using geological and petrophysical data to represent the heterogeneity at different scales (Li Ming, et Al, 2019).

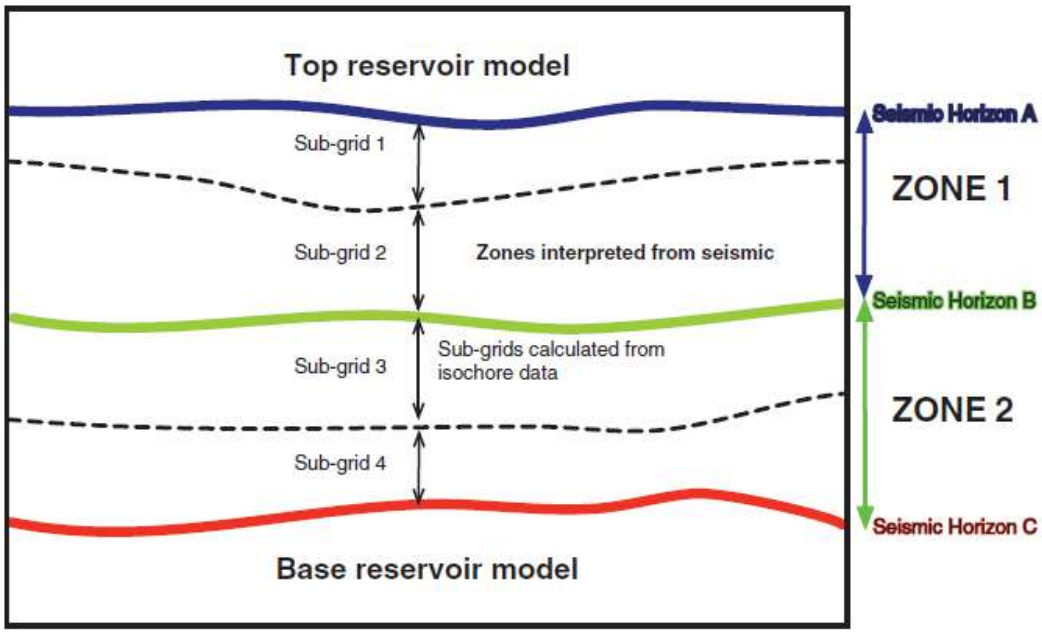

Figure 1-3: Horizon, zone and sub-grid nomenclature used in geocellular modelling

1-4-3-2 Model Gridding

One of the critical processes in property modelling is the design of the grid system for the geologic model. The design of the grid system for the model should be the key point for both static and dynamic models. The importance of the model gridding appears in the simplification of the presentation of the physical and petro-physical properties in a three-dimensional model which allows presenting the reservoir heterogeneity, in addition, the integration of this concept in the dynamic modelling is necessary, because it represents the only tool that can be used to apply the principle of fluid mechanics in a porous medium and which can be used to know the evolution of physical properties during the time (pressure, temperature) (Roger M. Slatt, 2013).

The selection of the grid system is closely related to the desired size of the static geological model, which could depend on the potential applications of the model, the quality and quantity of data, the availability of the data, the resources allocated to the project, and to the time constraints. The size of the grid system should be chosen on the basis of the scale of the data introduced in the geological model to capture the smallest change in geological features with the goal of presenting reservoir heterogeneity, selecting faults, identifying permeability barriers, and defining unconformities (Figure 1-4) (Benzagouta, M. S., et AL., 2001).

The number of grid cells is generally defined as an optimum number of cells that can correctly represent geological information adequately, computational storage, and execution time. The selection of this number of cells is necessary to avoid the loss of geological information, especially in heterogeneous reservoirs. The typical size of a grid cell is 20 m to a few hundred meters lateral resolutions (X and Y directions of the grid) and 0.3 m to up to 30 meters vertical resolution (Z direction of the grid). The maximum number of grid cells in a model is limited

by prevailing computer power, but an estimated static model can handle up to 100 million cells, which is typically two orders of magnitude more than dynamic models (Ma, Y. Z., 2019).

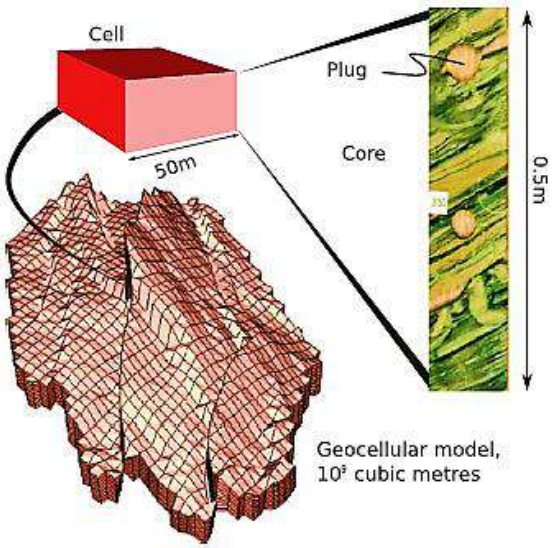

Figure 1-4: A dimension of 0.5 m of the core scale refers to 50 m in the dimensions of the Geocellular model **(Knut Bjorlykke, 2015)**

The orientation of the grids is considered to be one of the main factors to consider (Stephanie Agostini, 2011). Several approaches have been suggested for choosing the best grid orientation, such as; orientation from seismic lines, orientation from major faults, orientation from geological features, and orientation from the simulation grid (Ma, Y. Z., 2019). Therefore, the grid orientation must be closely related to several factors at a time to have a more representative model in terms of the preferred fluid path, sense of major faults, anisotropy, along seismic lines, and in terms of the type of environmental deposit. The grid orientation both vertically and laterally should follow the main directions of the heterogeneities (Figure 1-5).

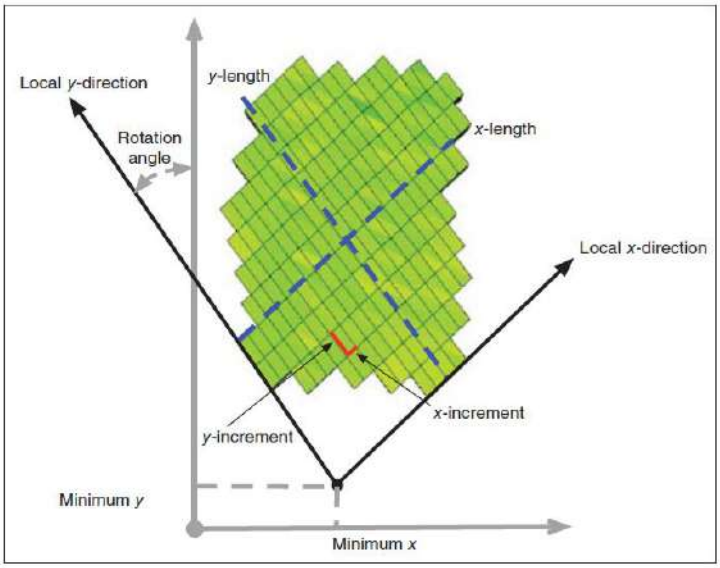

Figure 1-5: Grid orientation and axes nomenclature (Steve Cannon, 2018).

1-4-3-3 Layering Identification

Once the 3D structural framework has been created and stratigraphic sequences (reservoir units) have also been identified, the internal bedding geometries are defined within each sequence in order to capture heterogeneities, which have a significant impact on the fluid flow, the number of vertical layers, the orientation and size must be constructed such that these heterogeneities can be effectively modelled (Stanislav Ursegov, and Armen Zakharian, 2021). The creation of layers within each stratigraphic zone can model layering related depositional characteristics. Layering can vary between different reservoir zones in a geomodel, depending on the complexity of the reservoir morphology and properties that we are attempting to capture for each zone (Nnaemeka Ezekwe, 2011). The optimal number of layers has an important effect on the precision of the simulation results, the simulation time, and the convergence problems. According to geological understanding, four common layering geometries could be defined:

a- Layering Parallel to Top and on lap to Base

The onlap layering geometry typically occurs in siliciclastic reservoirs, especially in valleys or channelled deposits. It can also occur in carbonate deposits (Figure 1-6). The onlap layering can result in many null cells in the 3D model grid and can be computationally inefficient. The lowest layers of the stratigraphic sequence may not have correlable well data in the onlap layered stratigraphic zone (Ma, Y. Z., 2019).

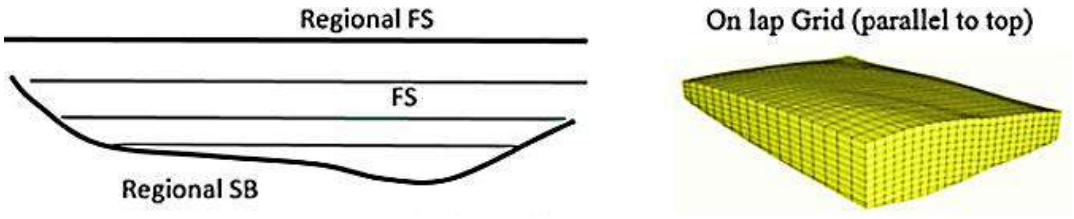

Figure 1-6: Figure showing the on lap layering geometries **(Ma, Y. Z., 2019)**.

b- Layering Parallel to Base with Truncation to Top

Top truncation layering geometry occurs in siliciclastic and carbonate deposits. As with onlap stratification, this can result in many null cells in the 3D model grid and can be computationally inefficient (Figure 1-7). The highest layers of the stratigraphic sequence may not have correlable well data in the stratigraphic zone in truncation layers (Ma, Y. Z., 2019).

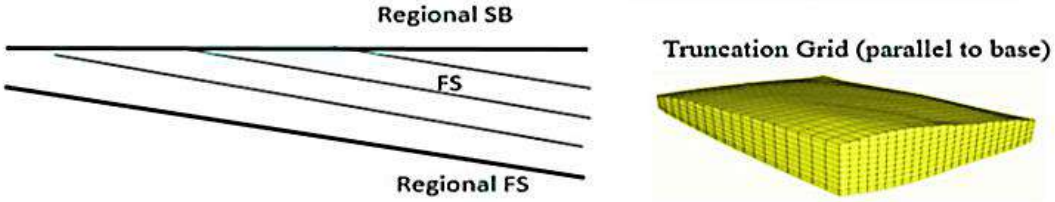

Figure 1-7: Figure showing layering parallel to base with truncation to top **(Ma, Y. Z., 2019)**.

c- Proportional Layering

The proportional layering geometry can occur in siliciclastic and carbonate deposits and is frequently used in layered stratigraphic zones. Typically, when the deposition sequences do not show a clear layering geometry, proportional layering is used because it is more computationally efficient and avoids vertical zero values in the grid. Additionally, well data can be honoured more easily because all layers are proportionally stretched and compressed to fit between the top and base surfaces (Figure 1-8). In many cases, a proportional stratification represents better fluid flow and reservoir continuity (Ma, Y. Z., 2019).

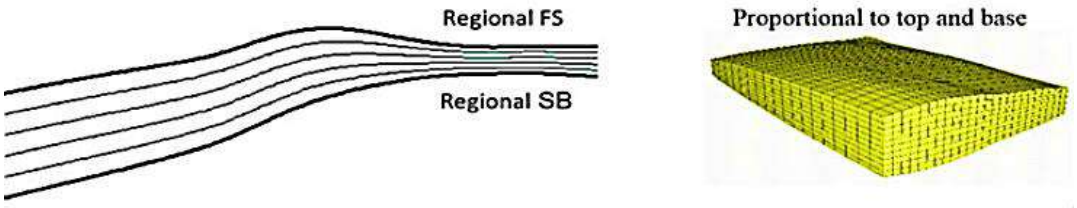

Figure 1-8: Figure showing Proportional layering **(Ma, Y. Z., 2019)**.

d- Depositional Layering or Parallel to an External Depositional Grid

Internal layers in this layering scheme generally truncate both the top and bottom surfaces. The layering geometry is based on deposition that is not parallel to either the bottom or top surface (Figure 1-9). This occurs frequently when the top surface is an unconformity or regional sequence boundary (Ma, Y. Z., 2019).

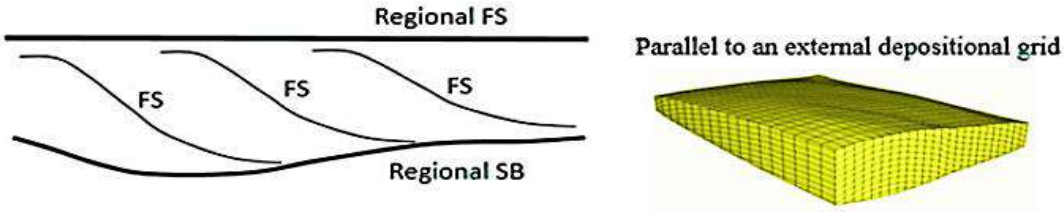

Figure 1-9: Figure showing Depositional Layering **(Ma, Y. Z., 2019)**.

Proportional layering is more commonly used in practice than the other layering schemes because it is less likely to cause gridding issues and is more computationally efficient. Furthermore, depositional layering geometries are not always clearly identifiable (Ma, Y. Z., 2019).

1-4-4 Rock typing

Rock typing is an important step in the reservoir characterization and the development of geological models for reservoir simulation (Al-Jawad, S. N. A. et Al., 2020). A static rock type is defined as a rock unit characterised by similar depositional and digenetic processes that result in a characteristic and unique Poro-Perm relationship and capillary pressure curve (Kadkhodaie, A. & Kadkhodaie, R., 2018). The identification of reservoir representative rock

types contributes to a better understanding of reservoir fluid movement and oil recovery (Heydari-Farsani, E. et Al., 2020).

1-4-5 Upscaling lithofacies and continuous variables to 3D Grid

The construction of the reservoir model involves the population of reservoir rock types in a 3D reservoir model. The 3D reservoir model is discretized into x cells in the I direction, y cells in the J direction, and z cells in the K direction (Steve Cannon, 2018). Before going through the distribution of the reservoir properties in the I and J directions, the upscaling of the well log data in the cells which are initially defined in the section of stratigraphic modelling in the K direction should be necessary. Each of those cells must be characterized by a single code of the facies, a single value of porosity, a single value of permeability, and a single value of saturation (Ali, A. M. et Al., 2022). The upscaling method could be related to the type of the parameter we need to upscale, for example, the upscaling of categorical variables such as lithofacies from a well-log to a 3D grid could be generated by several approaches, such as:

- Most-off method based on the selection of the most frequent code of the facies in the cell
- Mid-point pick method that selects the code closest to the grid center in the cell
- Random-pick method that selects a code randomly within the window covering the grid cell.

For continuous variables such as porosity and saturation, the arithmetic mean might be the most common method for upscaling porosity and saturation logs, on the other hand, to upscale the well log permeability, two averages technics could be used; geometric mean and harmonic mean (Permeability Upscaling Techniques for Reservoir Simulation, 2007). The geometric mean may give a value less than the arithmetic mean, and the harmonic mean may give a value even smaller than the geometric mean. The application of one of these methods could be linked to the comparison of the upscale permeability profile with its initial profile (Belhouchet, Houssem Eddine, 2015).

1-4-6 Property Modelling

Once the grid construction is completed, the lithofacies and continuous variables are upscaled. The modelling of these properties consists of distributing them in the grid, so each cell is assigned various petrophysical values such as porosity, permeability, and fluid saturations, as well as discrete values like facies and region identifiers (Knut Bjorlykke, 2015). The main objective of property modelling is to describe the geology of the reservoir in such a way as to represent a conceptual model of the depositional environment and to estimate the reserves in place. According to Knut Bjorlykke, 2015, the rock properties could be classified into two main categories:

1-4-6-1 Discrete or Categorical Properties (facies modelling)

For reservoir modelling, a facies is an architectural element that has a variable geometry and a specific distribution closely related to the depositional environment. The facies system was developed to categorise rocks based on their type, mineralogical composition, diagenetic, pore geometry, lithology, and sequential stratigraphy. In other words, there are clear distinctions between the quality of the sandstone and shale reservoirs, and often between limestone and dolomite (Knut Bjorlykke, 2015). Facies modelling may be one of the tools used for the exploration and development of the field. Generally, the facies model complexity depends greatly on the geological complexity of subsurface formations and the objective of reservoir modelling (Ma, Y. Z., 2019).

The objective of the facies model is to integrate the reservoir heterogeneity interpreted by the sedimentary study, constrained by well data and seismic attribute data, in the geocellular grid. The resulting model should be suitable for deterministic or stochastic modelling of rock properties (Steve Cannon, 2018). Therefore, the identification of the depositional environment of the field and associated facies is considered the first task for the construction of the facies model, followed by the analysis of facies geometrical characteristics and their spatial distributional patterns (Ma, Y. Z., 2019).

The modelling of the discrete facies is a means of improving the understanding of the characteristics of the deposit environment; the selection of the modelling parameters is based on the combination of the sedimentologic data interpreted at the borehole (strategic sequence, lithology) and the regional deposit models to illustrate the overall concept of facies distribution. Depending on the type, the quality, and the number of these parameters, geostatistical methods such as deterministic, stochastic-deterministic, or stochastic can be selected and applied for modelling reservoir properties. The modelling process at this point requires strict quality control both visually and quantitatively (Steve Cannon, 2018).

1-4-6-2 Continuous Properties (petrophysical property modelling)

Petrophysical property modelling is the process of distributing petrophysical property values (porosity, permeability, and saturation) into the geological grid. This is performed individually for each reservoir zone and each facies of the geological grid (Knut Bjorlykke, 2015). The objective of property modelling is to distribute properties between the accessible wells; therefore, it realistically preserves the reservoir heterogeneity and matches the well data. So, property modelling is the method of filling the cells of the grid with distinct rock types or continuous (petrophysics) properties (Abeed, A. T. et Al., 2019). A petrophysical analysis is a critical step in a reservoir study because it provides a primary source of input data for integrated reservoir characterization and resource assessment (Ma, Y. Z., 2019).

The process of the petrophysical properties modelling starts with porosity modelling, which is a static property that should be straightforward if the data are partitioned correctly into facies or zones, followed by permeability modelling which is a dynamic property that has traditionally been linked to porosity through a log-linear relationship, and completed by water saturation

modelling which is a function of pore volume, permeability, capillary pressure and height above the free water level (FWL). These parameters are the main petrophysical properties that should be distributed.

a- Porosity Modelling

Porosity is defined as the ratio of pore volume to total rock volume and describes the fractional volume of pores in the rock. The pore volume is the difference between the total rock volume and the grain volume of the rock (Charles R. Fitts, 2013). The porosity is one of the parameters required for reservoir characterization; therefore, determining and modelling the porosity is critical for any reservoir study, due to its importance in estimating the hydrocarbons in place, describing storage capacity, and impacting the modelling of other reservoir properties such as fluid saturation and permeability, which are closely related to the porosity (Yanbin Yao, and Jun Liu,, 2019).

First, the porosity distribution determines the pore volume of the reservoir model and thus impacts the estimation of hydrocarbon volumes. Secondly, since the fluid saturation and permeability are correlated to the porosity, their distributions in the 3D reservoir model may be affected by the porosity distribution (Kejian Wu, et Al., 2006). Therefore, the porosity model can have an impact not only on the estimation of hydrocarbon in place but also on the estimation of recoverable volumes and well planning (Ma, Y. Z., 2019).

Geostatistics can be described as the application of mathematical methods based on statistics in analysing, integrating, interpreting, and distributing geologic, petrophysical, or any other property-based data in a geologic model (Nnaemeka Ezekwe, 2011). Several geostatistical techniques can be used to model porosity. They include methods of kriging, stochastic simulation, and co-localized cosimulation (Ma, Y. Z., 2019).

b- Permeability Modelling

Permeability is a measure of fluid flow in a porous medium, and it describes the capacity of a material for fluids to flow through it. Permeability characterizes the dynamics of fluids in the rocks, and thus it is a critical petrophysical parameter for hydrocarbon production, reservoir simulations, and performance forecasts (Ma, Y. Z., 2019). The reservoir permeability (K) factor is considered the key parameter for reservoir characterization, and it can also be used to determine the reservoir quality index. Accordingly, several methods have been developed to estimate the permeability from well-test interpretation, wireline formation testers, and core data (Belhouchet H.E. & Benzagouta M.S., 2019).

In heterogeneous reservoirs, the permeability varied significantly from many small values to many less large values, and it generally provided a much skewed distribution. Due to the limited number of measurement data points, the permeability modelling process becomes difficult. Hence the development of a mathematical relationship should be necessary to calculate the permeability as a function of porosity. However, the relationships between porosity and permeability are complex and can be caused by lithofacies, clay content,

cementation, grain size, sorting, fractures, and depositional environments (Ekpoudom, O. et Al., 2004), (Ma, Y. Z., 2019).

Permeability values are commonly derived from an empirical relationship between the core porosity and permeability constrained by the rock pattern. Due to the availability of porosity data compared to other data, great importance should be given to the relationship between porosity and permeability, and this is to develop a good permeability model capable of matching historical data, and enhancing well-performance prediction (Ma, Y. Z., 2019).

c- Water saturation Modelling

Water saturation is defined as the ratio of water volume to the total pore volume. The determination of water saturation is the most critical property in petrophysical calculations (Petrowiki, 2015), thus, it could be used to estimate hydrocarbon saturation. At borehole levels, this parameter can be predicted from core data, well logs, or seismic attributes directly or can be estimated from an intermediate parameter such as shale volume in sandstone reservoirs (Alimoradi, A., Moradzadeh, A. and Bakhtiari, M. R., 2011).

The determination of water saturation is one of the most important items in reservoir characterization according to its impact on the calculation of hydrocarbon volume in place, identifying net pay zones, predicting trap boundaries, and planning hydro-fracturing jobs (Deng, Y. et Al., 2020). A precise prediction of the saturation model could give a better understanding of the reservoir fluid flow in the porous medium and improve oil recovery (Lian, P. Q. et Al., 2016). The water saturation distribution within a reservoir depends on the height above the free water level, hydrocarbon type, pore throat-size distribution, and pore geometry (Al-Otaibi, M. H. et Al., 2012).

The most common approach to estimating water saturation is based on the well log interpretation, which should calibrate the core water saturation data recorded in the laboratories (Mollajan, A. et Al., 2013). This saturation will be upscaled to have a single saturation value in each cell. Once the water saturations are available, the property will distribute in the grid to generate a saturation model (Lian, P. Q. et Al., 2016). The obtained model may encounter failures in water saturation estimation in the transition zone, and for this purpose, several techniques have been developed to estimate the water saturation in this zone as a function of porosity, permeability, rock type, and capillary pressure (Harrison, B. and Jing, X. D., 2001).

1-4-7 Reserve Estimation

Once the geological model is built, the estimation of hydrocarbon volumes in place is necessary to prepare the field development plan and to assess the profitability of the discovered area (Nasar, A. O., Abusaleem, J. A. & Tabar, E. M., 2018). To this effect, the estimation of hydrocarbon volumes in place will act as a starting point that will allow getting a decision for drilling one or more other extension wells and preparing an exploitation and development strategy for the field (Roger M. Slatt, 2013). Therefore, estimating the hydrocarbon volume is a complex process that involves integrating geological, geophysical, and engineering data.

According to the amount and quality of static information available (John R. Fanchi, 2010), especially after the construction of the geological model, which describes geometrically the volume of hydrocarbons in the reservoir, a volumetric analysis could be used to estimate the OOIP and the OGIP (Sustakoski, R. J. & Morton-Thompson, D., 1992).

One basic equation for original oil in place (OOIP) in an oil reservoir is given by:

$$OOIP = 7758 * \ A * h * \emptyset * (1 - S_w)/B_{oi} \quad (1)$$

Where;
$OOIP$: Original oil in place, (STB)

7758: Conversion factor from acre-ft. to bbl.

A: Area of the reservoir (acres) from map data

h: Height or thickness of pay zone (ft) from log and/or core data

$\emptyset$: Porosity (decimal) from log and/or core data

S_w: Connate water saturation (decimal) from log and/or core data

B_{oi}: Formation volume factor for oil at initial conditions

For gas filed, the original gas in place is given by:

$$OGIP = 43560 * \ A * h * \emptyset * (1 - S_w)/B_{gi} \quad (2)$$

Where:

OGIP: Original gas in place, OGIP (SCF)

43560: Conversion factor from acre-ft. to ft^3

B_{gi}: Formation volume factor for gas at initial conditions (Res. ft^3/SCF)

1-4-8 Upscaling

Upscaling is the process of converting a large number of the grid blocks of the geological model to a smaller number of coarse grid blocks of the dynamic model (Figure 1-10) taking into account the preservation of the geological properties (Benmadi, M. et Al., 2020). This process is required to reduce model run times (Knut Bjorlykke, 2015), in which the evaluation of alternative reservoir management strategies and the conduction of iterative simulation runs in a history matching process could be provided. Other reasons for upscaling geological models are the problem of limiting the storage of computer memory that can be produced in fine grid

simulation models, in addition, the cost associated with the output of the model processing (Nnaemeka Ezekwe, 2011).

The main principle in upscaling is to build a numerical simulation model that preserves pore volume, hydrocarbon pore volume (HCPV), transmissibility, reservoir geometry, geological features, and geological understanding. An adequately upscaled model can reproduce the key flow performance of the geocellular model (Ma, Y. Z., 2019). A challenge in upscaling the parameters of the geological model is to determine a sufficiently coarse reservoir grid cell size without losing the detail of the original structures, petrophysical properties, the layered nature of the reservoir, and the heterogeneity of the reservoir. (Benmadi, M. et Al., 2020).

Depending on the fin grid system, two types of properties can be distinguished for upscaling: static properties and dynamic properties. Upscaling static properties requires the preservation of the volumetric properties, and upscaling dynamic properties requires the preservation of fluid flow behaviour. The related volumetric properties include structural framework, lithofacies, porosity, fluid saturation, and net-to-gross (NTG). The main dynamic property is permeability; however, structural framework is also a contributing factor due to its impacts on fluid flow (Ghedan, S. G. et AL., 2002), (Ma, Y. Z., 2019). Several methods have been applied to develop the upscaling including arithmetic, harmonic, geometric, power law, pressure solver, and weighted averages algorithms. The choice of one of them depends closely on the comparison of the rock property before and after upscaling (Benmadi, M. et Al., 2020).

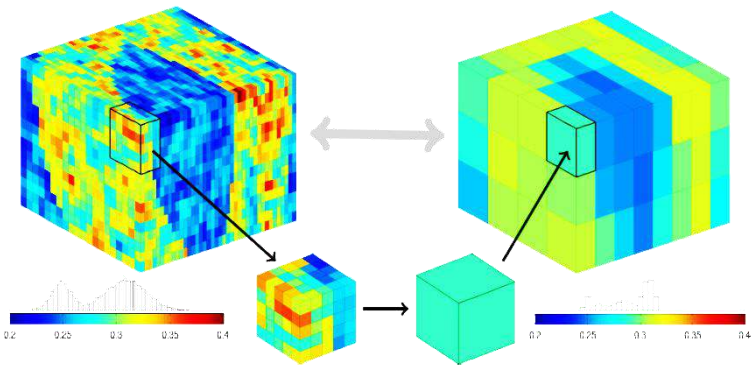

Figure 1-10: An overview of upscaling fine scale grid (Geological model) to coarse scale Grid (Dynamic model)

1-5 Dynamic Reservoir Model

Reservoir simulation is a numerical model based on the collection of all materials used in the petroleum industry such as physics, mathematics, geology, reservoir engineering, and computer programming to develop a practical tool for predicting the future performance of hydrocarbon reservoirs according to different operating strategies (Abou-Kaseem, J. H. et Al., 2020). In addition, the reservoir simulation model could be defined as the process of numerical modelling based on integrating all the properties arising from the geological model (network and petrophysical properties), PVT analysis, rock-fluid interaction (capillary pressure and relative permeability), and well data with the application of fluid flow equations in the porous

medium to simulate the distribution of pressure and hydrocarbon saturation in space and time (Scott K. Laudeman, 1992), (John R.Fanchi, 2002), and (Knut Bjorlykke, 2015).

Numerical simulation is an essential and necessary tool in any reservoir study, due to its effective role in helping to develop oilfields and improve reservoir management. For optimal reservoir management, it's critical to determine reserves, recovery factors and economic limits as quickly as possible before the project start-up (Islam, M. R. et Al., 2016). The objective of building a numerical simulation model is to understand the dynamic behaviour of the reservoir, identify the different development options, plan a strategy for exploiting the field, and optimize the commercial value of a hydrocarbon accumulation (Knut Bjorlykke, 2015, Belhouchet, Houssem Eddine, 2015).

1-5-1 Types of dynamic reservoir simulator

Before going through the construction of a dynamic model, the selection of the type of dynamic model is essential (Roger M. Slatt, 2013). This selection is essentially related to the original reservoir fluid type (oil, volatile oil, dry gas, condensate) and is also influenced by the field development strategy to be implemented; miscible gas injection or steam injection (Scott K. Laudeman, 1992), (Fevang, Ø. et Al., 2000). Accordingly, several types of simulators have been defined to represent the mechanisms related to these points. The three basic types of simulators that are used in the dynamic model are black-oil, compositional, and thermal.

1-5-1-1 Black oil model

The term "black oil" refers to the fluid model in which different phases are explicitly modelled together as individual components (Sun, S. & Zhang, T., 2020). This type of isothermal model applies to reservoirs containing immiscible oil, gas, and water phases (Luca Cosentino, 2001). The properties of these components may vary with temperature and pressure, but the composition remains constant over time, which means that the mass does not transfer between phases (Sun, S. & Zhang, T., 2020). These models can be used to reproduce most reservoir mechanisms, including solution gas drive, gas-cap drive, water drive, water injection, and immiscible gas injection (Scott K. Laudeman, 1992).

1-5-1-2 Compositional model

The compositional model is the process in which reservoir fluids are represented as hydrocarbon components: methane (C1), ethane (C2), propane (C3), butane (C4), etc. (Roger M. Slatt, 2013). The number of hydrocarbon components is generally optimized to minimize simulation calculation time without losing the initial phase diagram scheme. (Luca Cosentino, 2001). Compositional characterization refers to fluid properties that are pressure, temperature, and composition dependent, and should be described by some equation of state (EOS) (Ertekin, T. el Al., 2001). Isothermal compositional models are used when the hydrocarbon phase compositions and properties vary significantly with pressure below the bubble point or the dew point. Typical applications of these models are the depletion of volatile oil and gas-condensate reservoirs, gas-cycling projects, or the injection of CO_2 via miscible gas injection (Luca

Cosentino, 2001). In addition, enhanced oil recovery processes require the application of the compositional model in order to predict the reservoir dynamic behaviour (Islam, M. R. et Al., 2016).

1-5-1-3 Thermal model

The thermal model is the thermodynamic system that can be used when the temperature varies in the reservoir. These models are used mainly to simulate cyclic steam injection, hot water injection, continuous steam flooding, or more complex process like in-situ combustion. In this type of model, the fluid and rock-fluid properties should be characterized as a function of pressure and temperature (Luca Cosentino, 2001). Therefore, the thermal model is the process used for modelling heavy oil reservoirs, where the reservoir fluid is characterized by high viscosity, and the temperature has a significant impact on this property (Duncan Paterson, 2019).

1-5-2 Data needed

The technical data of the reservoir include data related to the geological and dynamic understanding of the reservoir (Adolfo, H. et Al., 1990). Typical data that we need to build a reservoir model are:

- Geological data present in the geological model are characterized by a grid, filled with petrophysical properties (porosity, permeability, net to gross (NTG), and saturation) (Cavero, J. et Al., 2016).
- PVT data are used to establish the PVT model which is used to present the state of the reservoir fluid during the exploitation of the field and to estimate its physical properties as a function of pressure and temperature changes (Almehaideb, R. A. et Al., 2000).
- Relative permeability data which are used to determine the effective permeability of one fluid in the presence of another fluid when several non-miscible fluids are presenting in the reservoir, estimate the initial saturation of each phase in each cell, therefore, it is introduced to predict the rate of production, injection, and recovery during all drainage mechanisms (Mattax, Calvin C., and Robert L. Dalton, 1990).
- Capillary pressure data are used to estimate the initial pressure and the saturation of each phase in the transition zone, so they are indirectly used to estimate the original oil in place (Andre, B. J., and Hawkins, J. T. , 1992).
- The wire-line formation test data are required to estimate the initial conditions (pressure and temperature), define the compartments, identify the different types of reservoir fluids, and determine the contacts between these fluids (Belhouchet, H. E. et Al., 2021).
- Well data is presented by well coordinates, wells deviation, perforation intervals, and the type of completion, with the goal of developing a well model that represents the flow between the bottom hole and the reservoir (Nnaemeka Ezekwe, 2011).
- Static pressure data is recorded from well tests (DST), these tests are generally performed before the start-up of production and injection. The purpose of this information is to estimate reservoir pressure and determine the permeability around wells (Belhouchet H.E. & Benzagouta M.S., 2019).

1-5-3 Reservoir Model Initialisation

The initialization of the reservoir model is the process of rendering a subsurface rock/fluid model at a representative starting point to illustrate the hydrostatic equilibrium state of the reservoir prior to the production start-up (Fawakhiri, A. Y. et Al., 1989). This step is essential once the reservoir model is built as it allows presenting the distribution of volumes in place, pressure, saturation, and fluid contacts in the reservoir and identifying the reservoir fluid gradients and compartments, and, of course, confirming the PVT model (Sylvester, O. et Al., 2015). The basic idea of reservoir initialization is to deliver a prototype reservoir model that aims to provide a representative, consistent, and stable model.

The initialization of the reservoir simulation models is the process where the reservoir simulation model is reviewed to make sure that all input data and volumetric values are internally consistent with those in the geomodel (Kachuma, D. et Al., 2021). Volumetric calculations are performed on the simulation model as a form of quality control to ensure consistency with the geo-model. Correct initial volumes are the foundation for correct production estimates (Steve Cannon, 2018).

1-5-4 History matching

Reservoir model calibration is the process of adjusting petrophysical properties and well parameters from the real data measured on the surface and subsurface (Nnaemeka Ezekwe, 2011), (Shuyu Sun & Tao Zhang, 2020). This process is effectively based on the integration of any new data linked directly or indirectly to the performance of the wells and the reservoir behavior in the dynamic model, and launching the numerical simulation to ensure the quality of history matching (Hye Young Jung, 2015). The data to be matched by the reservoir model can include; rates, ratios, volumes, static pressures, saturation profiles, flowing pressures, tubing head pressures, production and injection profiles, salinity, fluid composition, and interference tests (James R. Gilman and Chet Ozgen, 2013). The process of history matching depends considerably on the reservoir model type, the quality and quantity of available performance data, and the objectives of the study (Nnaemeka Ezekwe, 2011). Consequently, the objective of the history matching is to establish a reservoir model that faithfully reproduces the production history and the observed events to predict the future behaviour of the reservoir and to use it to optimize the development plan of the field under various drainage mechanisms (John R.Fanchi, 2002), (Rwechungura, R. et Dadashpour, M., 2011).

1-5-5 Reservoir Model Updating

Reservoir model updating is the process of reconstructing a dynamic or geological model based on newly obtained data. Typically, the model is updated as soon as additional data is available, such as a new seismic interpretation, new well drilling, new well logging data, and a new log interpretation, in addition to the availability of new core data and new wire-line formation pressures recorded. These pieces of information can improve the understanding of reservoir behaviour and petrophysical properties distribution and thus allowing for the presentation of a

more realistic conceptual model (Ma, Y. Z., 2019). This update could also be related to comments and inferences from reservoir simulation and history match understanding. For example, during reservoir and production monitoring, a lot of information could be deduced and thus could be used to discover the degree of communication between wells, permeability barriers (faults, stratigraphic barriers), distribution of petrophysical properties, the validity of PVT and SCAL models (capillary pressure, relative permeability), and hydrocarbon distribution, which may help improve the quality of the reservoir model (Xiongyan Li and Hongqi Li, 2013).

The changes made to the simulation model to match field performance history can be fed back as additional conditioning data to update the geocellular model. The feedback process makes it possible to maintain reservoir models that honour both the initial reservoir description data and field performance history. Depending on the quality of the history matching and the availability of the new data, the update of the reservoir model can be implemented locally or globally (Ma, Y. Z., 2019).

1-5-6 Forecast

Reservoir simulation forecasting is the process of predicting the future performance of oil or gas fields from the initial and historical data to clarify the future vision of the project, which aims to determine the appropriate exploitation strategy for such a field and optimize its development plan (Shuyu Sun & Tao Zhang, 2020). This process is initiated once the dynamic model is constructed and well calibrated (Nnaemeka Ezekwe, 2011).

A forecasting study is essential in the petroleum industry to realize a project economically viable, and this requires carrying out advanced studies on the geology of the reservoir, the type of the reservoir, the reservoir fluid type, and the constraints of the plant (Roger M. Slatt, 2013). These studies aim to use the reservoir model to improve oil recovery, minimize expenses, and extend the life of the field. Production forecasting and optimal depletion require knowledge of all the uncertainties associated with reservoir characterization and modelling to avoid any unexpected business surprises (Ma, Y. Z., 2019).

1-6 Summary

Reservoir characterization is the process of identifying and estimating reservoir properties using all types of data, which are directly or indirectly related to any parameter introduced in the property specification. This information can be useful to identify; the type and age of the geological formation, the type of deposit environment, the heterogeneity of the reservoir, and the volumes of hydrocarbons in place. This information is collected and used to build a geological model that reflects our understanding. This model is integrated with the physical properties of the fluids and the rock-fluid characteristics, in addition to the pressure and its gradient recorded in boreholes to establish a numerical simulation model, which will be used to optimize the development plan of the field and estimate the recovery of the hydrocarbons expected in current and alternative strategies.

Chapter 2: Rock typing as input for reservoir characterization: Approaches and Materials in need

2-1 Introduction

Rock typing is the process of classifying and specifying rocks according to mineralogical composition, digenesis, physical properties, electrical properties, chemical properties, grain shape, type, texture, structure, pore size distribution (PSD), rock fluid interaction, and the degree of clay. This process is applied generally in the petroleum industry to predict reservoir properties in non-explored zones, identify reservoir homogeneity/heterogeneity, describe the reservoir areas, and establish the link between static and dynamic properties. It has a significant impact on the original oil and gas in-place estimation. Rock typing has become one of the main steps in reservoir characterization due to its potential to improve the quality of the geological model and, therefore, to have a more representative dynamic model.

The rock typing process consists of using all the information coming from different sources such as seismic, drilling, fields, and cores. The integration, analysis, and synthesis of these data became necessary to define reservoir characteristics from different angles in order to ensure good coverage and a good understanding of those parameters. Rock type attributes could be sedimentary such as lithology, fossil content, sedimentary textures, digenesis, and petrophysical like electrical log and reservoir core parameters (porosity, permeability, and capillary pressure). Generally, any significant classification of reservoir rocks differentiated by particular reservoir characteristics can be attributed to the same rock type. These characteristics could be related to sedimentary attitudes (type of sedimentary rocks), petrophysical well logs (electrofacies), and the properties of the pore system (flow unit). Thus, these properties could be extended to seismic data (seismic facies), geomechanical parameters, and dynamic data.

The goal of this chapter is to present the various methods used to classify reservoir rock types while taking into account all physical aspects (lithology, electrical, and petrophysical properties) in order to develop a workflow that will be followed in our case study. It is also recommended to include an overview of machine learning approaches and their applications in the oil and gas industry for the need for their use in the identification, classification, and prediction of reservoir rock types.

2-2 Data needed

Basic information needed for reservoir characterization includes facies, porosity, permeability, water saturation, and net/gross ratio. These data can be extracted from two main sources; direct sources of reservoir information include core and cuttings data, and indirect methods include log data, well tests, and seismic data.

2-2-1 Core data

In order to explore a virgin field and depending on the drilling program, a coring interval must be defined to have more details on the reservoir section. Usually, the core dimension is between

9 and 27 meters, depending on the thickness of the reservoir. During the process of handling and preserving the core, any physical alteration of the rock material should be minimized. The cores are cut into sleeves of one meter and transported in wooden crates. Preserving the cores with wax is more effective, but this is only done for SCAL testing or when the cores are not to be tested for a long time. Therefore, cores are the main source of information for any reservoir assessment and characterization project. According to various disciplines and experiments carried out on corps, several types of information can be exported from core analysis like rock properties, anisotropy, organic matter content, maturity, fluid content, electrical properties, and geochemical properties. This information can be used to calibrate well logs and seismic measurements in order to generate logs and seismic profiles in non-cored wells. The main information that can be obtained from the core analysis are:

- Lithology
- Deposit environments
- Dating the absolute age and establishing the chronological sequence
- Correlation on a regional scale.
- Digenesis.
- Fracture analysis
- Pore typing
- Geochemistry studies
- Porosity determination
- Permeability measurement
- Hydraulic flow unit determination
- Fluid saturation
- Acoustic velocity
- Gamma ray
- Grain density
- Electrical properties
- Wettability
- Relative permeability
- Capillary pressure
- Pore volume Compressibility
- Geomechanical properties like compressive strength, Young's modulus, Poisson coefficient, and hardness.

2-2-2 Well log data

Well logs are the most recommended data in reservoir studies. They are accessible from all wells and reservoir intervals. These data can be considered as the main sources necessary to extend the reservoir properties in the non-cored sections based on the cores - logs correlation in the core areas. To develop these logical correlations between the logs and the core data, well logs should be chosen on the basis of their electrical indications linked to the reservoir properties (lithology and petrophysical properties). The main logs that can reach these

conditions depending on the definition are the gamma-ray, NPHI, RHOB, sonic (DT), resistivity, lithodensity log (PEF), and NMR.

2-2-2-1 Gamma ray:

Gamma ray logging is a method of measuring the radioactivity of sedimentary rocks, in which different types of rocks emit different amounts and different spectra of natural gamma radiation. In particular, clays are generally more radioactive than the other sedimentary rocks such as sandstone, gypsum, salt, coal, dolomite, and limestone. Therefore, this difference in terms of radioactivity makes it possible to separate clays and sandstones/carbonate rocks and indirectly makes it possible to identify reservoir zones.

2-2-2-2 NPHI

It is defined as a log, which occurs by the bubbling of the formation and by high-energy neutrons to measure the hydrogen index in the reservoir. The hydrogen index of a formation is the ratio of the concentration of hydrogen atoms in a cm3, and as hydrogen atoms are present in both reservoirs filled with water and oil, therefore, measuring the quantity of hydrogen makes it possible to estimate the quantity of porosity filled with liquid. The hydrogen index could be one of the factors used in porosity estimation.

2-2-2-3 RHOB

The density log is a log based on the sending of gamma rays into the formation to measure the bulk density of the formation. The absorption of these rays depends on the number of electrons struck by the gamma rays (The Compton effect), the more the formation is denser, the more gamma rays are absorbed. Bulk density is determined from a correlation between the intensity of gamma rays at the detectors, which is an inverse function of bulk density, and the data used for tool calibration. Geologically, the bulk density of rock is determined by the density of the minerals forming the rock (i.e. a matrix) and the fluid trapped in the pore spaces. Density logs were used to calculate formation density, estimate rock porosity, and identify oil-gas contacts.

2-2-2-4 Sonic

Sonic logging is the recording of the required time for a sound wave to pass through a formation. This sound travel time is inversely proportional to the speed of the sound in different formations. The speed depends on the elastic properties of the rock matrix, the porosity of the formations, the saturation and composition of the fluid, the geometry of the pores, and the pressure to which the rock is subjected (Silva, F. & Beneduzi, C., 2017). In the hard formations, which are well cemented and compacted, sound logging is used to estimate the amount of fluid in the formations, estimate the rock porosity, indicate the presence of gas, and distinguish between oil and water (TIXIER, M. P. et al., 1958).

2-2-2-5 Resistivity

Resistivity logs are electrical records that measure the conductivity or the resistivity of the formation. Depending on the conditions of the well, three types of resistivity could be defined

shallow, medium, and deep. These types of resistivity were performed to estimate the resistivity of the formation of the washed zone, transient zone, and virgin zone. These logs were used both to deduce information about the porosity of the formation, the water saturation, the presence of hydrocarbons, and the identification of contacts.

2-2-2-6 NMR

It is one of the electromagnetic logs based on the measurement of the induced magnetic moment of hydrogen protons contained in fluids stored in the porous medium. The amplitude of the NMR signal is proportional to the number of hydrogen nuclei present in the formation, so it can be calibrated to estimate the formation porosity without knowing the type of lithology (Chardaire-Riviere, C. and Roussel, J. C., 2006). The majority of hydrogen nuclei are presented in water molecules, which implies that the NMR method specifically and directly indicates the presence or absence of water in the porous medium, as well as estimating the hydrodynamic characteristics of this medium (Boucher, M. et al., 2005). This technique was introduced in the petroleum industry to determine porosity, pore size distribution, rock wettability, permeability, composition, viscosity, and the distribution of fluids.

2-3 Rock typing approaches

The identification of reservoir rock types is one of the key parameters for reservoir characterization due to its function in the specification and the identification of physical properties which are considered an essential element for successful drilling, optimal production, injection optimization, reservoir studies, simulation, and management of reservoirs.

Based on the reservoir rock properties and depending on the type of information, several approaches have been applied to determine reservoir rock types. These approaches have focused on the use of different sources of information via different data collection methods. In the literature, the identification of rock types can be divided into three main categories.

2-3-1 Lithofacies classification

Lithofacies are defined and delimited by rocks that have the same lithological, mineralogical, texture, digenesis, fossil content, deposit environment, and tectonic characteristics (Lee, J., 2018). These properties are defined based on the description of the core and its macroscopic and microscopic analysis (Wen, Xu. et Al., 2022). The primary goal of lithofacies classification is to define the different facies of the desired area and their characteristics in order to have a global view of the facies distribution in the reservoir and determine the relative impact of the deposition media, digenetic process, and rock structure on fluid flow in the porous medium (Moreton, D.J. and Carter, B.J. , 2015).

2-3-2 Petrofacies determination

Petrofacies are rocks with identical hydraulic units, which produce distinct permeability-porosity relationships, pore radius, relative permeability, capillary pressure, and water saturation profiles (Genliang Guo, et Al., 2007). These petrofacies are identified in order to

determine the most robust and promising hydraulic unit models for identifying reservoir heterogeneity and predicting petrophysical properties in non-core areas (Vahid Tavakoli, 2018).

In reservoir engineering, the petrofacies determination is based on the identification of hydraulic units, pore sizes, and rock fabric numbers (Attia M. Attia and Habibu Shuaibu , 2015). These petrofacies could be used to predict permeability (K) in non-core sections, and estimate water saturation (Sw) (Mahjour SK, et al., 2015). The determination of petrofacies is based on the use of reservoir petrophysical properties coming from core data such as porosity, permeability, saturation, pore radius, relative permeability, and capillary pressure (Binfeng Cao et Al., 2021). The presence and availability of all these parameters could be a powerful tool to define the different rock classes and their potential contribution in the expected recovery (Rezaei, A. et Al., 2020). Several methods are published in the literature for the usual classification of rock types.

2-3-2-1 Hydraulic Flow Unit (HFU)

Hydraulic flow units (HFU) are defined by reservoir rock areas that can be mapped, correlated, and have the same petrophysical and geological properties affecting fluid flow in the porous medium (Khalid, M. et Al., 2020). These properties are similar in the same flow unit and differ from unit to unit. The determination of the hydraulic units requires a complete and intensive study of the anticipated area (Askari, A. A. & Behrouz, T., 2011). The collection of information from different sources is essential to defining the different classes that share the same petrophysical characteristics. This subdivision can be developed from the classification of rocks according to; mineralogical composition, pore size distribution, pore geometry, grain size distribution, and pore communication (Orodu, O. et Al., 2009). In this regard, several studies have been carried out based on these aspects to define hydraulic units;

a. Flow Zone indicator

The flow zone indicator technique was introduced by Amaefule, J. O. et al., in 1993 for the identification and characterization of hydraulic flow units (Amaefule, J. O. et al., 1993). This technique was initiated by the combination of the modified Kozeny-Carmen equation and mean hydraulic radius for permeability determination. The equation is as follows:

$$k = \frac{\emptyset_e^3}{(1-\emptyset_e)^2}\left[\frac{1}{F_s \tau^2 {S_{gv}}^2}\right] \quad (3)$$

With

k: Permeability.
$\emptyset_e$: Effective porosity.
F_s: Shape factor
τ; Tortusity.
S_{gv}: Specific grain surface.

The term $F_s\tau^2$, called Kozeny constant, is dependent on hydraulic unites (Amaefule, J. O. et al., 1993).

Dividing both sides of equation (3) by effective porosity and taking the square root of both sides, the equation became (Salehi, F. and Salehi, A., 2009):

$$\sqrt{\frac{k}{\emptyset_e}} = \left[\frac{\emptyset_e}{1-\emptyset_e}\right]\left[\frac{1}{\sqrt{F_s}\tau S_{gv}}\right] \quad (4)$$

In case of the permeability unit is in millidarcy (mD.), equation (4) can be written as (Abdi, Y., 2007):

$$RQI = \emptyset_z * FZI \quad (5)$$

Where:

$$RQI = 0.0314\sqrt{\frac{k}{\emptyset_e}} \quad (6)$$

$$\emptyset_z = \frac{\emptyset_e}{1-\emptyset_e} \quad (7)$$

$$FZI = \frac{1}{\sqrt{F_s}\tau S_{gv}} = \frac{RQI}{\emptyset_z} \quad (8)$$

With:

RQI; Rock quality index (μm).
$\emptyset_z$; Ratio between the pore volume and solid volume (fraction).
0.0314 is the conversion factor from m-Darcy to μm.
FZI: Flow zone indicator.

According to (Djebbar, Tiab and Erle, C. Donaldson, 2016), introducing the logarithm on the equation (8) on both sides becomes:

$$log\ (RQI) = log\ (\emptyset_z)\ + log\ (FZI) \quad (9)$$

For the identification of hydraulic units, the method consists of plotting the rock quality index calculated from equation 6 versus $\emptyset_z$ which is calculated from equation 7 on a log-log plot. Samples belong in the same cluster showing a line with a linear slope (Amaefule, J. O. et al., 1993). The intersection of this line with $\emptyset_z = 1$ represents the FZI of the cluster. Samples with different FZI values will be found in parallel lines (Djebbar, Tiab and Erle, C. Donaldson, 2016). Each straight line could be representing a hydraulic flow unit where samples from that group can have the same pore throat characteristics. The permeability of each cluster can be calculated by:

$$k = 1014 * FZI_{mean}^2 \left[\frac{\emptyset_e^3}{(1-\emptyset_e)^2}\right] \quad (10)$$

b. Normal Probability plot

The normal probability curve is a technique based on the use of FZI to identify hydraulic flow units. It consists of plotting the cumulative FZI log as a function of FZI. The deviation point of the curve shows the separation between two hydraulic units. This method could be a powerful tool for FZI interval identification of the hydraulic units (Belhouchet H.E. & Benzagouta M.S., 2019).

c. Discrete Rock Type method (DRT)

Genliang, G. et Al., (2007) introduced a new approach based on the conversion of the continuous rock type defined by the FZI method into a discrete rock type (DRT), in which each rock type is specified by a discrete value (Genliang, G. et Al., 2007). These DRTs can be a device with an application role made for facilitating the summing up of the FZI values into flow units. This method is highly recommended and useful for sandstone reservoir characterization and numerical simulation according to its speed, quality, and precision (Belhouchet H.E. & Benzagouta M.S., 2019). FZI values could be converted to discrete rock type (DRT) using the following equation:

$$DRT = Round[2 * ln\,(FZI)\ + 10.6] \quad (11)$$

2-3-2-2 Pore Throat radius

Pore throat radius is defined as the pore throat size deduced from mercury pressure curves obtained when injecting 35% of the pore volume of a non-wetting fluid (mercury) into the rock. This approach was initiated by Winland in 1972 to develop an empirical relationship between porosity, air permeability, and pore throat aperture size corresponding to a 35% of mercury saturation. The formula was used and published by Kolodzie, S., 1980, and it is given by the following relation (Stanley Kolodzie, Jr., 1980):

$$log\ R_{35}\ = 0.732 + 0.588 * log\ k\ - 0.864 * log\ \emptyset \quad (12)$$

In 1992, Pitmann based on Winland's approach to develop mathematical correlations of pore throat corresponding to mercury saturation from 10% to 75% (Pittman, E. D., 1992):

$$log\ R_{10}\ = 0.452 + 0.500 * log\ k\ - 0.385 * log\ \emptyset \quad (13)$$
$$log\ R_{15}\ = 0.333 + 0.509 * log\ k\ - 0.344 * log\ \emptyset \quad (14)$$
$$log\ R_{20}\ = 0.218 + 0.519 * log\ k\ - 0.303 * log\ \emptyset \quad (15)$$
$$log\ R_{25}\ = 0.204 + 0.531 * log\ k\ - 0.350 * log\ \emptyset \quad (16)$$
$$log\ R_{30}\ = 0.215 + 0.547 * log\ k\ - 0.420 * log\ \emptyset \quad (17)$$
$$log\ R_{35}\ = 0.255 + 0.565 * log\ k\ - 0.523 * log\ \emptyset \quad (18)$$
$$log\ R_{40}\ = 0.360 + 0.582 * log\ k\ - 0.680 * log\ \emptyset \quad (19)$$

$$log\ R_{45} = 0.609 + 0.608 * log\ k - 0.974 * log\ \emptyset \quad (20)$$
$$log\ R_{50} = 0.778 + 0.626 * log\ k - 1.205 * log\ \emptyset \quad (21)$$
$$log\ R_{55} = 0.948 + 0.632 * log\ k - 1.426 * log\ \emptyset \quad (22)$$
$$log\ R_{60} = 1.096 + 0.648 * log\ k - 1.666 * log\ \emptyset \quad (23)$$
$$log\ R_{65} = 1.372 + 0.643 * log\ k - 1.979 * log\ \emptyset \quad (24)$$
$$log\ R_{70} = 1.664 + 0.627 * log\ k - 2.314 * log\ \emptyset \quad (25)$$
$$log\ R_{75} = 1.880 + 0.609 * log\ k - 2.626 * log\ \emptyset \quad (26)$$

Where

k: Permeability, $\emptyset$: Porosity. R_{xx} : Pore radius calculated at saturation of xx % (Hg).

In the literature, several authors have worked on pore throat radius to define reservoir rock types. The latter has got a direct effect on permeability (K) and fluid rate (Q) (Al-Khidir, K. E. et Al., 2011). According to (Cranganu, C. et Al., 2009) and (Attia M. Attia and Habibu Shuaibu , 2015), rock types can be classified based on pore throat into 5 types as follows:

- Mega porous hydraulic units ($R_{35} > 10\ \mu m$)
- Macro porous hydraulic units ($2.5 < R_{35} < 10\ \mu m$)
- Meso porous hydraulic units ($0.5 < R_{35} < 2.5\ \mu m$)
- Micro porous hydraulic units ($0.2 < R_{35} < 0.5\ \mu m$)
- Nano porous hydraulic units ($R_{35} < 0.2\ \mu m$)

Parallel to the application of the DRT method, to convert a continuous FZI function to a discrete value, Tillero, E., 2012 proposed a new approach based on the conversion of continuous rock type variable R_{35} calculated by Winland method into a discrete value ($DRT_{R_{35}}$) which considered as a rock typing indicator (1, 2, 3, … n) (Tillero, E., 2012). This discrete value can be calculated by the following relation:

$$DRT_{R_{35}} = Round[10 * (1.7 * log\ R_{35} + 5.2)] \quad (27)$$

Since the discrete rock type index ($DRT_{R_{35}}$) is related to R_{35}, it may be possible to extend the definition of $DRT_{R_{35}}$ as a function of porosity versus permeability relation. It means that the permeability may be estimated from porosity if the discrete rock type value is known and vice versa (Rushing, J. A. et Al., 2008); (Tillero, E., 2012); (Attia M. Attia and Habibu Shuaibu , 2015); (Belhouchet H.E. & Benzagouta M.S., 2019).

2-3-2-3 Global Hydraulic Element (GHE)

The method of global hydraulic elements (GHE) is a method developed by (Corbett, P. W. M. and Potter, D. K. , 2004), this method has a similar concept to the HFU method, and it is based on the quantification of the value of FZI on Base-Map and predicting subsequent permeability. Therefore, the permeability can be calculated by a reengagement of equation 10 as follows:

$$k = \emptyset * \left[\frac{FZI * \left(\frac{\emptyset}{1-\emptyset} \right)}{0.0314} \right]^2 \quad (28)$$

Thus, the aim of this method is to define 10 global hydraulic elements by determining the limits of the hydraulic units from the selection of a systematic series of FZI values which are calculated by the equation (8). The definition of these limits is selected arbitrarily in order to divide a wide range of possible combinations of porosity and permeability into a manageable number of GHEs.

This method provides an easy way to compare porosity - permeability data of any reservoir against the same GHE, in contrast to the hydraulic unit approach which is based on plotting RQI as a function of $\emptyset_z$ and seeks on unit slopes which are equivalent to hydraulic units. The table below illustrates the values of GHEs and their specific FZI values that represent boundaries between classes.

GHE	FZI
10	48
9	24
8	12
7	6
6	3
5	1.5
4	0.75
3	0.375
2	0.1875
1	0.0938

Table 2-1: FZI Value for each type of GHE after **(Corbett, P. W. M. and Potter, D. K. , 2004)**

The plot of FZI versus GHE shows a good mathematical relationship (Figure 2-1), which means, this correlation can be used to predict FZI barriers in the presence of more than 10 rock types (heterogeneous reservoirs).

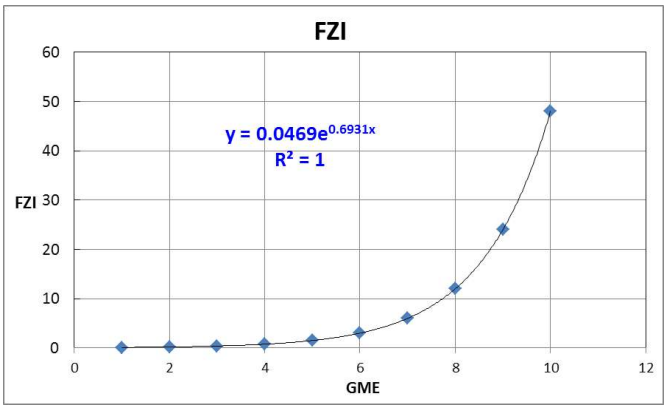

Figure 2-1: Flow zone indicator (FZI) versus Global hydraulic unit (GHE).

According to (Corbett, P. W. M. and Potter, D. K. , 2004), the advantages of the GHE approach are:

- The petrophysical parameters (porosity and permeability) for any reservoir refer exactly to the same location frame.
- The determination of conventional hydraulic units (HU) for each well in a particular investigation is not needed according to the GHE template, which saves time.
- The GHE template helps to select minimum representative training data for prediction from any available porosity and permeability data, even if these baseline data are relatively limited.

2-3-2-4 Pore Geometry Structure (PGS)

In 2013, Wibowo, A. S. and Permadi, P. developed an approach for rock grouping based on the relationship between pore geometry and pore structure at a particular scale (Wibowo, A.S. and Permadi, P., 2013). According to Prakoso, S., Permadi, P. et Winardhie, S., (2016), pore geometry is simply an equivalent to mean hydraulic radius, while pore structure is a pore attribute influenced by pore shape, pore tortuosity, and internal surface area (Prakoso, S., Permadi, P. et Winardhie, S., 2016). In 1927, Kozeny, J. developed a mathematical correlation defining the relationship between permeability, porosity, and specific surface area, and the general form of the equation is (Kozeny, J., 1927);

$$\left(\frac{k}{\emptyset}\right)^{0.5} = \emptyset\left(\frac{1}{F_s \tau S_b^2}\right)^{0.5} \tag{29}$$

and

$$\frac{k}{\emptyset^3} = \frac{1}{F_s \tau S_b^2} \tag{30}$$

The equation 29 became:

$$\left(\frac{k}{\emptyset}\right)^{0.5} = \emptyset\left(\frac{k}{\emptyset^3}\right)^{0.5} \tag{31}$$

Where k is the permeability, and $\emptyset$ is the porosity, F_s is the shape factor, τ is the tortuosity, and S_b is a specific internal surface area with reference to bulk volume. The variable $\left(\frac{k}{\emptyset}\right)^{0.5}$ is called the pore geometry variable and $\frac{k}{\emptyset^3}$ is the pore structure.

Plotting $\left(\frac{k}{\emptyset}\right)^{0.5}$ as the dependent variable against $\frac{k}{\emptyset^3}$ as the independent variable in the log-log plot yields a straight line with a positive slope of 0.5. Equation 31 may be written in a more general form as a power-law equation:

$$\left(\frac{k}{\emptyset}\right)^{0.5} = a\left(\frac{k}{\emptyset^3}\right)^{b} \quad or \quad \left(\frac{k}{\emptyset}\right)^{0.5} = a\left(\frac{1}{F_s \tau S_b^2}\right)^{b} \tag{32}$$

Where a is considered a correction factor for volumetric fluid flow efficiency for irregular pore systems and b is the power-law exponent, and is considered an indicator of the complexity of the pore structure (Wibowo, A.S. and Permadi, P., 2013). For smooth tortuous capillary tubs, the maximum value of b is 0.5 (Harmsen, G. J., 1955). Natural porous rocks with similar microscopic geological characteristics have a b value of less than 0.5. More this value is lower; the pore structure could be more complex.

In 2013, Wibowo, A.S. and Permadi, P. developed a correlation plot between pore geometry and pore structure, where the pore geometry is plotted in the Y-axes and the pore structure is plotted in the X axes, these correlation diagrams are used to generate typical curves for reservoir rock type classification. Therefore, the PGS method determines the rock type by plotting $\left(\frac{k}{\emptyset}\right)^{0.5}$ versus $\frac{k}{\emptyset^3}$ coming from RCA and SCAL data on the PGS type curve of the PGS method (Figure 2-2).

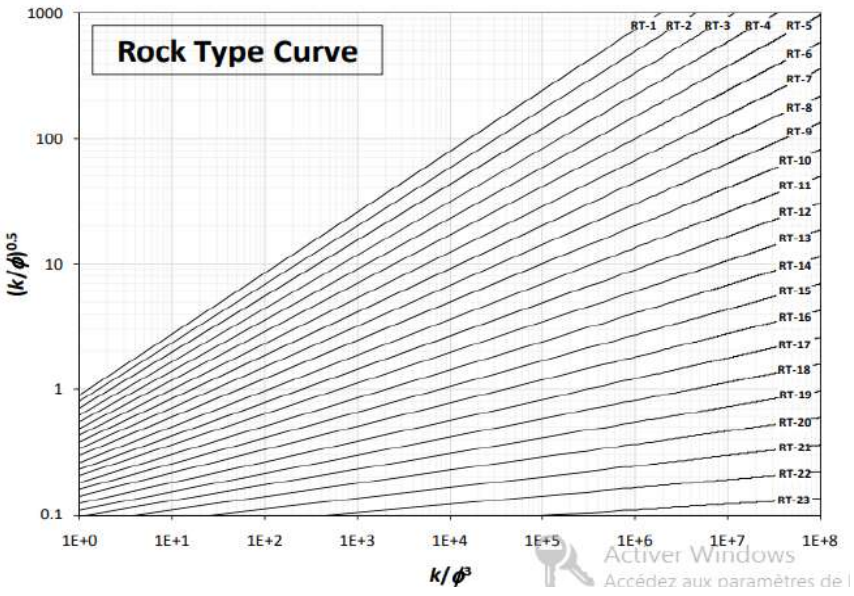

Figure 2-2: PGS Type Curves according to (Jennings, J. W. et Lucia, F. J., 2003) and (Wibowo, A.S. and Permadi, P., 2013)

2-3-2-5 Jennings-Lucia Method: Rock Fabric Number (RFN)

Permeability and capillary pressure properties of interparticle pore space can be related to interparticle porosity and geologic description of particle size and sorting called rock fabrics (Jennings, J. W. et Lucia, F. J., 2003). These rock fabrics were initially grouped into three

categories called rock-fabric petrophysical classes based on their porosity/permeability relationships and capillary properties. This method was applied generally for carbonate sedimentary rocks (Robert J. Dunham, 1962):

- Class 1 is composed of grainstones, dolo grainstones, and large crystalline dolostones.
- Class 2 is composed of grain-dominated packstones, fine and medium crystalline, grain-dominated dolopackstones, and medium crystalline, mud-dominated dolostones.
- Class 3 includes mud-dominated limestones and fine crystalline, mud-dominated dolostones.

In 1995, Lucia, F. J. introduced a new approach based on the correlation of rock fabric description to determine reservoir rock types through a correlation between interparticle porosity types, in which this interparticle porosity is not affected by vugs in the carbonate matrix (Lucia, F.J., 1995). According to Lucia, FJ., (1999), interparticle porosity has an important role in the hydraulic flow of carbonate rock. It is defined as (Lucia, FJ., 1999):

$$\emptyset_{inp} = \frac{\emptyset_T - \emptyset_v}{1 - \emptyset_v} \tag{33}$$

Rock fabric numbers can be determined by plotting the porosity and permeability data of a carbonate reservoir. The relationship between interparticle porosity (ϕ_{inp}), permeability (k), and rock fabric number (RFN) could be expressed by the equation:

$$log\ k\ = (9.7982 - 12.0838\ log\ (RFN)\ ) + (8.6711 - 8.2965\ log\ (RFN\ )) * log\ \phi_{ip} \tag{34}$$

2-3-3-6 Electrical rock type

In 2007, Razaee et al. introduced a new approach based on the identification of electrical rock types related to the electrical flow units (EFU), these are defined by the zones having similar electrical flow properties, and they are characterized by a current zone indicator (CZI) (Rezaee, M. R., Motiei, H. et Kazemzadeh, E., 2007):

$$CZI = \frac{\sqrt{\left(\frac{\phi}{F}\right)}}{\emptyset_z} \tag{35}$$

Where ϕ, F and are porosity (fraction), formation factor, and $\emptyset_z$ pore to matrix volume ratio respectively. The electrical radius indicator (ERI) is calculated by:

$$ERI = \sqrt{\left(\frac{\phi}{F}\right)} \tag{36}$$

Then,

$$CZI = \frac{ERI}{\emptyset_z} \quad (37)$$

2-3-3 Electrofacies prediction

An electrofacies is a set of logarithmic responses that characterize reservoir rock types. This concept was introduced by O, Serra, 1984 to link well log measurements at the borehole level to the interpreted facies of cores and cuttings data in order to predict the facies in the non-cored sections (Serra, O., 1984). Electrofacies can be defined manually by analysing well log shapes or using cluster analysis methods. However, these methods have been applied to ensure that the final groups have an interpretable geological significance based on stratigraphic analysis of core samples and geological knowledge of the study area. Electrofacies analysis is a system for identifying rock types with similar properties from wire logs.

2-4 Machine Learning (ML)

Machine learning is one of the artificial intelligence branches based on the development of algorithms that learn large data sets to enable computers to provide a learning function without programming the rules for each problem (Sircar, A. et Al., 2021). Machine learning algorithms are applied to build a model based on data samples known as training data in order to make predictions, recommendations, decisions, and various other intelligence-related tasks on hidden data called testing data, without the need for explicit programming instructions/rules (Ma, Y. Z., 2019).

Machine learning can be classified into three main groups: supervised machine learning, unsupervised learning, and reinforcement learning. These categories are associated with different machine learning algorithms that represent how the learning method works (Sarker, I., H., 2022).

2-4-1 Supervised learning

Supervised learning is a machine learning task based on the development of a prediction function that allows relating a set of input variables X to an output variable Y (Cunningham P. et Al., 2008). The algorithms of supervised learning are intended for analysing training data and inferring a function that can be used to map new examples. Furthermore, supervised learning approaches rely on algorithms that can use instances provided externally to produce a general hypothesis that makes predictions about future instances (El Bouchefry, K. et Souza, R. S., 2020).

2-4-1-1 Supervised learning types

Supervised machine learning is based on using a set of information to create models that can achieve the desired outcomes. This set of information must include valid inputs and outputs so that the model can learn over time. The selection of the algorithm can be related to the estimated accuracy by the root mean square error (RMSE), which is a measure used to calculate the root mean square difference between the predicted values by the model and the observed values.

Supervised machine learning can be separated into two main categories; classification and regression (Osisanwo F., Y. et Al., 2017).

a. Classification

Classification is a supervised learning task where the output has a discrete value. The objective of the classification is to predict discrete values belonging to a particular class and evaluate them on the basis of their accuracy. This class can be a binary or multi-class classification. In binary classification, the model predicts 0 or 1; yes, or no, but in the case of multi-class classification, the model predicts more than one class (Osisanwo F., Y. et Al., 2017).

b. Regression

The regression method is one of the most basic supervised learning tools used for prediction. The main objective is to develop a mathematical equation that defines y as a function of the variables x, and predict a continuous outcome variable as close as possible to the actual output value (Anemangely, M. et Al., 2019). The validation of the regression model could be related to the quadratic error (RMSE) between the predicted and the actual outcome (equation 38). Generally, the regression method is applied to understand the relationship between dependent and independent variables (Barbosa, L. F. F. M. et Al., 2019).

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T}(\widehat{y_t} - y_t)^2}{T}} \quad (38)$$

Where:

$\widehat{y_t}$: predicted value at time t.

y_t: observed value at time t.

T: time.

2-4-1-2 Supervised learning algorithms

Several algorithms and techniques of supervised machine learning can be obtained in the literature. These algorithms can be used either in classification or regression processes:

a- Neural networks

An artificial neural network (ANN) is a network or circuit of neurons composed of artificial neurons or nodes that use a mathematical model for information processing based on a connectionist approach to computation (El-Abbasy, M. E. et Al., 2014). In most cases, an ANN is an adaptive system that changes its structure in response to external or internal network information. Neural networks could be classified as statistical applications that enrich categorization models, or artificial intelligence approaches that generate formal logical reasoning and address artificial intelligence (AI) challenges (Saikia, P. et Al., 2020).

These artificial networks can be used for predictive modelling, adaptive control and other applications where they can be trained through a dataset. Self-learning resulting from experience can occur within neural networks, which can draw conclusions from a complex set of information (Sabah, M. et Al., 2019). This information must be trained by the artificial model by mimicking the interconnectivity of the human brain through layers of nodes. Each node is composed of inputs, weights, a bias (threshold), and an output (El-Abbasy, M. E. et Al., 2014). If the output value exceeds a given threshold, the node can be activated and forward the data to the next layer of the network (Figure 2-3). This process is iterated until we have a cost function equal to or close to zero, and therefore, we can be confident in the accuracy of the model to yield the correct answer (Kalogirou, SA. et Al., 2013).

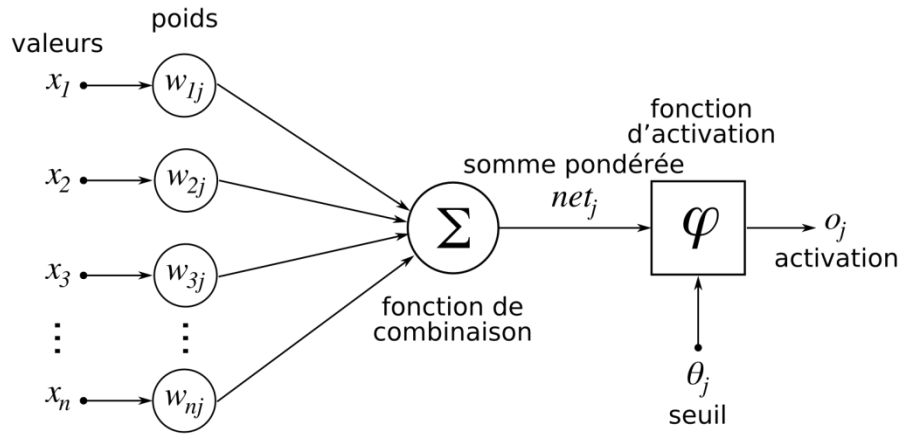

Figure 2-3: Structure of an artificial neuron.

The neuron calculates the sum of its inputs x, weighted by the weights w, then this value passes through the activation function phi to produce its output o.

b- Naive Bayes

Naive Bayes is a simple probabilistic Bayesian classification algorithm based on Bayes theorem with strong independence of assumptions for binary and multi-class classification problems. The basic concept of this approach assumes that the presence of a particular characteristic in a class is not related to the presence of any other characteristic (Saritas, M. M. and Yasar, A., 2019). This method is most commonly used in text classification, spam detection, and recommendation systems. Three types of Naïve Bayes classifiers could be found in the literature; Multinomial Naïve Bayes, Bernoulli Naïve Bayes, and Gaussian Naïve Bayes (Shobha, G. et Rangaswamy, S., 2018). The advantage of a Bayesian classifier is the minimum number of training data that might be needed to estimate the classification parameters, and the probabilistic model for this type could be a conditional model (Ren, J. et Al., 2009).

c- Linear regression

Linear regression was originally developed in the statistics domain and has been studied as a linear model which assumes a linear relationship between the input variables (x) and the single output variable (y) to make predictions about future outcomes (Siegel, A. F. et Wagner, M. R.,

2022). This technique was borrowed by machine learning to establish an algorithm allowing to obtain the best fit linear line and the optimal values of intercept and coefficients such that the error is minimized (Kalidas Yeturu, 2020). The input variable could be considered an independent variable and the output variable is considered the dependent variable. In the literature, two linear regression methods could be found: simple and multiple (Raghunath Arnab, 2017).

Simple linear regression is the method where only one independent variable can be present and the model has to find the linear relationship between it and the dependent variable (equation 39) (Forthofer, R. N. et Al., 2007).

$$y = b_0 + b_1 x \tag{39}$$

Whereas, Multiple Linear Regression is a technique where the independent variables can be more than one and the model has to develop a linear relationship between the independent and dependent variables (equation 40) (Yangchang Zhao, 2013).

$$y = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + \cdots .. + b_n x_n \tag{40}$$

For each of these types of linear regression methods, it seeks to draw a line of best fit, however, a mathematical representation must be related to the response to the predictor variables. Calculation of statistical properties such as means, standard deviations, correlation coefficient, and covariance should be necessary to confirm the best fit (Siegel, A. F. et Al., 2022).

d- Nonlinear regression

Nonlinear regression is a form of regression analysis in which data is fitted to a nonlinear model used to define a relationship between the dependent variable and a set of independent variables (Nisbet, R. et Al., 2009). The development of nonlinear models is more complicated compared to linear models due to the function obtained by a series of approximations (iterations) as a result of arbitrary relationships between independent and dependent variables (Pérez-Marín, S. et Al., 2007). Note that this technique is not recommended for simple polynomial models ($y = a + b * x^2$) which can estimate its parameters using traditional methods such as linear regression procedures.

The determination of the fit function is closely related to the application of different nonlinear functions such as logarithmic, trigonometric, exponential, power, Lorenz curves, Gaussian, and other fitting methods, to the training data set and finding the best fit function in which the quadratic error should be the minimum (Motulsky, H. J. and Ransnas, L. A., 1987). The general model could be presented as:

$$Y_i = f(x, \theta) + \varepsilon = f\left(x_i^{(1)}, x_i^{(2)}, x_i^{(3)}, \ldots\ldots, x_i^{(m)}; \theta_1, \theta_2, \theta_3, \ldots\ldots, \theta_p\right) + E_i \tag{41}$$

Where;

Y_i is the response variable, f is the function or model, x_i are the inputs, θ denotes the parameters to be estimated, and ε is the error.

e- Support vector machine (SVM)

Support Vector Machines are supervised machine learning algorithms that are used to solve discrimination and regression problems. It is, however, mostly employed in categorization difficulties (Figure 2-4). These algorithms were developed in the 1990s as a result of theoretical considerations on the development of a statistical learning theory and were implemented due to their rapid capacity to work with large amounts of data, a low number of hyperparameters, theoretical guarantees, and good practice results (Vapnik, N. V., 1998). The support vector machine works by constructing a hyperplane or set of hyperplanes in high or infinite dimensional space for classification, regression, or other tasks (Anifowose, F. et Abdulraheem, A., 2011). These methods are founded on two fundamental concepts: maximum margin and kernel function.

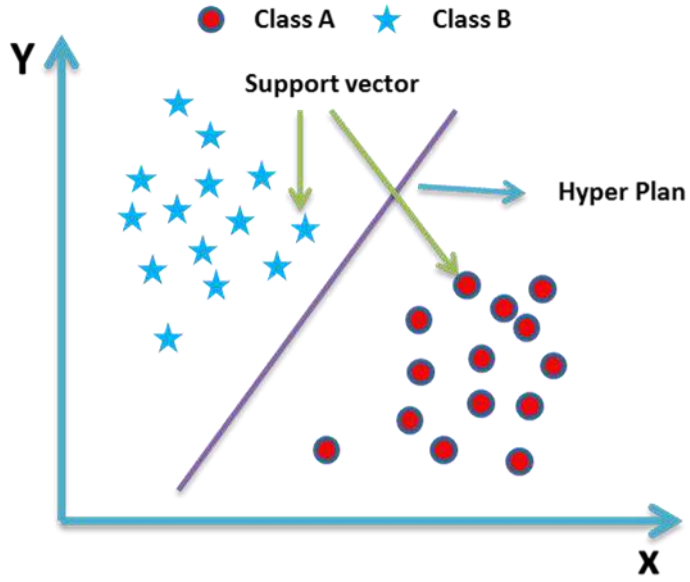

Figure 2-4: Schema showing the support vector machine (SVM) classification

Concept of maximum margin

The margin is defined as the distance between the separation boundary and the closest samples. In SVMs, the separation boundary is chosen as the one that maximizes the margin. This choice is justified by the statistical learning theory developed by (Vapnik, N. V., 1998), which shows that the maximum margin separation border has the smallest capacity. The problem is to find this optimal dividing border in a training set. This is done by formulating the problem as a quadratic optimization problem, for which there are known algorithms (Nugroho, A. S. et Al., 2003).

Concept of kernel function

This approach was introduced by Aizenman et al. (1964) to study nonlinear classification problems (Roth, V. & Steinhage, V., 2000). This method consists in transforming the representation space of the input data into a space of greater dimension in which a linear separation could be expected (Robert Strack, 2013). This is achieved thanks to a kernel function that must respect the conditions of Mercer's theorem, and has the advantage of not requiring explicit knowledge of the transformation to be applied for the change of space (De Mello, R. F. & Ponti, M. A., 2018). Kernel functions make it possible to transform a scalar product in a large space into a simple one-off evaluation function (ZHANG, L. & ZHANG, Bo, 2002). This technique is known as the "kernel trick".

f- K-nearest neighbour

The k-nearest neighbour (KNN) algorithm is one of the most fundamental and simple supervised machine learning algorithms that can be used to solve classification and regression problems (Shen, H. and Chou, K. C., 2005). These algorithms were introduced in statistical estimation and pattern recognition as a non-parametric technique at the beginning of the 1970s. KNN assumes that similar data points can be found in close proximity to each other. Therefore, the objective of this algorithm is to seek to calculate the distance between the data points via the function distance for continuous variables and the overlap (hamming) distance for discrete variables. In the KNN classification process, an input object is classified according to the majority of statistical results to the class that k nearest neighbours belong to, while in regression methods, the result is the average of the values of the k nearest neighbours (Gou, J. et Al., 2019). For the distance function, the KNN regression algorithms use the same distance functions as the KNN classification (Manocha, S. and Girolami, M.A. , 2007). For continuous variables, the distance functions could be defined by several methods such as:

- **Euclidean distance function**

The Euclidean distance between two points in Euclidean space is defined by the length of the line segment between two points (Gou, J. et Al., 2019). It can be calculated using the Pythagorean Theorem from the Cartesian coordinates of the points.

$$d = \sqrt{\sum_{i=1}^{k} (x_i - y_i)^2} \tag{42}$$

- **Manhattan distance function**

The Manhattan distance function is defined by the distance between two points measured along two axes at right angles (Rodrigues, É.O., 2018). It's given by the sum of differences of their corresponding components.

$$d = \sum_{i=1}^{k} |x_i - y_i| \quad (43)$$

- **Minkowski distance function**

The Minkowski distance is defined as the distance measured between two points in the normalized vector space (Youqiang, Z. et Al., 2019). The Minkowski distance of order p (p is an integer) between two points is given by:

$$d = \left(\sqrt{\sum_{i=1}^{k} (|x_i - y_i|)^p} \right)^{1/p} \quad (44)$$

In the case of categorical variables, Hamming function could be applied to define the distance which is considered a measure of the number of instances in which the corresponding symbols are different in two strings of equal length (Olatunji, O. O. et Al., 2020). The Hamming distance is defined by:

$$d_H = \sum_{i=1}^{k} |x_i - y_i| \quad (45)$$

If $x = y$, it implies that $d_H = 0$, otherwise $d_H = 1$.

Where x_i and y_i are two components on the real line (one dimension), k is the number of points

g- Random forest

Random forests or random decision forests are machine learning methods used for classification, regression, and other tasks that work by building a series of decision trees at the time of learning (Liu, Y. et Al., 2012). This latter was created in 1995 by Tin Kam HO using the method of random subspaces which is a tool for implementing the stochastic discrimination approach to the classification process proposed by Eugene Kleinberg (Tin Kam Ho, Random decision forests, 1995). The "forest" refers to a collection of uncorrelated decision trees that are then merged together to reduce variance and create more accurate data predictions (Tin Kam Ho, 1998).

For classification tasks, the random forest prediction is the most dominant class among the predictions of the individual trees that generate a particular instance (Suthaharan, S., 2016). In the case of T trees in the forest, the number of votes received by a class m is given by:

$$v_m = \sum_{i=1}^{T} I(\hat{y}_t == m) \quad (46)$$

Where $\widehat{y_t}$ is the prediction of t^{th} tree on a particular instance. The indicator function $I(\widehat{y_t} == m)$ takes on the value 1 if the condition is met, else it is zero. The final prediction model of the random forest is the class with the most votes:

$$\hat{y} = v_m \tag{47}$$

In the regression setting, the prediction of the random forest is the average of predictions made by the individual trees. The final prediction $\widehat{y_t}$ is:

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T} \widehat{y_t} \tag{48}$$

2-4-2 Unsupervised learning

Unsupervised learning is one of the machine learning types that learn patterns from unlabelled data (Gentleman. R. and Carey, V. J., 2008). The approach focused on exploiting a set of input information to generate results based on the characteristics and attributes of that data without any prior information about the results. The goal of unsupervised learning is to model the structure or underlying distribution of data in order to learn more about the data. The resulting model must figure out how it can learn from the input data (Qin. Z. and Tang. Y., 2014). Unsupervised learning models can be divided into three main types: grouping, association, and dimensionality reduction (Ghahramani, Z., 2004).

2-4-2-1 Clustering

Data clustering is one of the data analysis techniques used in unsupervised ML tasks to group them into homogeneous subsets sharing similar properties. This process simplifies data analysis by highlighting commonalities, and differences and reducing the number of variables in the data (Kiaei, H. et Al., 2015).

2-4-2-2 Association

It is considered one of the unsupervised machine learning techniques that involves determining relationships or interesting dependencies between variables in large datasets. This approach aims to identify strong association rules that can be used to extract knowledge from data and provide a reliable source of information for learning, understanding, and decision-making (Ali, N. et Al., 2023).

2-4-2-3 Dimensionality reduction

Dimensionality reduction is a machine learning process based on converting data from a large-dimensional space into a smaller-dimensional space (Yang, X. et Al., 2014). It focuses on reducing the number of input variables in a data set. The resulting output data should represent effectively the input data (Qiang, Q. et Al., 2022). This dimensional reduction could be implemented to simplify a classification or regression dataset to better fit a predictive model.

The dimensionality reduction approach could be used for noise reduction, data visualization, cluster analysis, and as an intermediate step to facilitate further analysis (Vlachos, M., 2011).

2-4-3 Reinforcement learning

Reinforcement learning is one of the approaches to machine learning focused on the reaction of the behaviour of intelligent agents to take actions in an environment in order to maximize the notion of cumulative reward (Andrew G. Barto, 1997). This optimal behaviour is learned through interactions with the environment and observations of the responses to these interactions. This approach could be considered a science of decision-making (Dayan, P. and Niv, Y., 2008).

2-5 Application of machine learning

Reservoirs are defined as the accumulation of oil and gas in a porous medium. These reservoirs may be developed primarily in sedimentary rock systems, although occasionally reservoirs can be generated in igneous and metamorphic rocks. Reservoir rocks can be characterized according to their lithology, mineralogical composition, electrical properties, petro-physical properties, and formation age. These formations could be saturated by different fluids such as oil, gas, and water. For this purpose, the identification of the reservoir rock properties can be achieved through several disciplines such as; reservoir engineering, petrophysics, geophysics, petroleum engineering, geology, and sedimentology. Each of these disciplines has its own vision to discover and identify reservoir characteristics. All these disciplines must combine their understandings to define the properties of a reservoir properties and understand its behaviour.

Due to the high cost of operations carried out during the exploration, development, and exploitation of the oil fields. The number of experiments, tests, and analyses must be well defined to provide the minimum data allowing to perform a complete reservoir study. The main concepts applied in this kind of study are in fact based on classification, regression, prediction, and optimization approaches which are indeed the main tasks of machine learning. According to its rapid response and its vigorous generalization abilities, machine learning models could be implemented to accomplish more efficiently many difficult and time-consuming tasks.

Over the past ten years, machine-learning activity has increased dramatically year after year in the petroleum industry due to its high-quality results. In 2011, Demyanov, V. et al. introduced an advanced approach based on Multiple Kernel Learning (MKL) to merge intelligently measured reservoir properties, and geological knowledge with seismic data to achieve a realistic reproduction of the geological properties of a complex fluvial reservoir system (Demyanov, V. et Al., 2011). For automatic fault detection, the Kernel Regularized Least Squares algorithm (Kernel RLS) was applied to identify and localize faults from not migrated seismic data (Zhang, C. and Frogner, C., 2014). Another task that could be targeted by machine learning is the prediction of well logs using seismic data by applying neural networks (Hampson, D. P. et Al., 2001). This technique can provide more reliable data regarding synthetic well logs in undrilled areas. These synthetic logs could be then used as a substitute to

predict the petrophysical and petroelastic reservoir properties, and be indirectly involved in the identification of reservoir rock types (Priezzhev, I. I. et Al., 2019).

In 2018, Wu, P. Y. et al. developed a new machine learning method based on the combination of three mathematical models; cross-entropy clustering (CEC), Gaussian mixture model (GMM), and the hidden Markov model (HMM) to improve the objectivity, efficiency, and consistency of log processing and interpretation workflows (Wu, P. Y. et Al., 2018). This approach was initiated mainly due to the lack of abundant training data and the strong correlation among well logs (Wu, P. Y. et Al., 2018). To establish a correlation between conventional well logs (gamma rays, formation resistivity, neutron porosity, bulk density) and core measurements, the support-vector regression technique (SVR) was implemented to build a prediction model which enables to estimate reservoir properties based on selected well logs in cored sections (Negara, A. et Al., 2016). Similarly, a support vector machine (SVM) can also be applied to understand these relations (Brendon Hall, 2016). Therefore, according to Bize Forest, N. et al., (2018), the combination of supervised and unsupervised machine learning techniques could be suitable for lithofacies classification and prediction (Bize Forest, N. et al., 2018). This approach is supported by the authors (Aliouane L., et Al., 2014), (Oki Dwi Saputro et al., 2016), and (Ameur-Zaimeche, O. et Al., 2020).

To conclude, a lot of research has been done on the basis of different algorithms and machine-learning techniques to determine reservoir parameters. According to some research published in the literature, the parameters extracted are: evaluation of the quality of the reservoir, identification of rock types (Hussein, M. et Al., 2020), facies classification (Alaudah, Y. et Al., 2019), prediction of facies distribution in a depositional environment in complex reservoirs (Bize-Forest, N. et Al., 2018), estimation of reservoir fluid saturation (Guo, Q. et Al., 2021), the spatial distribution of petrophysical properties (Demyanov, V. et Al., 2011), well location optimization (Mousavi, S. M., et Al., 2020), flow allocation, well locations and well paths optimisation (Dada, M. A. et Al., 2020), automated identification and optimization of deviated and horizontal well targets (Castiñeira, D. et Al., 2018), and many of the other projects in the same context could be found in the literature. Many researchers pointed out that machine learning is becoming one of the main tasks in determining the various reservoir parameters. These researchers highlighted that machine learning can add value to developing oil and gas projects, reduce costs and be less time-consuming.

2-6 Conclusion

Rock typing is one of the main procedures applied in reservoir characterization to have a more reliable reservoir model. The application of different reservoir rock typing approaches is necessary to select the best method to ensure the best estimate of reservoir properties such as lithology, porosity, permeability, and saturation.

The development of this process is closely related to the type, volume, and quality of the data. The use of all data related directly or indirectly to the reservoir properties is recommended, to have more control over the use of these resources, and reduce reservoir modelling uncertainties and convergence problems that can be expected in the numerical simulation.

Machine learning is one of the best practical solutions implemented in the oil and gas industry to solve classification, regression, forecasting and optimization problems. Thus, it is considered one of the most effective ways to develop oil and gas projects, reduce costs, help decision-making and be time-consuming.

Chapter 3: Reservoir rock type Characterization – Case study of Algerian oil field

3-1 Introduction

In recent years, reservoir characterization has become one of the main steps in the oil and gas industry, in which the latter may take more time and labour to get more details about reservoir characteristics. This technique was introduced in all reservoir studies in order to have the necessary information that could be used to identify the homogeneity, the type, and the quality of the reservoir. The understanding of the reservoir behaviour and the construction of a representative and realistic reservoir model is another perspective of the reservoir characterization for the purposes of improving the estimation of reserves, predicting future production, and evaluating different development scenarios for the concerned fields where the detailed target is the Lower Triassic Clayey Sandstone (TAGI) of the Berkine Basin (HEB) (Figure 3-1).

In the literature, reservoir characterization has been defined by the identification, specification, and determination of geological, electrical, and petrophysical properties of the reservoir such as lithology, electrofacies, and petrofacies, as well as reservoir heterogeneity. Benzagouta M. S., et Al., (2001), Benzagouta, M. S. et Amro, M. M., (2009), and Al-Khidir, K. E. et Al., (2011) were among those who investigated this topic. The identification of the relationships between all of these properties is a necessity for classifying reservoir rocks into groups with similar characteristics (Benzagouta M. S., et Al., 2001), (Benzagouta, M. S. et Amro, M. M., 2009), and (Al-Khidir, K. E. et Al., 2011). The prediction of different geological concepts in the field becomes possible. The identification of the relationships between all of these properties is a necessity for classifying reservoir rocks into groups with similar characteristics. The prediction of different geological concepts in the field becomes possible.

One of the approaches that can be used is aimed to use the core description and its analysis. Similar outcomes can be provided by geologists, who were performing different rock typing methods such as flow zone indicator (FZI), discrete rock typing (DRT), pore throat radius (R_{35}), DRT for pore throat (DRT_R_{35}) and global hydraulic unit (GHE) to determine the most efficient method for identifying petrofacies, which turned out to be vital. The combination of these methods should be necessary to check the relationship between lithofacies and petrofacies (Belhouchet, H.E., Benzagouta, M.S. Dobbi,A. et Al., 2020). Authors cited in that issue include (Porras, J. C., 1998), (Chehrazia, A. et Rezaee, R., 2012), (Kadkhodaie-Ilkhchi, R. et Al., 2013), (Choi, J. et Al., 2019) and (Liaghat, M., 2021).

3-2 Field description and wells presentation

As instructed in the introduction section, the Hassi Berkine oil field was discovered, with some reserves, in the 1950s (Lo, L.L. et Al., 2004). The Berkine basin is located in the south-east of Algeria, between 29 degrees and 33 degrees north latitude and 5 degrees and 9 degrees East longitude (Belhouchet, H.E., Benzagouta, M.S. Dobbi,A. et Al., 2020) and (Sonatrach WEC,

1999), and (Sonatrach WEC, 2007). It is bounded to the North by the southern border of the Dahar Mole, and to the south by the Mole D'Ahara, which separates it from the Illizi basin (Sonatrach WEC, 2004). The Berkine basin is delimited to the east by the Tunisian-Libyan border and to the west by the structural extension to the North of the Mole Amguide-El Biode-Hassi Messaoud (Figure 3-1). The Berkine basin, tectonically, is of the intracratonic type with a total area of 102 395 km2 (Souadnia and Mezghache, 2009). Several oil and gas fields and satellites have been discovered in the Berkine basin such as; BRN, BRW, HEB, BMS, ROM, HBNS, HBN, ZEA, Ourhoud, EMK, EKT, and ROME. These fields have been developed by several companies such as SONATRACH, Anadarko, Eni, Cepsa, TOTAL...etc (Peffer, J. et AL., October 2003).

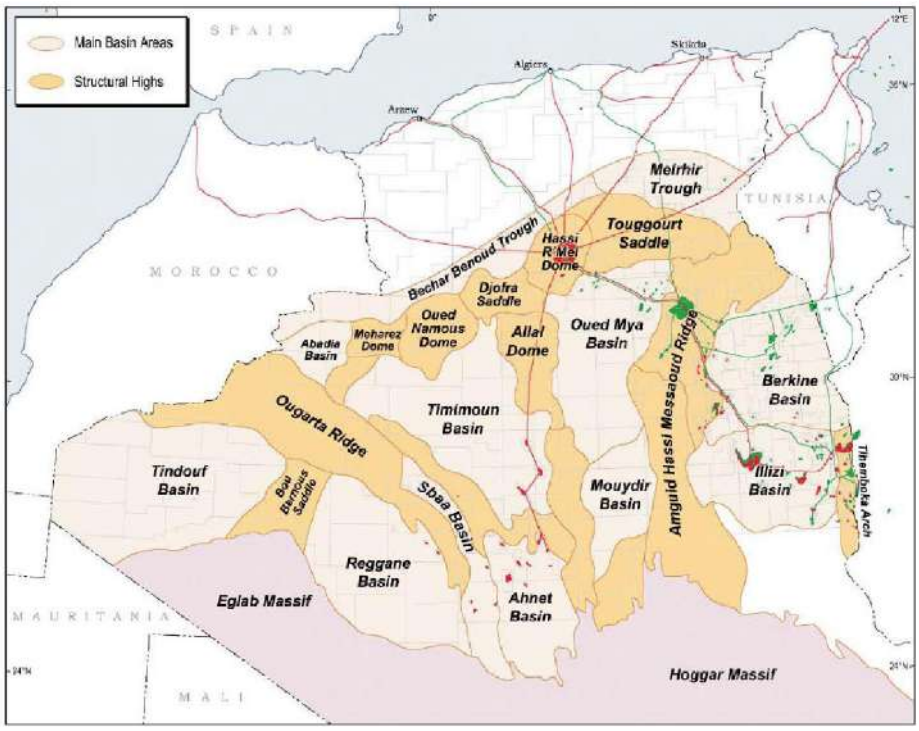

Figure 3-1: Overview of Berkine Basin location and surrounding structures **(Turner, P. et Al., 2001)**

In this conducted study, the focus is on the characterization of the Lower Triassic clay sandstone (TAGI) of the HEB field, which was discovered in 1991 by the well HEB1 in the 403a operating permit (Figure 3-1) (Peffer, J. et AL., October 2003). This field is approximately 315 kilometres southeast of Hassi Messaoud. HEB field is an anticlinal structure complicated by a series of faults parallel to the regional main fault (El Borma fault) as well as a series of minor faults with different orientations that tend to subdivide the entire field into blocks (Figure 3-2). The appraisal of the HEB structure was carried out by drilling the two wells HEB2 and HEB3 in the period 1993-1994 with the aim of extending the TAGI formation. The well 2 is located in the central part of the field, and it confirmed the potential of the field, whereas the well 3 was found implanted in the aquifer zone. For the development phase, 19 wells have been drilled to achieve the expected objectives (Figure 3-2).

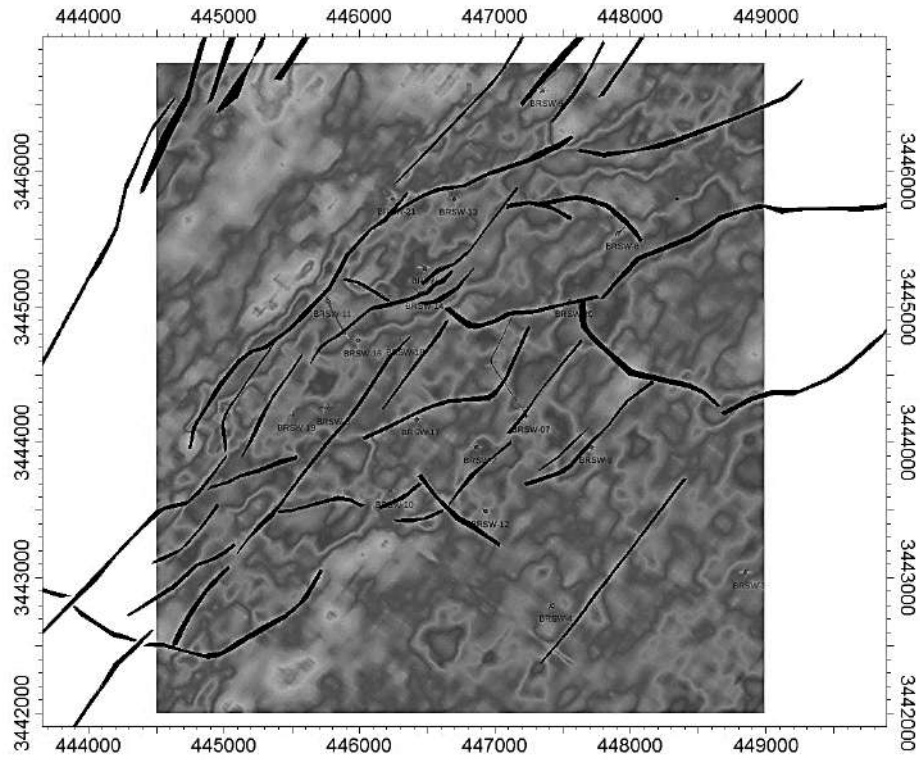

Figure 3-2: Major and minor fault directions, as well as well position in the concerned field **(Belhouchet, H. E. et Al., 2021)**

The main reservoir of the HEB field is the Lower Triassic clay sandstone (TAGI). Most of the studies carried out in this project indicate that the TAGI formation is a continental fluvial formation deposited at the top of the Frasnian schist exposed by the erosion surface in the Hercynian unconformity. It is characterized by sandstone and claystone deposits in a fluvial depositional environment. These deposits are sometimes interbedded with aeolian and deltaic layers.

Based on extensive baseline data and regional wireline log interpretations (Arezki Boudjema, 1987), (Benamrane, Oussalem, 1987), the TAGI reservoir can be divided into three main levels: upper (U), middle (M), and lower (L). From the top to the bottom. TAGI U and M are characterized by fine sandstone bodies and are very well classified, while TAGI L is characterized by medium and poorly classified. These levels can then be subdivided into a total of nine layers (Figure 3-3).

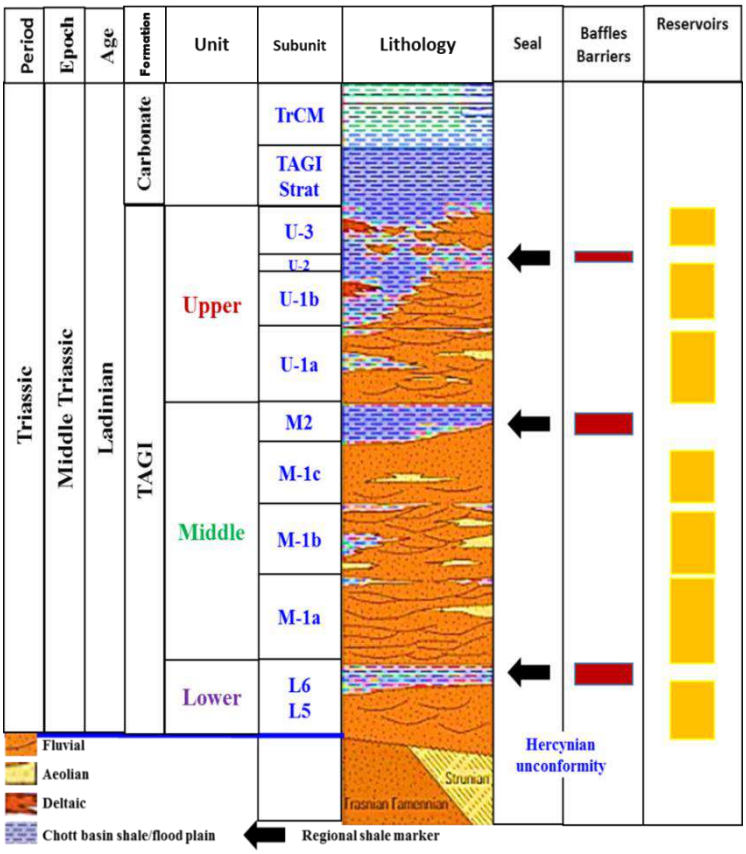

Figure 3-3: Subunits of the TAGI **(Zeroug S., Bounoua N. and Lounissi R., 2007)**

The sedimentological and stratigraphic subdivisions of the TAGI are as follows: ((Arezki Boudjema, 1987); (Hamid Aït-Salem, 1990); (Zeroug S., Bounoua N. and Lounissi R., 2007); (Sayed, A.E. and Bachagha, W. and Benzagouta, M.S., 2017) :

Upper TAGI (4 levels):

- U1a, a sandstone layer that is characterized by fluviatile deposits traversed by aeolian deposits and has a wide lateral extension
- U1b, a sandstone layer that includes some interbedded deltaic deposits and presents deteriorating reservoir quality in a south-easterly direction
- U2 is a relatively thin clay layer marked by lacustrine deposits that are assumed to be regionally continuous.
- U3, a layer of variable thickness in which the first sandstone beds interbedded with deltaic deposits are encountered.

Middle TAGI (4 levels):

- M2 is a clayish unit of highly variable thickness that is assumed to be a lacustrine deposit and is of regional extent.
- M1c, M1b, and M1a are sandstone layers with good reservoir characteristics and variable thicknesses that depend on the local channel distribution; the combined M1 layer has the greatest thickness variation of all the layers.

Lower TAGI (directly on the Hercynian unconformity; 2 levels):

- L5, a sandstone layer characterized by fluviatile deposits
- L6, a clay layer.

Reservoir characteristics have also been found of relatively up to good with porosity varying from 8 to 20% and permeability from 1 millidarcy to 7200 millidarcys (mD). The PVT (Pressure, Volume, and Temperature) analysis has indicated light oil, with a gravity of 40.4 API (Belhouchet, H.E., Benzagouta, M.S. Dobbi,A. et Al., 2020).

3-3 Permeability - Porosity relationship

In this research, the exploitation of whole cores data (3160 plugs) resulting from exploration boreholes in the oil field of Hassi - Berkine (Algeria), were used. Their identification was conducted towards the rock typing aim. These cores have been characterized, based on porosity and permeability properties. These parameters can be considered the main indicators for the reservoir rock type classification process (Benzagouta M.S , 1991). Prior to the rock typing classification process, a mapping of the permeability versus porosity relationship is required. This processing route becomes an essential priority. Permeability versus porosity relation, recorded from core analysis, may present a non – uniform cloud over which a representative mathematical model can be favoured. Support is from (Belhouchet, H.E., Benzagouta, M.S. Dobbi,A. et Al., 2020) who found that, in a led investigation, in the field of HEB TAGI case study, permeability versus porosity has been found as a non – uniform cloud. A mathematical model was established and was supporting a similar statement. The revealed illustration is well figured out in (Figure 3-4). For a better understanding of details, this predicted model can be set on the basis of a well-supplied correlation coefficient. Providentially, the procedure for classifying rock types begins with the application of porosity and permeability cut-offs complement (Benzagouta, M. S. et Amro, M. M., 2009), where points with values lower than cut-offs may be considered non-reservoirs. The selection of cut-off porosity in this research is closely related to the permeability required for the fluid flow. The cut-off values were well approached by Benzagouta, M. S. et Amro, M. M., 2009. These authors set cut-off values for the various parameters characterising the reservoir. They established, based on the numerous outcomes, the net pay from the gross pay for the considered reservoir case study (fig 3 in New approach for reservoir assessment using geochemical analysis: Case study, where a relation of cut-offs versus depth for the different facies have been set). In their case study, Benzagouta, M. S. et Amro, M. M., 2009 proposed such analysis outcomes on the basis of the use of logging tools (GR) in addition to core analysis. In this case study, the focus was on the wire-line formation pressure tools versus petrophysical results. These tools have been found as an efficient tool for permeability cut-off determination (Belhouchet, H. E. et Al., 2021). Results from the led investigation approach can be based on the identification of the minimum mobility value at which the selected point can be validated. This notification is sustained from the graphical analysis of the fluid mobility defined by the wire-line formation tool versus the permeability (fig 3-4). Records indicate that the mobility of 5 mD/cP may be the minimum value required to accept the measure. This threshold mobility limit is referred to viscosity and

permeability since and as known Mobility is equivalent to permeability/fluid viscosity (equation 49).

$$Mobility_{fluid} = \frac{Permeability}{fluid\ viscosity} \tag{49}$$

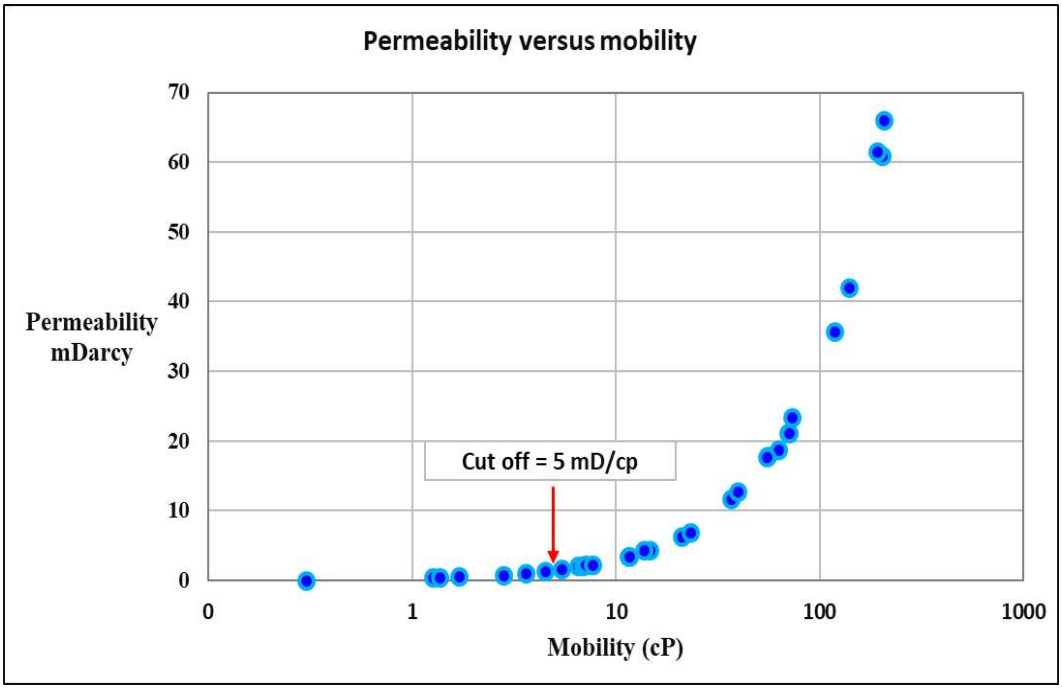

Figure 3-4: Permeability versus Mobility defined by wire-line formation tool

Moreover, in the case study, the permeability threshold is estimated and it is equivalent to a threshold of 1.75 mD. Regarding porosity, the application of this cut-off indicates that 75% of measured porosity values in the study area (HEB field) are lower than 10%. We assumed that this boundary limit can be considered as a porosity cut-off. Therefore, records data from the set plot, with porosity less than 10% and a permeability less than 1.75 mD, are removed (Figure 3.5). The results recorded between the permeability and the porosity of the baseline analysis show an adjustment line, crossing the group of points with a correlation coefficient of 0.4 (Figure 3-5). This low value of the correlation coefficient offers a considerable margin of error. All calculations, depending directly or indirectly on the absolute permeability, will be overestimated. For this purpose, a rock classification of rocks is required to establish mathematical models that allow for improving the estimation of permeability. With reference to parameters control, this request will possibly improve the absolute permeability calculation and subsequently extended to the uncored sections, thus, this prediction will be used to decrease the uncertainties surrounding the uncored zones.

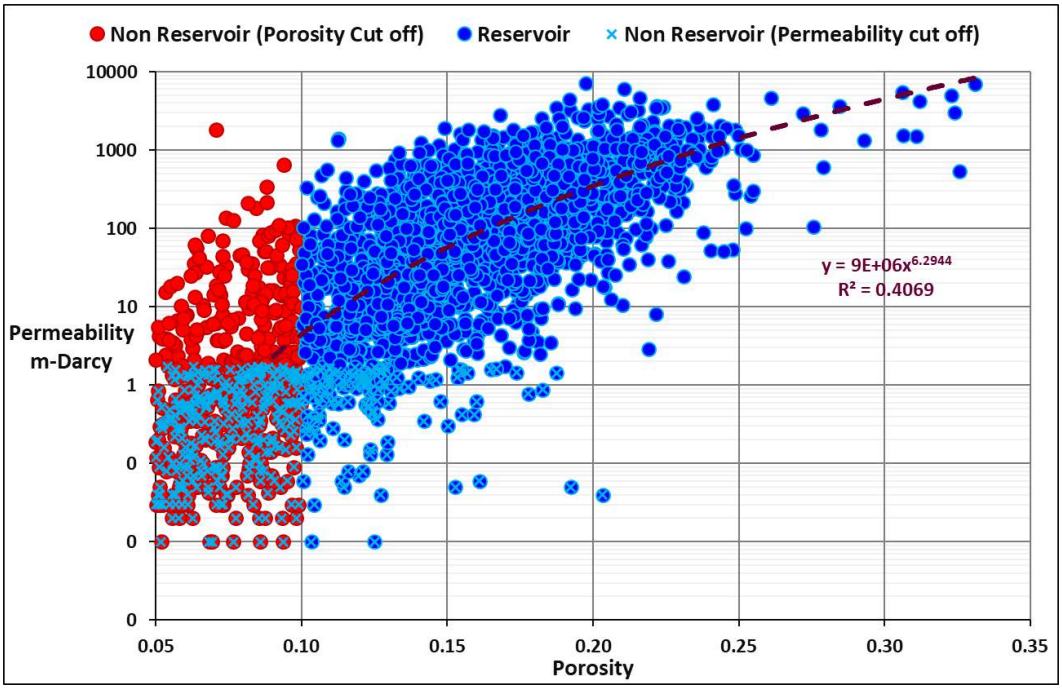

Figure 3-5: A cross plot indicating permeability versus porosity where heterogeneity is illustrated through a predetermined interval of distribution

3-4 Data availability and Quality Control (QC)

Data quality assurance and quality control are processes of synthesizing data to discover data inconsistencies and anomalies in order to improve data quality. These processes are implemented in all studies to ensure data integrity and minimize errors. In the oil and gas industry, to carry out a complete study on reservoir characterization, data collection must be prepared, verified and monitored as follows;

- Well logs and core data from cored wells should be prepared and quality controlled.
- Quality assurance of core data should be required; all cores destroyed during sampling should be removed.
- Porosity estimation from well logs should be calibrated to that calculated from cores, taking into account the overburden phenomenon.
- The core data depth correction must be adjusted to log data depth to ensure consistency and avoid losing the original information.

In our case study, 19 wells were drilled in the HEB field (Figure 3-2), and six wells have been selected to take samples from the reservoir (HEB1, HEB2, HEB3, HEB4, HEB5 and HEB6). These samples were able to cover all sections of the reservoir in order to extract real information related to lithology and petrophysical properties. These latter characteristics permit the identification of the reservoir rock types and reservoir homogeneity (Benzagouta, M. S., et AL., 2001). Well log measurements are also taken on all drilled wells to ensure the availability of continuous information and use them to predict reservoir characteristics in non-core areas (Belhouchet, H.E., Benzagouta, M.S. Dobbi,A. et Al., 2020).

3-5 Rock Typing; Identification and assignment

Reservoir rock typing is a process of rock classification based on the foremost rock properties such as mineralogical composition, grain size, shape, pore size distribution (PSD), rock – fluid interaction, fluid dynamic behaviour, and capillary effect into distinct units (Belhouchet, H.E., Benzagouta, M.S. Dobbi,A. et Al., 2020). The identification of these rock types should be grouped into specific sets and calibrated in terms of lithofacies and petrofacies. In such circumstances, the envisaged process can involve: integrating, analysing and synthesizing the real data supplied from different borehole records and core analysis.

From a geological point of view, rock types are characterized by similar geological conditions deposited in the same sedimentary environment and undergone similar diagenetic alterations. From a reservoir engineering point of view, it is characterized by identical fluid flow properties and identical dynamic behaviour. Based on these definitions, a given rock type can be assigned by a unique permeability - porosity relationship, a relative permeability profile, a capillary pressure profile, and saturation height functions above the free water level. (HFWL). Once the rock types were defined, an integrated workflow will be used to predict rock types with their petrophysical properties in non-core areas (Figure 3-6). In this conducted research, three main steps will be followed to identify and assign reservoir rock types.

- Lithofacies identification: the same type of rock in terms of lithology
- Petrofacies determination: is based on rock classification into sets where each facies will be characterized by the same hydraulic unit, the same pore size, the same relative permeability curve and the same capillary pressure profile.
- The assignment of petrophysical properties to lithofacies could be related to the compatibility between lithofacies and petrofacies.

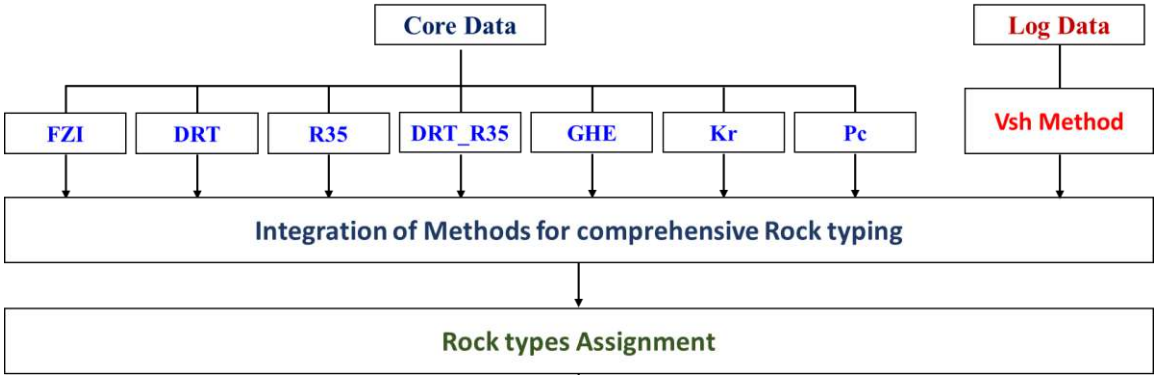

Figure 3-6: Rock type identification and assignment workflow

3-5-1 Lithofacies identification

The study and description of the core are fundamental in the development of the petrophysical model. This description allows finding the relationship between log data and routine and special core analysis. Lithofacies determination is derived from the description of the core and cuttings obtained during the drilling phase. As previously stated, the various lithological units

are classified based on similarities in rock composition, texture, and sedimentary structures. As a result, each lithofacies should be assigned to a specific rock type.

According to the carried-out description of the cores and the cutting, the whole material consists of detrital deposits. Therefore, the shaliness or clay content parameter is a fundamental parameter that can be used to differentiate between the various facies. The availability of gamma-ray records is a useful tool for this purpose (Turner, P. et Al., 2001), (Benzagouta M. S., et Al., 2001). For that purpose, the gamma-ray log has been used, as the main source for lithofacies identification and classification, matching the defined lithofacies from the core description and cutting (Table 3-1). Based on this, five lithofacies were defined in the Hassi Berkine Oil Field. Two defined types of lithofacies: organic-rich shale and shales are considered non-reservoir with regard to the others. Plotting core permeability versus porosity for defined reservoir subunits shows that three lithofacies could be considered as probable reservoir efficient facies; shaly-sandstone, sandstone and clean sandstone.

Commun lithological description		**Lithofacies**	**Codes**
Non-Reservoir	Dark clay rich in organic matter content	Organic-rich Shales	1
	Greenish clay deposits	Shales	
Reservoir (net pay)	Heterogeneous lithic facies alternating with fine to very fine sand and clay with some pebbles including coal fragments and some mud-clasts.	Shaly Sandstone	2
	fine to medium sandstone	Sandstone	3
	Medium to coarse clean sandstone	Clean Sandstone	4

Table 3-1: Table showing the main lithofacies characteristics in the considered reservoir according to (Asquith, G. B. & Gibson, C.R., 1982), (Turner, P. et Al., 2001) and (Benzagouta, M. S., et AL., 2001)

3-5-2 Petrofacies determination

Petrofacies are defined as intervals of rocks having the same hydraulic unit and a similar mean radius of the pore throat, as well as the same fluid flow characteristics. In reservoir engineering, the classification of petrofacies can be made on the basis of the identification of hydraulic units, planned for fluid circulation ability and determination. These hydraulic units (HU) can be implemented in reservoir studies to predict reservoir parameters such as permeability (K), net to gross and water saturation, and borehole parameters such as perforation intervals. The rock type can be defined on the basis of reservoir petrophysical properties, porosity - permeability cross-plot, pore throats, relative permeability, and capillary pressure curves, in addition to the water saturation height function profiles. Several approaches have been developed in the literature for petrofacies determination.

In this conducted study, and after the application of porosity and permeability cutoffs, 2106 plugs have been used. Conventional and special core analyses were performed. The obtained results of these core measurements were subsequently analysed by use of the RQI/FZI

technique, the discrete rock typing method (DRT), the pore throat radius approach (R_{35}), the pore throat discrete rock typing method (DRT_R_{35}), and the global hydraulic unit method. The objective was to select the best method which can be used for defining the fewest and most accurate rock types able to cover the whole reservoir ranges with reference to the best prediction of permeability. The number of these rock types should be minimal to reduce the simulation time and avoid convergence problems. The integration of the relative permeability and capillary pressure curves is considered an important source to give more support to reservoir rock type identification. In addition, each rock type should be specified by its relative permeability and capillary pressure.

3-5-2-1 Flow Zone Indicator

This approach was introduced in 1993 by Amaefule, J. O. et al., to identify hydraulic flow units. The method was based on plotting the Rock Quality Index (RQI) against the normalized porosity ($\emptyset_z$) on a logarithmic scale to determine the unit slopes, where each of these slopes represents a hydraulic flow unit. The results have been presented in the Figure 3-7. The application of this method on 2106 core data allow to identify 15 hydraulic unites (Figure 3-7 a). Each unit is printed by the mean FZI which is defined by the intersection of the slope of the unit with $\emptyset_z = 1$ and could have similar geological and petrophysical properties (Figure 3-7 b). This method is therefore used to classify rocks with the same unit of hydraulic flow into petrofacies, where a permeability model can represent each hydraulic unit (Belhouchet, H.E., Benzagouta, M.S. Dobbi,A. et Al., 2020).

The model must be tested by various mathematical models such as the linear model, the logarithmic model, the exponential model, and the power model in order to determine the best representative equation corresponding to each hydraulic unit (Figure 3-7 c). The best mathematical model, representing the same set of points, is coupled to the correlation coefficient. This correlative coefficient is used to measure the strength of the relationship between the two essential petrophysical parameters: porosity and permeability. Figure 3-7 (d) indicates a better correlation between the permeability calculated by the selected mathematical models and the permeability of the cores, with a high degree of precision of 0.97, which represents the utility of the FZI method on the classification of rock types and prediction of permeability.

For each hydraulic unit, the permeability factor was obtained from FZI_{mean} and effective porosity using the equation below (Equation 50) (Enaworu, E. et al., 2016). Consequently, various rock types are laid down (Figure 7b).

$$k = 1014 * FZI_{mean}^2 \left[\frac{\emptyset_e^3}{(1-\emptyset_e)^2}\right] \quad (50)$$

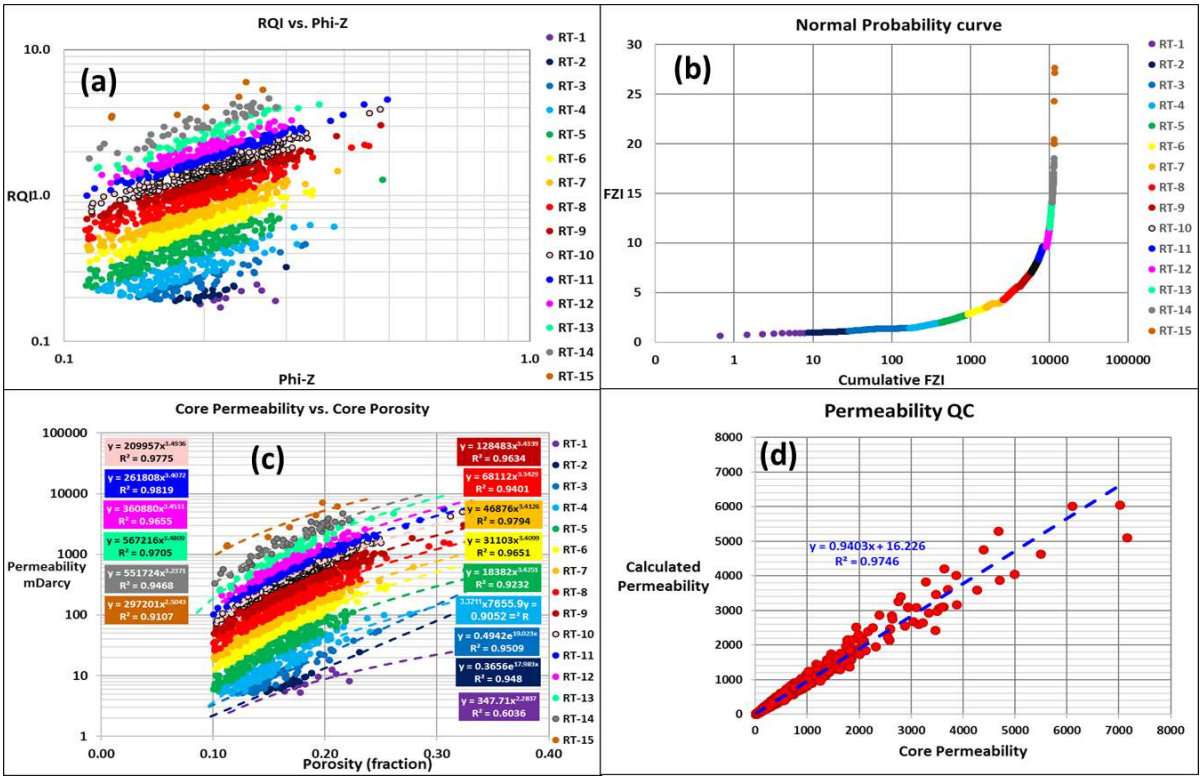

Figure 3-7: Permeability vs. porosity with the obtained different curves and correlation coefficient: Different clusters have come out with various hydraulic units leading to different rock types (Amaefule, J. O. et al., 1993)

Rock Types	FZI Intervals	FZI mean	Permeability mathematical Model
RT-1	FZI < 0.9684	0.8666	K = 347.71*Poro^2.2837
RT-2	0.9684 < FZI < 1.1460	1.0442	K = 0.3656*Exp(17.983*Poro)
RT-3	1.1460 < FZI < 1.4224	1.3628	K = 0.4942*Exp(19.023*Poro)
RT-4	1.4224 < FZI < 2.0036	1.7238	K = 7655.9*Poro^3.3211
RT-5	2.0036 < FZI < 2.8226	2.4207	K = 17337*Poro^3.3928
RT-6	2.8226 < FZI < 3.5234	3.1842	K = 30203*Poro^3.3936
RT-7	3.5234 < FZI < 4.2750	3.9029	K = 42997*Poro^3.3644
RT-8	4.2750 < FZI < 5.6017	5.0110	K = 71258*Poro^3.3686
RT-9	5.6017 < FZI < 7.0290	6.3432	K = 122266*Poro^3.4049
RT-10	7.0290 < FZI < 8.3810	7.6921	K = 190079*Poro^3.4348
RT-11	8.3810 < FZI < 9.6193	9.2662	K = 249714*Poro^3.3797
RT-12	9.6193 < FZI < 11.5561	10.4473	K = 341057*Poro^3.4191
RT-13	11.5561 < FZI < 14.0998	12.7726	K = 567216*Poro^3.4809
RT-14	14.0998 < FZI < 19.9886	15.7824	K= 498662*Poro^3.1794
RT-15	FZI > 19.9886	22.8005	K = 646632*Poro^2.9497

Table 3-2: Table summarizing the classification of rocks with its representative mathematical models based on FZI method

3-5-2-2 Discrete Rock typing (DRT)

To convert continuous reservoir rock typing defined by flow zone indicator, Genliang, G. et al., 2005 introduced a discrete rock typing model which is based on converting continuous FZI values to discrete values, where each DRT can represent a rock type. The objective of this approach is to speed the identification of reservoir rock types with a good prediction of their permeability. This method has been established by Belhouchet and Benzagouta 2019 on the Ordovician reservoir in Berkine field, in this research, the application of this method allows to define six rock types with an improved permeability calculation ($R\text{^}2 = 0.9039$).

The application of the discrete rock types method (DRT) on the 2106 plug data of the TAGI reservoir in the HEB field (Figure 3-8a) allowed the identification of eight rock types. The revealed results are well illustrated in the Figure 3-8b. For a better prediction of the permeability, several mathematical models such as exponential, power, linear and logarithmic, have been applied to each cluster. Thus, the correlation coefficient can be the selecting parameter of the permeability model (Figure 3-8c). The application of these mathematical models to the core data improved the prediction of the permeability in this case study. This statement was confirmed by plotting the calculated permeability against the core permeability where the achieved correlation coefficient was about 0.93 (Figure 3-8d).

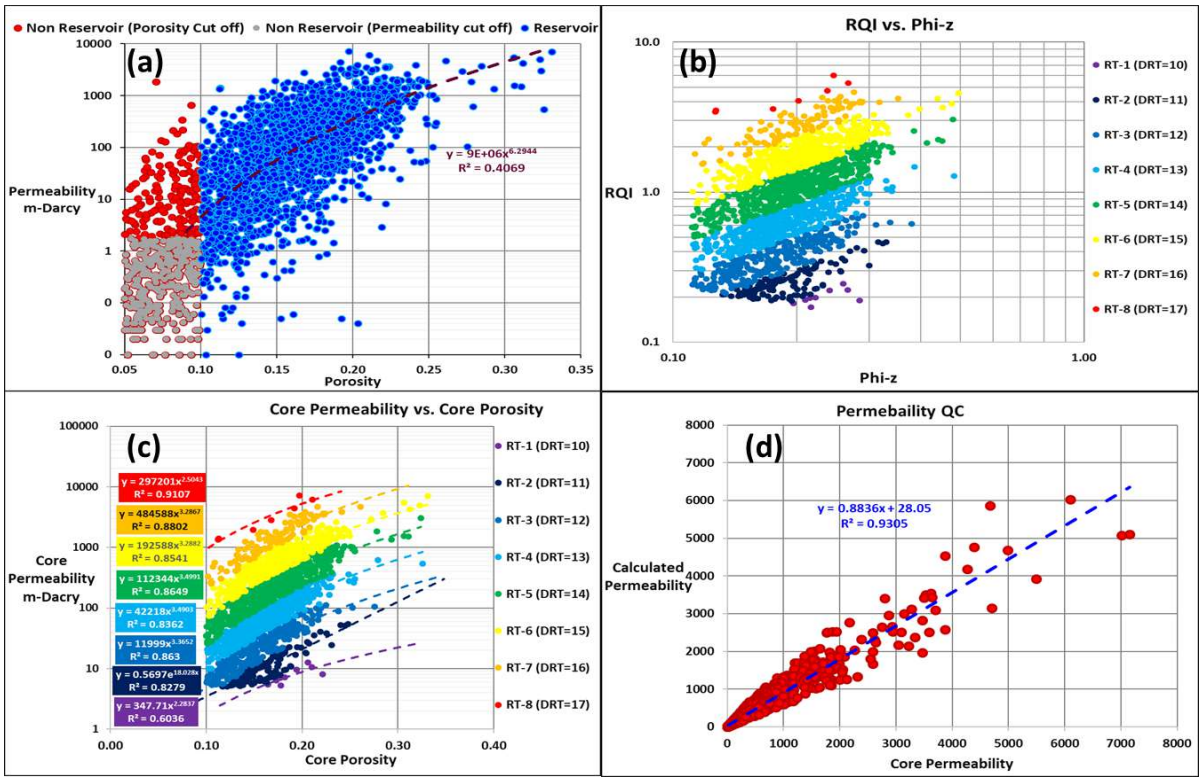

Figure 3-8: Permeability vs. porosity with the obtained different curves and correlation coefficient: Different clusters have come out with various hydraulic units defined by the DRT method

Rock Types	DRT	Permeability mathematical Model
RT-1	10	K = 347.71*Poro^2.2837
RT-2	11	K = 0.5697*Exp(18.028*Poro)
RT-3	12	K = 11047*Poro^3.3194
RT-4	13	K = 37292*Poro^3.4213
RT-5	14	K = 111613*Poro^3.4953
RT-6	15	K = 186511*Poro^3.2694
RT-7	16	K = 386660*Poro^3.1569
RT-8	17	K = 646632*Poro^2.9497

Table 3-3: Table summarizing the classification of rocks with its representative mathematical models based on DRT method

3-5-2-3 Pore throat (R_{35})

This method has been applied in carbonate and sandstone reservoirs where several authors such as (Constantin C. et Al., 2009), (Zahra Riazi, 2018) and (Kadkhodaie, A. & Kadkhodaie, R., 2018) have been working on the identification of reservoir rock types. Winland's equation is considered one of the powerful methods used to estimate pore throat (Al-Khaider, K. E. et Al., 2011), and (Khaled J. Al-Qenae & Salman H. Al-Thaqafi, 2015). The largest statistical correlation shows that the pore throat size can be matching the cumulative mercury saturation curve of 35% (R_{35}). The determination of R_{35} is given by Amaeful equation, which is:

$$\log R_{35} = 0.732 + 0.588 * \log k - 0.864 * \log \emptyset \qquad (51)$$

The porosity – permeability cross plot of the 2106 plug data of the TAGI reservoir in the Hassi Berkine oil fields is well stated in the Figure 3-9 a. The application of equation 51 on this available data makes it possible to calculate R_{35} for each plug. The range of these values of R_{35} permits the determination of reservoir rock types. These ranging intervals are defined on the basis of plotting the log of R_{35} sorted versus the cumulative value of R_{35}: the obtained results indicate changes in the slope of the line. Each change in slope indicates a new rock type. Similar results are well indicated in the Figure 3-9 b. Based on such observations, 19 rock types can be defined (Figure 3-9 c). For a worthy expectation of the permeability, several mathematical models such as exponential, power, linear and logarithmic have been generated for each rock type, and the correlation coefficient can be the deciding factor for the permeability model (Figure 3-9c). The application of these mathematical models to the plug data (2106) improved the correlation coefficient from 0.4069 to 0.9716. This observation was confirmed by plotting the estimated permeability against the core permeability, where the achieved correlation coefficient is about 0.9716 (Figure 3-9d).

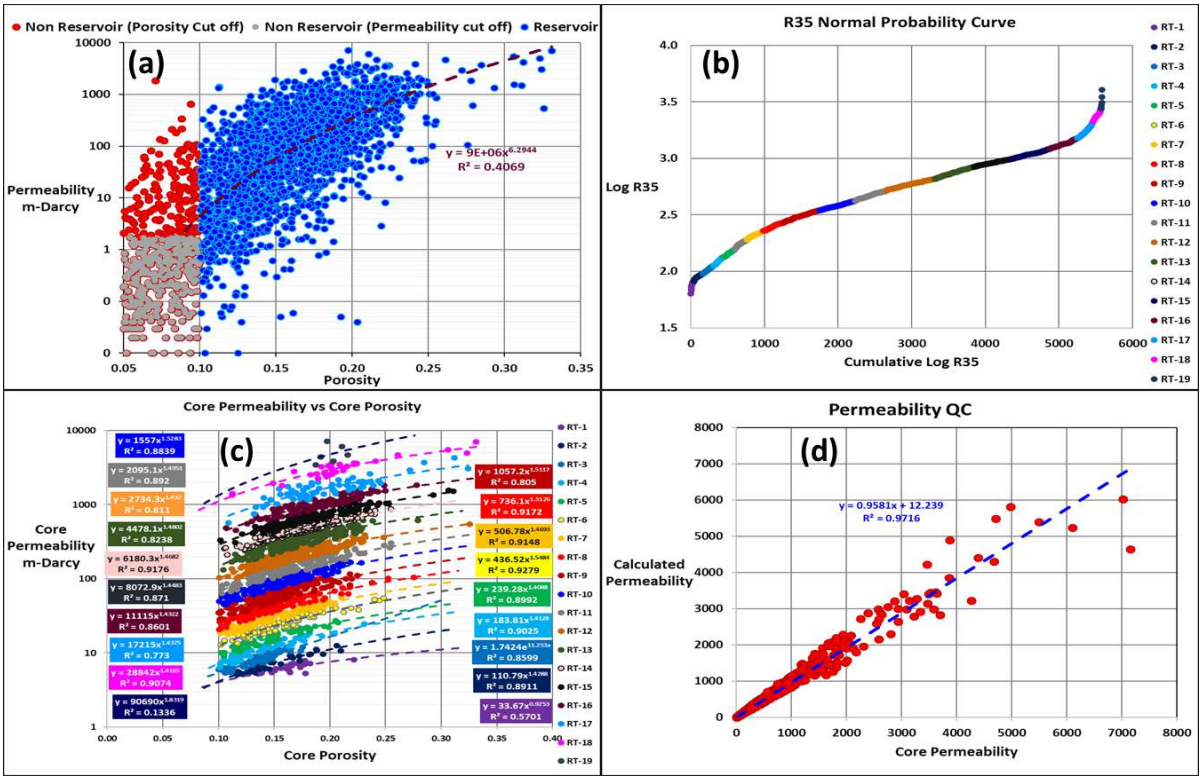

Figure 3-9: Permeability vs. porosity, shows various curves and correlation coefficients obtained: Different clusters have emerged with different rock types hydraulic units, resulting from R_{35} method

Rock Types	R_{35} Intervals	Permeability mathematical Model
RT-1	$R_{35} < 82.1395$	k = 33.67*poro^0.9253
RT-2	$82.1395 < R_{35} < 95.5183$	K= 110.79*Poro^1.4288
RT-3	$95.5183 < R_{35} < 112.8206$	K = 1.7424*Exp(11.253*Poro)
RT-4	$112.8206 < R_{35} < 134.1302$	K = 183.81*Poro^1.4128
RT-5	$134.1302 < R_{35} < 157.9907$	K = 239.28*Poro^1.4088
RT-6	$157.9907 < R_{35} < 192.0603$	K = 436.52*Poro^1.5484
RT-7	$192.0603 < R_{35} < 227.6531$	K = 506.78*Poro^1.4693
RT-8	$227.6531 < R_{35} < 269.1049$	k = 736.1*Poro^1.5126
RT-9	$269.1049 < R_{35} < 347.0269$	K = 1057.2*Poro^1.5117
RT-10	$347.0269 < R_{35} < 420.6425$	K = 1557*Poro^1.5283
RT-11	$420.6425 < R_{35} < 522.6450$	K = 2095.1*Poro^1.4951
RT-12	$522.6450 < R_{35} < 658.5252$	K = 2734.3*Poro^1.432
RT-13	$658.5252 < R_{35} < 839.1446$	K = 4478.1*Poro^1.4802
RT-14	$839.1446 < R_{35} < 991.3668$	K = 6180.3*Poro^1.4682
RT-15	$991.3668 < R_{35} < 1218.4195$	K = 8072.9*Poro^1.4483
RT-16	$1218.4195 < R_{35} < 1512.0556$	K = 11115*Poro^1.4322
RT-17	$1512.0556 < R_{35} < 2127.6641$	K = 17215*Poro^1.4375
RT-18	$2127.6641 < R_{35} < 2754.0824$	K = 28842*Poro^1.4165
RT-19	$R_{35} > 2754.0824$	K = 90690*Poro^1.8319

Table 3-4: Table summarizing the classification of rocks with its representative mathematical models based on pore throat method (R_{35})

3-5-2-4 Pore throat discrete rock typing (DRT_R_{35})

Following the pore throat radius method, a new approach was introduced by Tillero, E., in 2012. Theoretically, this method, chiefly, is identical to the DRT method. It is based on the conversion of the continuous variable R_{35} calculated by the Winland method to discrete values. Each of these discrete values can be considered a rock type and can be calculated by the following equation (Tillero, E., 2012):

$$DRT_{R_{35}} = Round[10 * (1.7 * \log R_{35} + 5.2)] \quad (52)$$

The application of this approach to the petrophysical data (porosity and permeability) of 2106 plugs, extracted from the Berkine field, allowed the identification of six types of rocks (Figure 3-10 a). In a similar manner as above, each rock type should be tested by one of the mathematical models such as exponential, power, linear, and logarithmic. The optimal model must be based on the correlation coefficient. The designated models are presented in Table 3-5. These mathematical models are used to estimate permeability. The achieved correlation coefficient was improved from 0.4 (Figure 3-5) to 0.8026 (Figure 3-10 b).

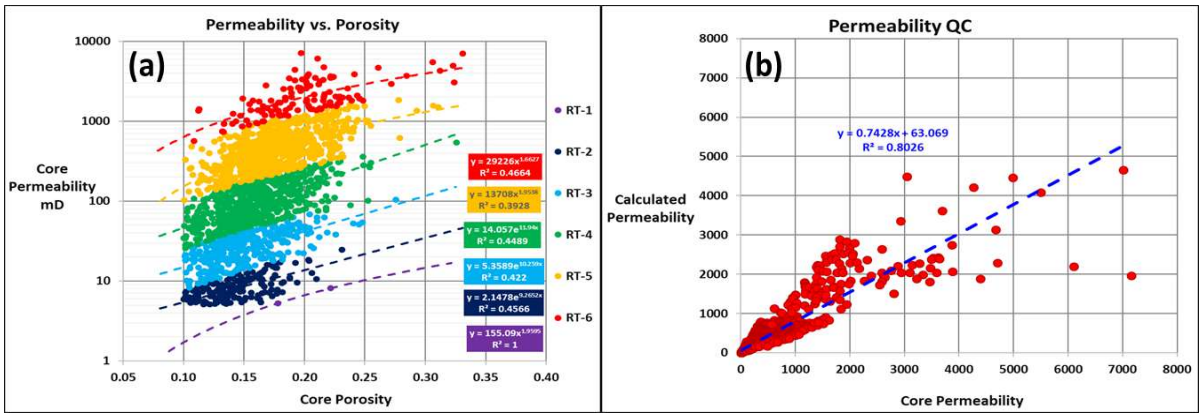

Figure 3-10: Permeability vs. porosity with the obtained different curves and correlation coefficient: Different clusters have come out with various hydraulic units resulting from DRT_R_{35} method

Rock Types	DRT R_{35}	Permeability mathematical Model
RT-1	56	K = 155.09*Poro^1.9595
RT-2	57	K = 2.1478*Exp(9.2652*Poro)
RT-3	58	K = 5.3589*exp(10.259*Poro)
RT-4	59	k = 14.057*exp(11.94*Poro)
RT-5	60	k = 13708*Poro^1.9538
RT-6	61	K= 29226*Poro^1.6627

Table 3-5: Table summarizing the classification of rocks with its representative mathematical models based on Pore throat discrete rock typing method (DRT_R_{35})

3-5-2-5 Global hydraulic element (GHE)

This method was developed by Corbett, P.W.M., and Potter, D.K., in 2004. It is based on the quantification of FZI values using Base-Map. The purpose of this method is to fix 10 global hydraulic elements by determining the limits of the hydraulic units from a selective systematic series of FZI values. According to Corbett, P.W.M., and Potter, D.K., the identification of these limits is picked arbitrarily in order to divide a wide range of possible combinations of porosity and permeability into a manageable number of GHEs. These limits are well expressed in Table 2.1, where each global hydraulic unit was specified on the basis of the FZI boundary.

The application of this approach to the 2106 plug data retrieved from the Berkine field (Figure 3.11 a) made it possible to find out 6 rock types (Figure 3.11 b). In the same approach as previous work, and to ensure a good estimation of the permeability, several mathematical models have been developed such as the exponential model, power model, linear model, and logarithmic model. Each model should provide a correlation coefficient, which can be used to extract the most representative model (Figure 3-11 c). The selected models are used effectively to predict permeability. The plot of calculated permeability versus core permeability shows an acceptable correlation coefficient ($R^2 = 0.8689$) (Figure 3-11d).

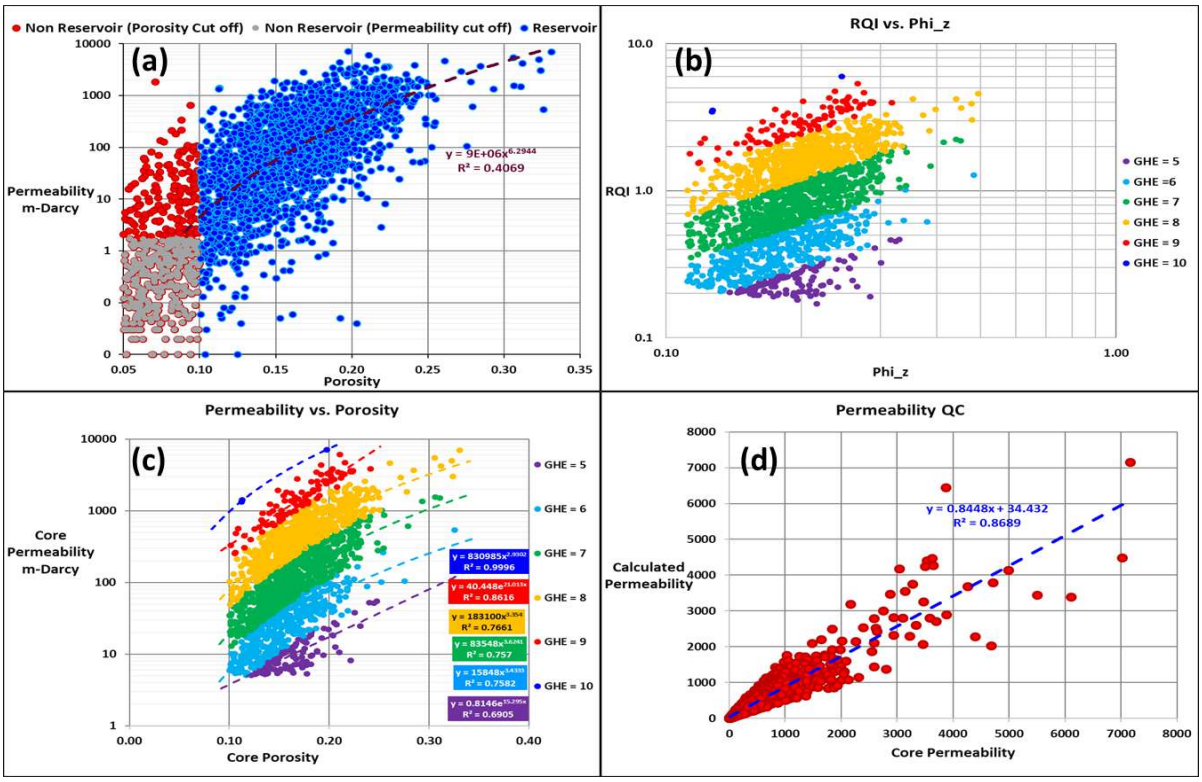

Figure 3-11: Permeability vs. porosity with the obtained different curves and correlation coefficient: using GHE method

Rock Types	GHE	Permeability mathematical Model
RT-1	5	K = 0.8146*exp(15.295*Poro)
RT-2	6	K = 15848*Poro^3.4333
RT-3	7	K = 83548*Poro^3.6241
RT-4	8	k = 183100*Poro^3.354
RT-5	9	K = 40.448*EXP(21.013*Poro)
RT-6	10	k = 830985*Poro^2.9302

Table 3-6: Table summarizing the classification of rocks with its representative mathematical models based on global hydraulic unit method (GHE)

3-5-2-6 Relative permeability curves

Following the results of rock types identified by different approaches, relative permeability curves can also be considered as another technique for identifying reservoir rock types. This approach is effectively based on the grouping of rocks with the same relative permeability curve for the same rock type. The understanding behind this approach is to consider that the relative permeability can be closely related to the rock wettability which varies from one rock type to another. This investigation was supported by several authors, such as (Genliang, G. et Al., 2007), (Compan, A. L., Bodstein, G. C., & Couto, P., 2016) and (Brandon, Y. A., Behzad, G. and Sahimi, M., 2021). In their led research, correlation analysis was conducted to acquire the correlations between petrophysical data and relative permeability curves. It is, furthermore, conducted to determine the rock type classes from relative permeability. This latter parameter is obtained from experimental data by applying the clustering method associated with an optimization procedure.

In this study, we invoke relative permeability to find out reservoir rock types and to confirm the classification obtained by the above techniques (FZI, DRT, R_{35}, DRT_R_{35} and GHE). In this case study research (Hassi Berkine), only seven plugs were taken from the first exploration borehole and were sent to the laboratory. The purpose was to extract the relative permeability of water-oil and oil-gas systems. The results are well expressed in figures 3-12a and 3-12b. Regarding the laboratory outcomes, and based on the FZI method, only four rock types were obtained: RT-6, RT-7, RT-10 and RT-11.

Graphical analysis has shown that the identification of the clusters characterizing the rock types becomes difficult to be grouped. This outcome can be due to a change in the petrophysical characteristic ranges. Thus, and for a similar task, the normalization method has been applied to set the relative permeability data in the same conditions (Figure 3.12 c and d). The normalization of the relative permeability of oil, water, and gas is calculated by the following formula:

$$Kr_w^* = \frac{Kr_w}{Kr_w \ @ \ So_r} \tag{53}$$

$$Kr_o^* = \frac{Kr_o}{Kr_o \ @ \ Sw_i} \tag{54}$$

$$Kr_g^* = \frac{Kr_g}{Kr_g \ @ \ 1 - (Sw_i + So_r)} \tag{55}$$

For water saturation normalization, the following formula can be used:

$$Sw_n = \frac{S_w - S_{wi}}{1 - S_{wi}} \tag{56}$$

and for normalized gas saturation, it is given by the formula below,

$$Sg_n = \frac{S_g - S_{gc}}{1 - S_{wi} - So_r - S_{gc}} \tag{57}$$

Based on the rock types defined by the FZI method, cores with the same rock type can be represented by the same relative permeability profile, especially for the water relative permeability within the water-oil system and the gas relative permeability in the oil-gas system. For the oil relative permeability, all the profiles of the typical rock types are superimposed. This means that all rock types can be denoted by the same oil relative permeability curve. Consequently, the relative permeability of water can be considered a significant criterion for rock type classification and specification.

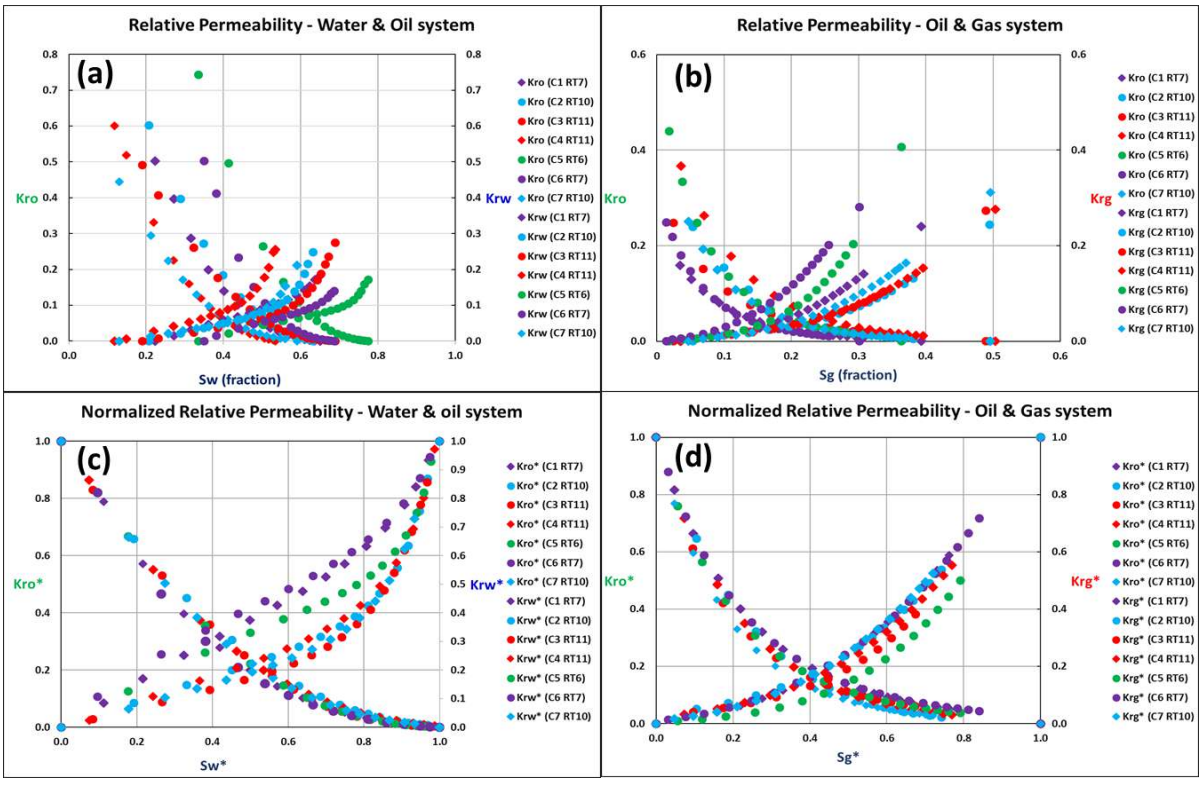

Figure 3-12: Relative Permeability for Rock type classification

3-5-2-7 Capillary pressure and Height above free water level

According to Fanchi, JR., and Christiansen, RL, (2017), capillary pressure (PC) is defined by the pressure difference across the curved interface between two immiscible fluids in contact in

the porous medium. In general, the PC is related effectively to the interfacial tension, the contact angle, and the pore throat. Interfacial tension is the force of attraction between molecules at the interface of two fluids. It is a function of pressure, temperature, and the composition of each phase (Hemmati-Sarapardeh, A. et Al., 2020). Conventionally, the contact angle is defined as the angle formed between a liquid-vapour interface and a liquid-solid interface at the solid-liquid-vapour three-phase contact line (Long, J. and Chhen, P., 2005).

In fact, several authors have noted that capillary pressure curves may be helpful in identifying the reservoir rock types. The PC is used, in such circumstances, for defining rock types: since it can be set that Pc relation to the pore throat and rock wettability can define the same characteristics for any considered rock type category. (Jooybari, S. H., Mowazi, G.H. and Jaberi, S. R., 2010), (Dakhelpour-Ghoveifel,J., Shegeftfard,M. & Dejam,M., 2019) & (Yisheng, L. et Al., 2019).

In our case study, a total of 77 capillary pressure measurements have been performed on the Berkine field within an oil-water system. As a result, the capillary pressure versus normalized water saturation is well stated in the figure 3-13. Obviously, this number of experiments can cover most of the reservoir rock types defined by the FZI method. However, the behaviour of the capillary pressure shown in the figure below (Figure 3-13) represents the dissimilarity of rock types. This latter statement can be related to reservoir fluid type, the contact angle, and the interfacial tension in relation to reservoir fluid circulation, where formation factor and tortuosity are specific involved factors. Thus, the incorporation of fluid properties versus solid parameters constitutes another aspect for better consideration. The overall gathering factors can be a generating source responsible for capillary pressure differentiation within the same rock type.

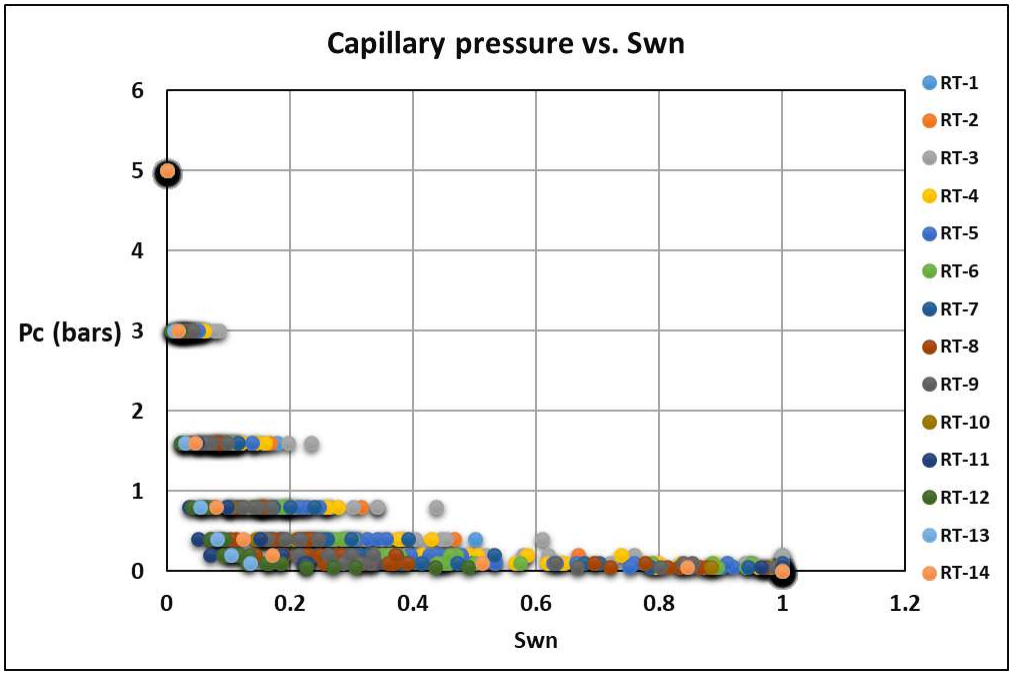

Figure 3-13: Capillary pressure versus normalized water saturation for different rock types

For sorting out and perceiving any ambiguity in this context, an elaboration of a mathematical model of the capillary pressure for each rock type must be carried out. Based on this assumption, several mathematical models such as exponential, power, and rational were tested using capillary pressures with normalized water saturation measured for each rock type. In a similar method published by (Belhouchet, H.E., Benzagouta, M.S. Dobbi,A. et Al., 2020), the best mathematical model must give a minimum objective function (Equation 58) and the limit of the capillary pressure, when the normalized water saturation tends to 1, the Pc is equal to zero (Equation 59). The generalized reduced gradient (GRG) method was implemented to solve the nonlinear optimization problem and calculate the optimal model parameters according to the chosen subject function (Maia A. et al., 2017).

$$Pc\_Obj_{function} = minimze\left(\sum_{i=1}^{n}\left(P_{c_{Obs}} - P_{c_{calc}}\right)^2\right) \tag{58}$$

Where:

$Pc\_Obj_{function}$: Objective function for capillary pressure

$P_{c_{Obs}}$: measured capillary pressure

$P_{c_{calc}}$: calculated capillary pressure

n: the number of measured capillary pressure for each rock type

$$\lim_{Sw_n==1} Pc = 0 \tag{59}$$

The generalised mathematical model deduced for capillary pressure can be formulated by:

$$P_c = \frac{1}{a + b * \exp(c * Sw_n)} \tag{60}$$

Where; a, b, and c are fitting parameters, and they changed from one rock type to another rock type.

The execution of this model makes it possible to present the capillary pressure for each rock type, where each profile of capillary pressure corresponds to a specific hydraulic unit (Figure 3-14 a). Using these profiles, HFWL can be estimated for each rock type. The results are shown in Figure 3-14 a.

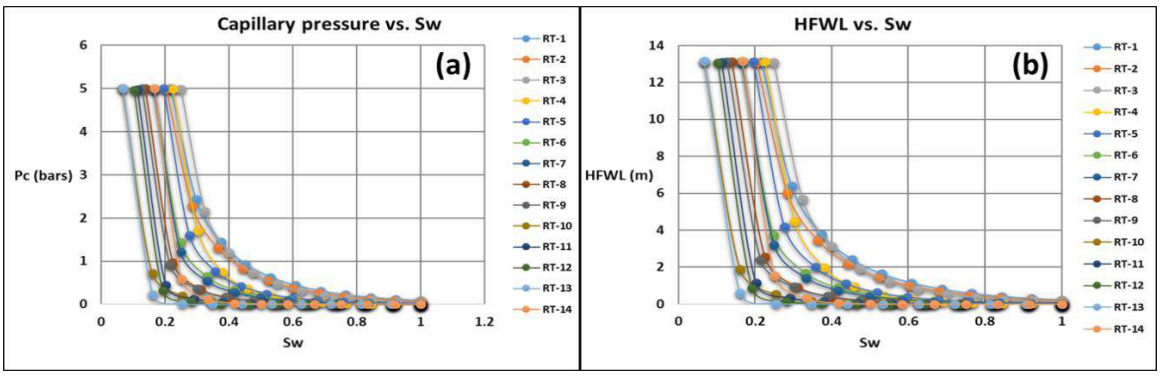

Figure 3-14: Capillary pressure and Height free water level (HFWL) versus water saturation for different rock types

According to the outcomes of previous rock typing approaches, the presence of more than one hydraulic unit and dissimilarities in the capillary pressure profiles can be attributed to reservoir heterogeneity or the variation of lithological distribution. Similarly, the height free water level (HFWL) indicates that the interstitial water saturation changes from one rock type to another (Figure 3-14 b), which supports this hypothesis by calculating pore size distribution from capillary pressure. The results are well presented in Figure 3-15.

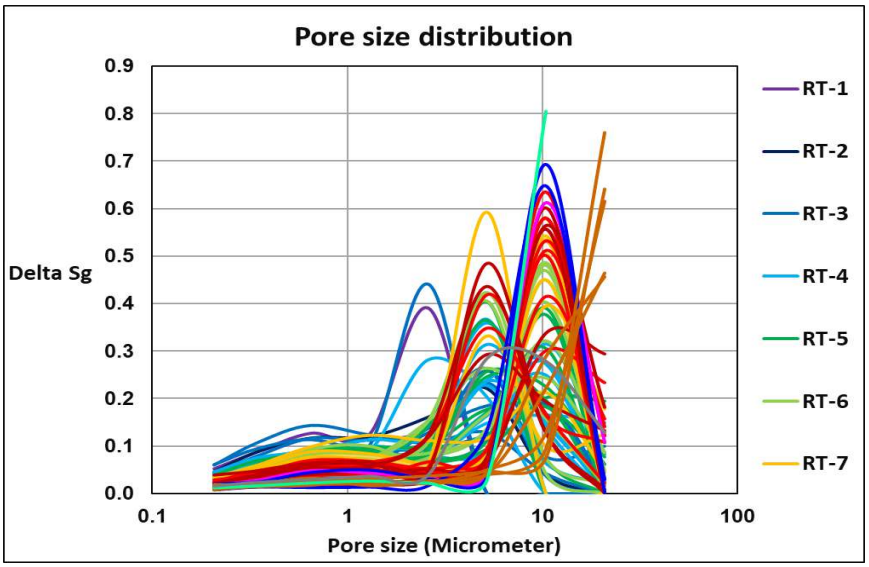

Figure 3-15: Pore size distribution deduced from capillary pressure (MICP method)

Graphical analysis shows that the pore throat radius is mainly macroporous type, with a pore throat radius fluctuating between 2.5 and 10 micron meters, with minor variations in the mesoporous category (0.5 - 2.5 micron meters) and microporous (0.2 - 0.5 micron meters). Accordingly, the reservoir quality type is closely related to the porosity, permeability, hydraulic units, relative permeability, capillary pressure, and pore throat radius. The pore size distribution can be considered an effective device for the assessment of reservoir heterogeneity degree. In addition to the presence of more than one hydraulic unit, and based on the pore size distribution profiles, the TAGI reservoir could be considered relatively heterogeneous along sections of the terrain. This means that the use of all the information deduced from the different reservoir characterization approaches becomes essential.

In conclusion, according to the outcomes of figure 3-13, for reservoir rock type classification using capillary pressure profiles, it's required to use only the experiment results coming from the desired area, which means in our case study, the capillary pressure profiles extracted from HEB wells should be used. Among the 77 samples used in the previous step, there are only five plugs reserved for special core analysis experiments. These data are not sufficient to cover all reservoir areas, but based on the capillary pressure behaviour shown in the figure 3-16, it is possible to support the use of capillary pressure profiles for rock type identification.

The graphic analysis of the capillary pressure profiles of the desired zone (HEB field) shows that the rock types defined by the FZI method can have the same capillary pressure profile (Figure 3-16 a). This information is also confirmed by the HFWL which says that rocks of the

same rock type have the same interstitial water saturation (Figure 3-16 b). This analysis confirms the approach proposed by (Dakhelpour-Ghoveifel,J., Shegeftfard,M. & Dejam,M., 2019) who supposed that capillary pressure curves can be used for reservoir rock type classification.

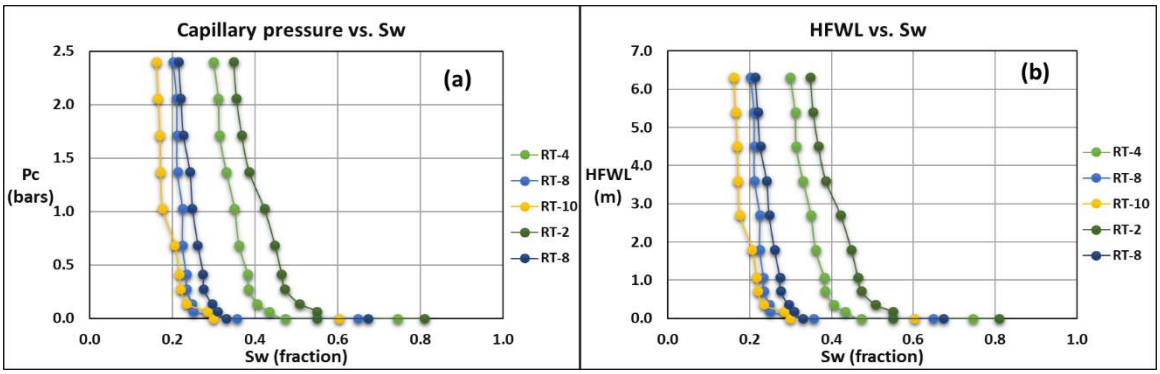

Figure 3-16: Capillary pressure and Height free water level (HFWL) versus water saturation for HEB field

3-5-3 Rock typing assignment

Following facies and cutting descriptions carried out by a field geologist, four lithofacies have been defined, such as shale, shaly sandstone, sand, and clean sandstone. Among these facies, three lithofacies: shaly sandstone, sand and clean sandstone are considered reservoirs. To strengthen these analyzes, the identification of the hydraulic units and the determination of petrophysical properties must be necessary. For this reason, 427 plugs have been taken from 6 wells. To achieve these objectives, several methods, such as FZI, DRT, R_{35}, DRT_R_{35}, and GHE, have been established. These methods define, respectively, 15 rock types, 8 rock types, 19 rock types, 6 rock types, and 6 rock types. The selection of the method should be effectively related first to the correlation coefficient, which is defined according to the plot of calculated permeability versus core permeability, and secondly to the number of rock types. The results expressed in the figure 3-17 show that the FZI method gives a high correlation coefficient ($R^2 = 0.97$) with a relatively high number of rock types (15 rock types).

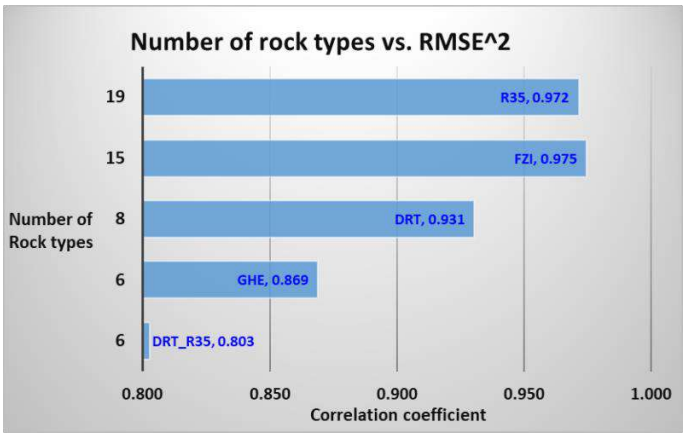

Figure 3-17: number of rock types versus correlation coefficient delivered by each rock type method

Based on relative permeability curves and capillary pressure profiles. The reservoir rock types identified by the FZI method ought to be the same rocks identified by capillary pressure and relative permeability. Therefore, the FZI method can be considered a reference scheme for reservoir rock type identification. On the other hand, based on the simulation objectives of using as few rock types as possible to avoid convergence problems and reduce simulation time, the discrete rock typing technique (DRT) may be an alternative method that can be adopted for the hydraulic flow unit determination and the estimation of petrophysical properties. Note that this method can give eight rock types with a correlation coefficient of 0.93, which is relatively close to that defined by the FZI method (0.97).

As a result, Hassi Berkine oil field reservoir rock types (RRT) have been classified into four lithofacies and eight petrofacies, with no compatibility between lithofacies and petrofacies.

3-6 Conclusion

- Data collection and quality control are indispensable tasks that must be performed for any reservoir study, especially when issues of identification, classification and prediction are faced.
- The quality of data available for any study has a direct impact on the quality of the results, where the expectations of the project can skew, and thus can provide technical, economic and time-wasting issues.
- Preparing the data, ensuring its quality, and covering all disciplines, in addition to understanding it, is considered the first half of the roadmap.
- A lithofacies method is useful for describing lithology, predicting net to gross volume, and linking core and well log data. This approach can also be considered an important tool for determining porosity and permeability.
- The lithofacies process is a supportive tool that can be used to link core data to Well log column data.
- Rock typing can be defined as the integration and analysis of data from boreholes and core analysis.
- Rock types can be identified in a variety of ways, with each method examining the properties from a different perspective than the others and so providing extra information.
- Identification of hydraulic unit parameters such as HFU and FZI can be a vital compilation between the real cores and petrophysical characteristics.
- The flow zone indicator method approach is the most accurate way of classifying reservoir rock types and forecasting reservoir permeability for Lower Triassic clay sandstone formations. As a result, this method has the potential to improve prediction accuracy by up to 97 percent.
- The discrete rock typing method (DRT) is a FZI-derived method that can be used to reduce the number of rock types while avoiding simulation convergence issues. This method can maintain a prediction accuracy of up to 93 percent.

- Capillary pressure and saturation height function are influencing factors regarding reservoir rock type classification.
- Relative permeability curves and capillary pressure profiles are two other methods for classifying reservoir rock types. The results reveal a good consistency between these approaches and the FZI method, with the rock type characterized by a relative permeability curve and a capillary pressure profile being the same as the rock type identified by FZI.
- To achieve appropriate categorization using the capillary pressure profile, the data must come from the same reservoir with the same pressure, temperature, and fluid characteristics.
- Pore size distribution (PSD) could be introduced to identify the reservoir degree of homogeneity or heterogeneity versus various impacts.

Chapter 4: Petrophysical properties prediction

4-1 Introduction

Following the rock typing results described in the previous section, where the inconsistency was revealed between the lithofacies identified by the shale volume (V_{sh}) approach and the identified petrofacies using the DRT method. The development of a mathematical model has become more than necessary to find a technique permitting the determination of petrophysical properties in non-core areas. The main rock properties that should be defined are porosity, permeability, and water saturation. These properties are generally obtained from the core analysis, well test interpretation, and the wireline formation testing tool reading. This assumption is well-supported by the authors (Belhouchet H.E. & Benzagouta M.S., 2019). The use of well logs such as Gamma Ray (GR), neutron porosity (NPHI), bulk density (RHOB), and sonic (DT) can be an efficient and effective tool for the expectation of porosity and permeability properties. In addition, the use of deep and shallower resistivity logs combined with porosity logs (RHOB, NPHI & DT) can be more useful specifically concerning water saturation determination. For that purpose, multiple regression techniques can be introduced. Sustainability concerning this focus is well approved by Belhouchet, H.E., Benzagouta, M.S. Dobbi,A. et Al., (2020). This method and an important aim can be fitting better a limited number of data.

The application of regression methods may be a desirable option for developing mathematical models. However, the drawback of this method is its limitation towards big and vast data. For this reason, the integration of machine learning techniques may be one of the best solutions that can be approached to identify these models. According to Karpenko, O., (2018), artificial neural networks (ANNs) can be implemented for making empirically grounded decisions. This option is related to cases where the mathematical model or the process theory is absent or underdeveloped. The radial basis function neural network is one of the artificial intelligence methods that can be used to improve the relationship between the defined petrofacies and the selected well logs (GR, RHOB, NPHI, DT, and resistivity).

4-2 Porosity determination

Porosity is a rock property defined by the ratio between the volume of the pore space and the total rock volume. It is closely related to the storage capacity of the reservoir. According to (Mark Alberty, 1992), and (Benzagouta M. S., 2001), several approaches can be applied to estimate the porosity from porosity logs. These logs are referred to, particularly as density logs, neutron logs, sonic logs, or density-neutron combined logs. In this conducted research, the workflow started with the adjustment of the well log depth versus the core depth, based on calibrating process: the porosity log has to be calculated from different methods with regard to the core porosity. Three methods were tested to get a better estimation of the porosity. These methods are essentially concerning the application of conventional methods, regression methods, and neural network techniques. The method with the best porosity assessment will be selected to predict the porosity of non-core areas.

4-2-1 Conventional methods

These methods are based on the determination of the porosity from conventional well logs such as neutron logs (NPHI), density logs (RHOB), sonic logs (DT), and density–neutron logs (NPHI-RHOB). These methods are generally applied where the core data is missing. The following formulas indicate the calculation of the porosity from these different porosity logs applied in this case study;

a- Porosity from Density *(Schlumberger, 1997)*

$$\emptyset_D = \frac{\rho_{Ma} - \rho_b}{\rho_{Ma} - \rho_{fl}} \tag{61}$$

Where:

$\emptyset_D$ = porosity calculated from log density
ρ_{Ma}: matrix density
ρ_b**:** formation bulk density (log value)
ρ_{fl}: density of the fluid saturating the rock immediately surrounding the borehole

The matrix density is related to the lithology and it's presented in the table 4-1.

Lithology	Density g/cc
Sandstone	2.61
Limestone	2.71
Dolomite	2.876
Anhydrite	2.977
Salt	2.032

Table 4-1: Table illustrating matrix density (g/cc) as a function of the lithology

b- Porosity from sonic *(Schlumberger, 1997)*

$$\emptyset_S = \frac{\Delta t - \Delta t_{Ma}}{\Delta t_{fl} - \Delta t_{Ma}} \tag{62}$$

Δt : acoustic transit time (µsec/ft)

Δt_{fl}: acoustic transit time of interstitial fluids (µsec/ft)

Δt_{Ma}: acoustic transit time of the rock matrix (µsec/ft)

c- Porosity from density–neutron logs *(Schlumberger, Log Interpretation Charts, 1997)*

$$\emptyset = \sqrt{\frac{\emptyset_N^2 + \emptyset_D^2}{2}} \tag{63}$$

Where $\emptyset$ is percent porosity, $\emptyset_N$ is neutron porosity, and $\emptyset_D$ is density percent porosity.

The results of the log porosity calculated respectively from neutron, density, sonic, and density-neutron are well illustrated in the figure 4.1 (a, b, c, and d). Graphical analysis shows a low correlation coefficient (0.0846, 0.1263, 0.0514, and 0.1527), which indicates a weak coherence between core porosity and log porosity. A nonlinear regression method has been implemented for this purpose.

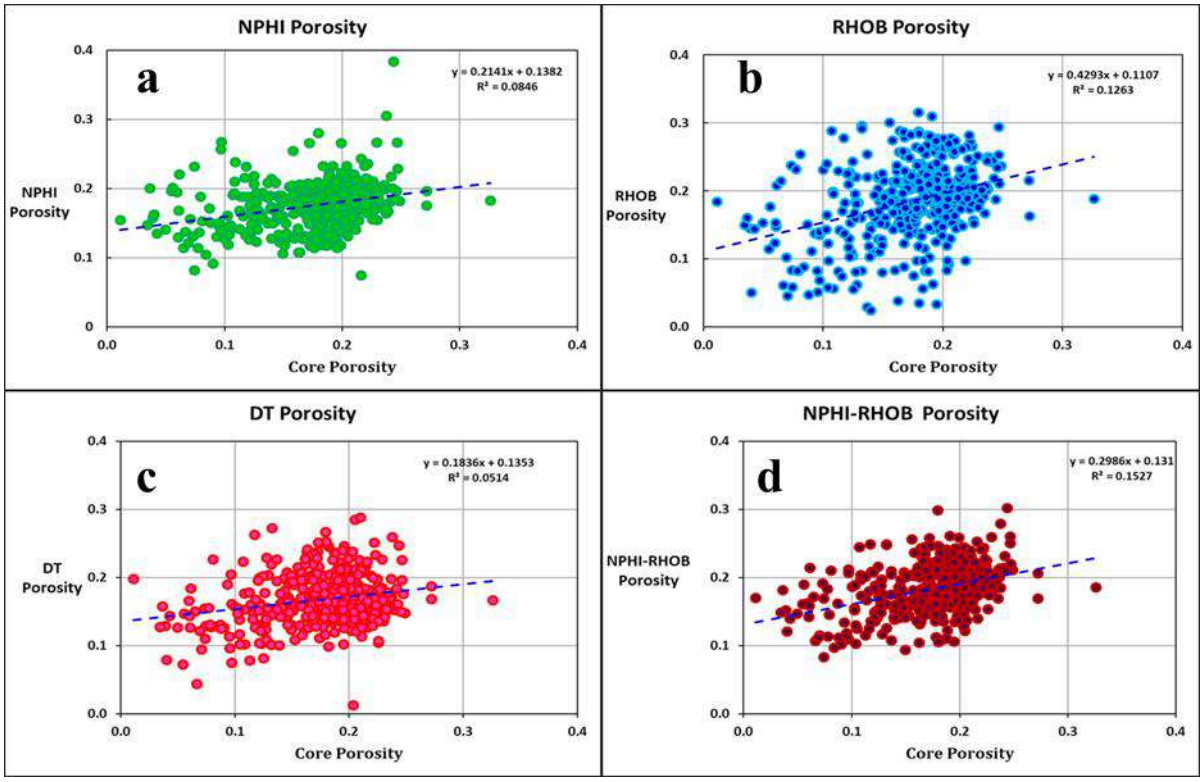

Figure 4-1: porosity estimation from neutron log, density log, sonic log, and neutron-density

4-2-2 Regression methods

These methods were first published by Legendre in 1805 and by Gauss in 1809 with the aim of adjusting the parameters of a developed mathematical model (Adrien Marie Legendre, 1805) and (Gauss, C.F., 1825). The goal is to have a minimum error between the observed data and the predicted data. In this led research, a mathematical model should be developed to calculate normalized porosity from standard porosity logs such as GR, NPHI, RHOB, and DT. A good adjustment of the porosity generated from the logs and the core is of significant consideration. To achieve this goal, several mathematical models such as exponential, logarithmic, power, and rational functions were tested. The optimal model must ensure a minimum objective function that seeks a minimum quadratic error between the experimental and calculated data (equation 64). The objective function can be defined by the following formula:

$$Poro\_Obj_{func} = minimize\left(\sum_{i=1}^{n}\left(Poro^{*}{}_{Exprimental} - Poro^{*}{}_{Calculated}\right)^{2}\right) \qquad (64)$$

Where;

$Poro\_Obj_{func}$: Porosity objective function

$Poro^*_{Exprimental}$: Normalized experimental porosity data
$Poro^*_{Calculated}$: Normalized calculated porosity data
n: the number of plugs presented in this study ($n = 430$)

The normalization of these data can be an alternative proposal that can be implanted to express the finest model. This approach is basically applied to scale a variable to have values between 0 and 1. The normalized log X_i^* can be calculated by the following equation (Shier, Daniel E., 2004).

$$X_i^* = \frac{X_i - minX_i}{maxX_i - minX_i} \quad (65)$$

Where X_i, $minX_i$, $maxX_i$ are values coming from X_i log (porosity log).

Due to a large number of data and according to the limitation of regression methods in this kind of event, and own to three lithofacies presence, a mathematical model must be developed for each one. Well log data combined with the normalized data can be a suitable tool to extract the optimal model for each facies.

In this investigation, several mathematical models were evaluated to choose a representative model. These models are based on the use of raw and normalized data issues from GR, RHOB, NPHI, and DT logs, as inputs. Each mathematical model is characterized by adjustment parameters, defined by applying the generalized reduced gradient (GRG) method. This latter method is widely applied to solve optimization problems (minimization/maximization). This approach is well supported by (Lasdon, L. S. et Al., 1974). Thus, the mathematical models deduced for the lithofacies are correspondingly given by:

- **Shaly-Sandstone & Sandstone:**

$$\emptyset^* = a * RHOB^{*b} + c * NPHI^{*d} + e * \Delta T^{*f} + g * GR^{*h} + i \quad (66)$$

Where a, b, c, d, e, f, g are presented in the table below:

Adjustment parameters	Shaly Sandstone	Sandstone
a	-1.15878	-1.38496
b	0.01047	2.17722
c	0.32135	1.76865
d	4.10198	9.39806
e	-0.17129	-1.95944
f	3.12751	4.59074
g	0.92346	0.86991
h	0.39188	0.47719
i	0.98559	0.03912

Table 4-2: Table presenting the adjustments parameters using in the mathematical models for Shaly-Sandstone and Sandstone facies

- **Clean Sandstone:**

$$\emptyset^* = \frac{a}{b + c * (RHOB + NPHI)^d} \quad (67)$$

Where the adjustment parameters are given in the table 4-3:

Adjustment parameters	Clean Sandstone
a	2267.695
b	3454.529
c	3.44E-08
d	25.51585

Table 4-3: Table giving the adjustments parameters using in mathematical models for clean sandstone facies

The application of non-linear regression methods improved the correlation coefficient from 0.1527 (Figure 4-1) to 0.367 (Figure 4-2). Due to the limitation of regression methods in front of big data, this factor is still too low. According to that prior setting, neural networks have been introduced to improve porosity determination.

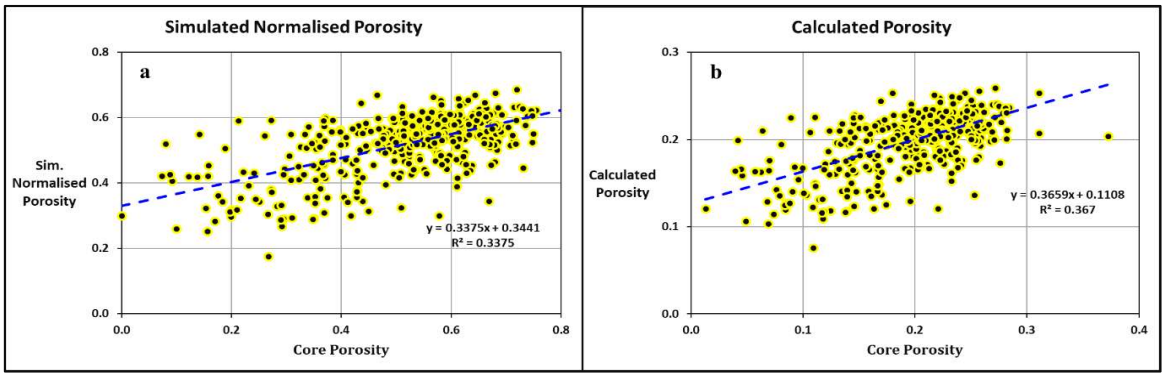

Figure 4-2: indication of the calculated porosity from regression methods

4-2-3 Neural Network approach

These networks were introduced due to their ability to generate a prediction for each record on which supervised learning algorithms are applied. This dealing out is effectively based on the processing of the inputs, the comparison of the expected output regarding the observed output, and the calculation of the resulting errors. These errors should be minimized by modifying the weights that control these networks. This operation should be repeated until these errors are reduced. This means that the same data set is processed multiple times as the weights between the layers of the network are refined during network training. Similar consideration is well supported by (Yi-Ping Phoebe Chen, et Al., 2010).

The general procedure applied in neural network systems is effectively based on the construction of a mathematical model from the input data. These records are generally divided into three data sets: training, validation, and testing. The model is initially fitted to the training

dataset, which is used to refine the parameters of the model. The fitted model is used to predict the feedback responses in the validation dataset to provide an unbiased assessment of a suitable model for the training dataset while adjusting the hyperparameters of the model. The test data set is sent to provide an unbiased assessment of a final fitting model for the training data set.

Once the parameters of the final model are well defined, model validation is usually associated with the correlation coefficient, quadratic error, relative error, and absolute error (Ameur-Zaimeche, O. et Al., 2020). However, for regression models, the expected data should fall within the initial range of the observed output data. Thus, it can be considered another required factor for model validation (Belhouchet, H.E., Benzagouta, M.S. Dobbi,A. et Al., 2020). Finally, in order to have a stable mathematical model, the application of normalization processes is required; therefore, predictions are set between zero and one.

According to (Djuris, J. et Al., 2013) several neural networks have been published in the literature review. We can list Modular Neural Networks (MNN) , Probabilistic Neural Networks (PNN), Learning Vector Quantization Networks (LVQ), Cascade Correlation Networks (CCN), Functional Link Networks (FLN), Kohonen Networks (KN), Hopfield Neural Networks (HNN), Gram-Chalier Networks (GCN), Hebb Networks (HN), Adaline Networks (AN), Hetero-associative Networks (HaN), Hybrid Networks (HN), Holographic Associative Memory (HAM), Spiking Neural Networks (SNN), Cascading Neural Networks (CNN), Compositional Pattern-producing Neural Networks (CPPNN), multilayer perceptron (MLP), recurrent neural network (RNN), Lagrange programming neural network (LPNN), radial basis neural network (RBNN), back propagation neural network (BPNN). Bayesian neural networks (BNN)… etc. All of these networks are used generally for classification purposes, modelling and optimization, or even induction of rules (Djuris, J. et Al., 2013), (Paras Q. Memon et Al., 2015).

In this conducted research, a radial basis neural network (RBNN) was applied for the identification of mathematical models allowing the estimation of the porosity according to standard well logs. This neural network has a different infrastructure compared to the other neural networks, where most of these networks contain multiple hidden layers, while the RBNN network involves only an input layer, a hidden layer, and an output layer (Paras Q. Memon et Al., 2015). The input can be modelled as a vector of real numbers $x = [x_1, x_2, x_3, \dots\dots\dots, x_n]$. The output of the network is then a scalar function of the input vector $y = [y_1, y_2, y_3, \dots\dots\dots, y_n]$. The hidden layer contains a number of neurons that apply a nonlinear transformation to the input variables, using a radial basis function as an activation function. This function is defined by the following formula:

$$\emptyset_i = exp\left[-\frac{(\|x-u\|)^T(\|x-u\|)}{\sigma^2}\right] \tag{68}$$

Where,

x: represents the input data points of the network

u: is the center of the radial basis function ($u = 0$)

σ: represents the radius of the radial basis function (RBF) ($\sigma > 0$)

Once the hidden neuron is calculated, based on the radius of RBF. The final network output layer y_n can be calculated by the sum of the product between the hidden layer neuron $\emptyset_i$ and weight vector w_i (equation 69) (Paras Q. Memon et Al., 2015).

$$y_n = \sum_{i=1}^{n} w_i \emptyset_i \tag{69}$$

To achieve these objectives, standard well logs such as GR, RHOB, NPHI, and DT were selected as input layers. The target output layer is the core porosity. To improve the performance of the model and facilitate the selection of its parameters, the normalization of these inputs and outputs must be carried out. The normalization of these parameters is calculated by equation 65. The typical structure of a radial basis neural network that can be applied in this perspective is given in Figure 4-3.

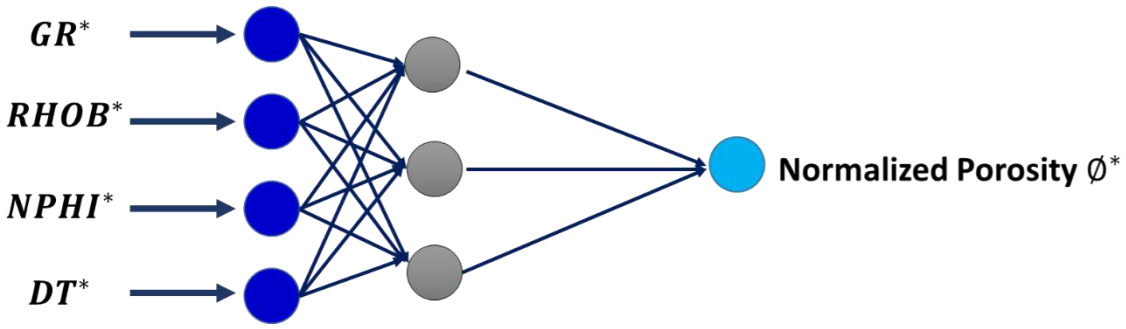

Figure 4-3: Artificial neural network (ANN) representation for normalized porosity prediction

The main objective of this practice is to minimize the quadratic error between the porosity calculated by the RBNN model and the actual porosity. This error was previously defined by equation 64. Normalization of the porosity should be calculated to restrain it between zero and one. The principle of operation of this neuron network is to use one dataset for training, another set for model validation, and the third dataset for testing. In this case study, 75% of the input data was used for the training, 10% for the validation, and 15% for the test.

The neural network shown in the figure 4-3 is a representation of a normalized porosity model that was run using the inputs, which are the normalized logs such as GR, RHOB, NPHI, and DT to predict the output normalized porosity of 380 plugs. The obtained model can be used to estimate the porosity in the non-cored section. The ANN model sketched in the figure 4-3, which is a simple-minded representation of a neural network, was modelled using Radial Basis Neural Networks (RBNNs) in Matlab to predict porosity based on the previously mentioned inputs.

Classically, the RBNN model requires mandatory data such as input data, output data, and the goal (the root mean square error), and optional data such as spread, the maximum number of neurons, and the number of neurons to be involved between displays. Thus, as defined earlier, this kind of neural network adds neurons automatically to the hidden layer of a radial basis network until it reaches the specified root mean square error target. For this purpose, the first action is to run the model with the required data. The objective is to achieve a root mean square error of around 0.000001. The execution of this model is conducted to improve the correlation coefficient from 0.3375 (estimated by regression methods) to 1 (RMSE^2 = 1) and reach the main goal (Figure 4-4. a). The final number of hidden neurons needed is 350 neurons, and the mean squared error (MSE) attained is 8.26629 e-05. The de-normalization of the porosity can be calculated by equation 70. The plot of this porosity versus the core porosity shows a good correlation coefficient around 1 (RMSE^2 = 1). The results are well shown in the figure 4-4 b.

$$Poro = Poro^{*} * (\max Poro - \min Poro) + \min Poro \qquad (70)$$

Where;

$Poro$: Porosity (de-normalised porosity)

$Poro^{*}$: Normalized porosity

$\max Poro$: Maximum porosity

$\min Poro$: Minimum porosity

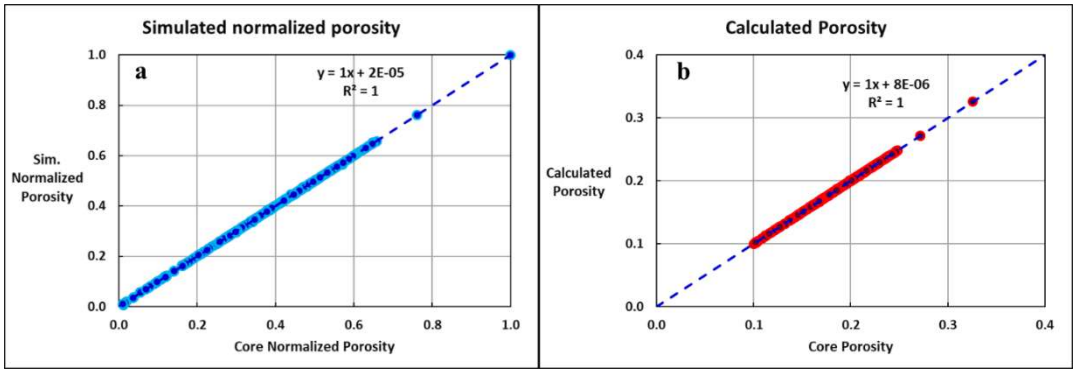

Figure 4-4: Normalized and Calculated porosity

The prediction of the normalized porosity in the non-core areas shows the presence of out-of-range values (more than 1 and less than zero), which is practically unacceptable. To improve the response of this model, the spread has been changed several times until the prediction response of the model improves and has a result between zero and one. The obtained spread for the porosity normalization prediction model is 0.04. Therefore, the log porosity can be calculated by equation 70, and the prediction results are well revealed in figures 4-5 and 4-6. Graphical analysis shows a good match of the porosity log to the experimental data, which indicates the effectiveness of applying this type of neural network (RBNN) to solve identification problems for big data.

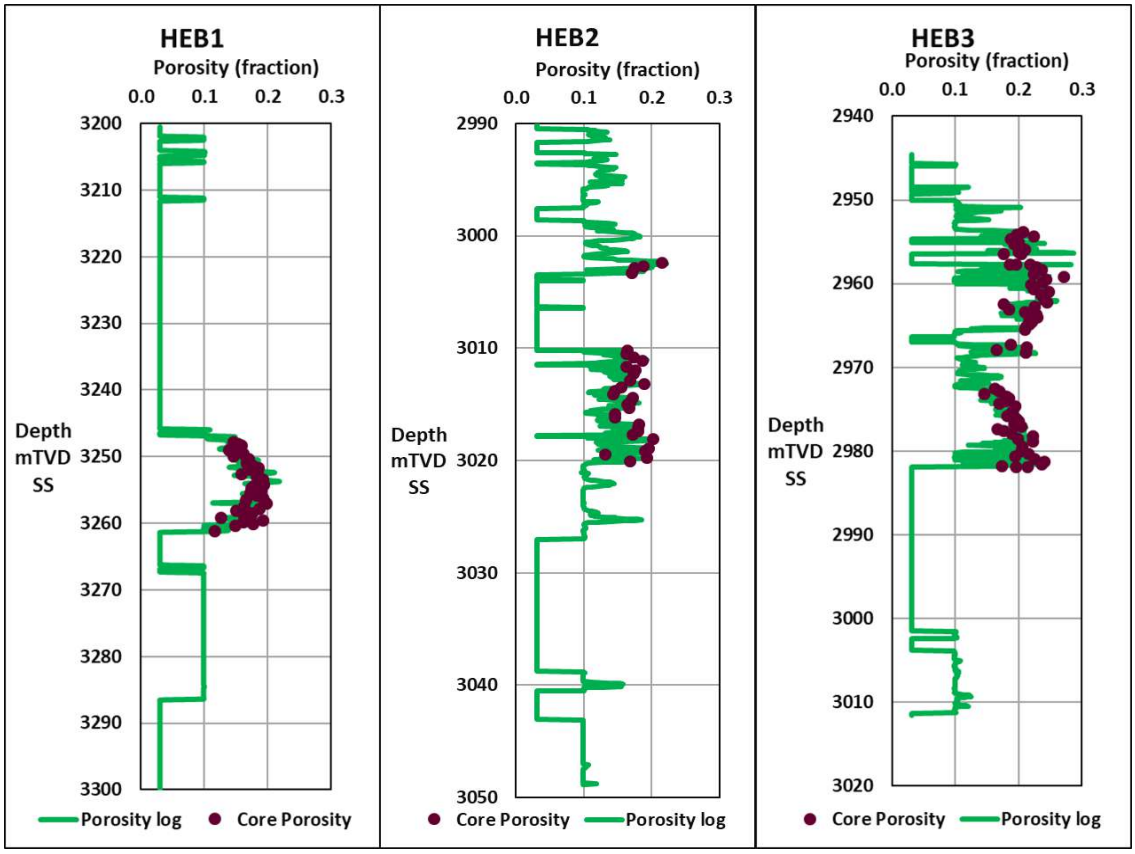

Figure 4-5: Porosity log prediction for HEB1, HEB2 and HEB3 wells

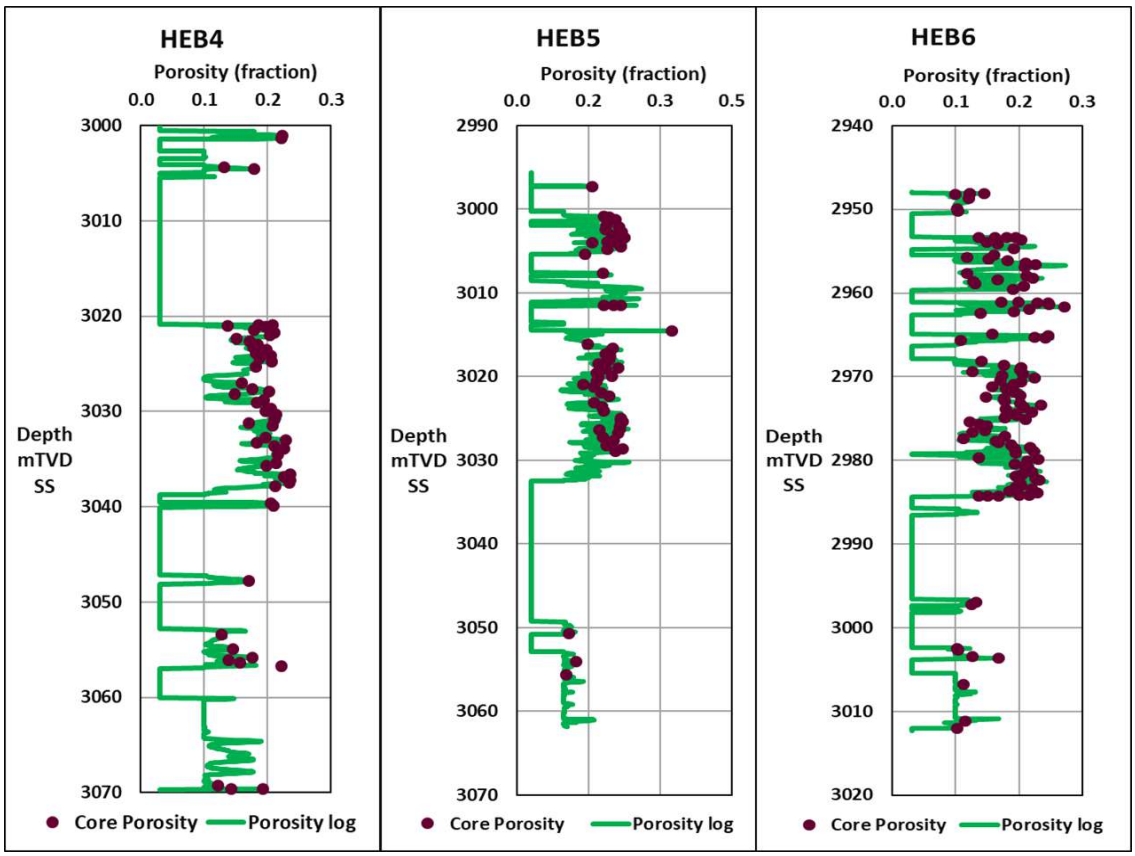

Figure 4-6: Porosity log prediction for HEB4, HEB5 and HEB6 wells

4-3 Permeability prediction

Permeability is one of the most important petrophysical parameters for formation evaluation and reservoir characterization. Depending on the data required and procedure availability, permeability can be defined by several methods such as well test interpretation, wireline formation testers, and core data (Belhouchet H.E. & Benzagouta M.S., 2019). These methods are still limited in determining and predicting permeability due to the high cost and limited information available, which cannot cover all the reservoir areas. For that aim, well log records can be an interesting sustaining tool to be used in estimating permeability for any borehole cored and non-cored zones (Belhouchet, H.E., Benzagouta, M.S. Dobbi,A. et Al., 2020).

Traditionally, the log permeability is estimated based on the relationship between core permeability and core porosity. As indicated previously, the permeability versus porosity relationship, recorded from core analysis, shows a non-uniform cloud with a correlation coefficient of 0.4069 (Figure 3-5). The application of this mathematical model made it possible to estimate the log permeability according to the log porosity. The plot of the calculated permeability versus the core permeability has shown a very low correlation coefficient equivalent to 0.2888 (Figure 4-7). This low value offers a considerable margin of error. According to (Belhouchet, H.E., Benzagouta, M.S. Dobbi,A. et Al., 2020), all calculations, depending directly or indirectly on absolute permeability, will be overestimated. Therefore, the numerical simulation model does not represent the real field performance.

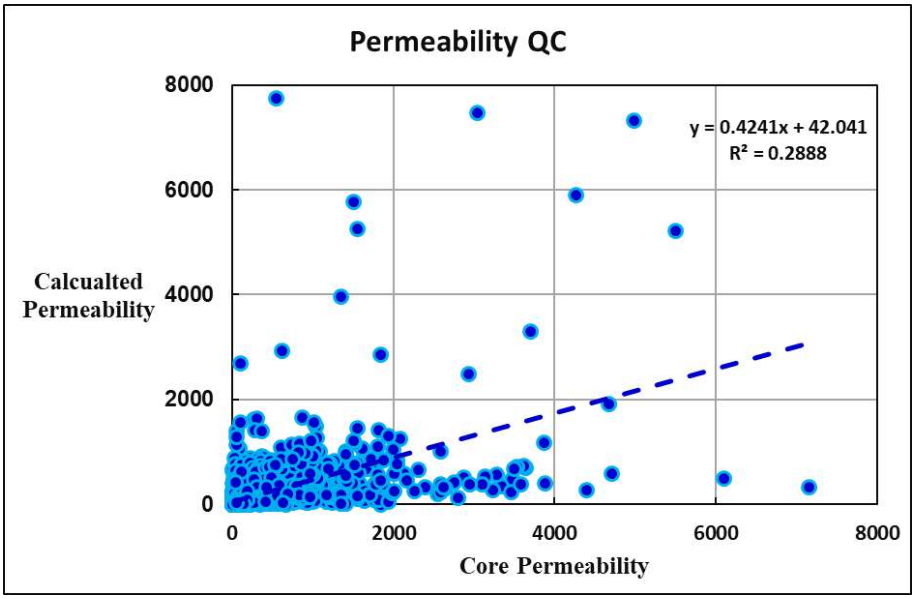

Figure 4-7: A cross plot indicating the permeability calculated from Poro-perm relationship versus the core permeability of 3160 plugs

For this purpose, the integration of the rock typing method turns out to be necessary. This request will possibly improve the absolute permeability calculation and be subsequently extended to the non-cored sections. Thus, this prediction will be used to decrease the uncertainties surrounding the non-cored zones. According to the investigations carried out previously, a good correlation coefficient (RMSE^2 = 0.9746) was observed in the figure 3-7.

It was produced according to the plot of the calculated permeability versus core permeability. This outcome was obtained according to the application of the FZI method to identify reservoir rock types. Therefore, FZI can be considered the best method for permeability prediction and the main parameter for discrete rock type identification. For this reason, mathematical models must be developed to define this parameter (FZI) from conventional well logs. In this conducted research, two approaches were assessed to identify these patterns:

- Regression method
- Neural network method

4-3-1 Regression methods

As mentioned in the porosity section, the regression method is applied to fit the parameters of a developed mathematical model. According to Tanmay Chandra (2008), the mathematical model of FZI can be calculated from the combined use of well logging data such as Gamma Ray (GR), NPHI, RHOB, and Sonic (DT) (Equation 71), and therefore FZI can be set as:

$$FZI = f(GR, NPHI, RHOB, DT) \quad (71)$$

In this research, our approach focuses mainly on the development of a mathematical model that allows calculating the FZI from well logs for the first exploration borehole and then displaying to estimate the FZI in the advanced drilled boreholes. This approach is recommended to provide a general strategy for characterizing a reservoir, starting from the exploration phase, where the data is limited, and reaching the development phase, where new data is available. This technique can therefore be tracked to improve the obtained model.

For accomplishing the precedent purpose, well-log data should be used for analysis and interpretation. It will provide an approach that allows non-cored section classification to be introduced within reservoir rock types. Thus, in such a setting, FZI and permeability models can be applied. For the case study, the GR interpretation allows subdividing the reservoir into five sub-zones. The sub-zones have been defined as organic-rich shales, shale, shaly-sandstone, sandstone, and clean sandstone (Table 3-1). Cores are located in the net pay zone, which constitutes three separate subzones: shaly-sandstone, sandstone, and clean sandstone (Figure 4-8). This approach is well supported by (Belhouchet, H.E., Benzagouta, M.S. Dobbi,A. et Al., 2020).

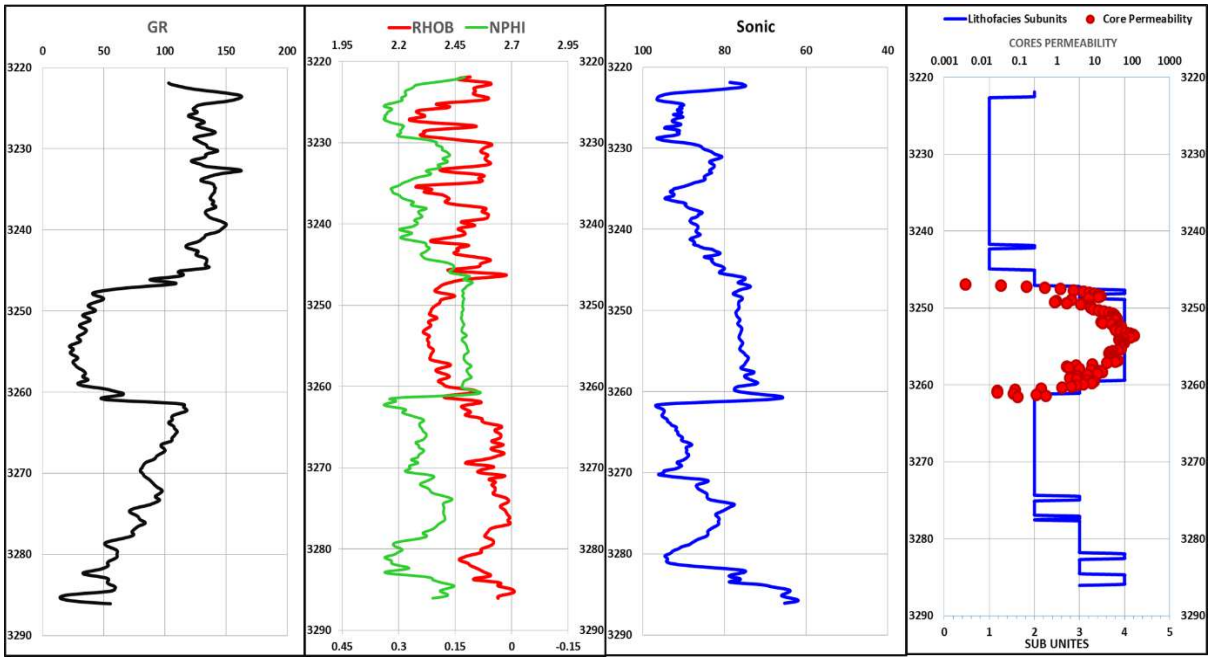

Figure 4-8: Well log interpretation based on GR classification indicating the emplacement of core data in reservoir zones for the first exploration borehole (HEB1)

Once the lithofacies and petrofacies are well-defined, empirical Modelling (EM) is applied. This later is intended to construct mathematical models based on the experimental data to predict the normalized FZI model from well logs. Accordingly, the obtained model is used in permeability calculation through the application of the reservoir rock typing process. In order to achieve this objective, several models were produced on the basis of the combination of mathematical functions such as linear, exponential, logarithmic, power, and rational functions using conventional well logs such as; Gamma-ray, NPHI, RHOB, and DT. The best mathematical model must be related to the optimal objective function and characterized by its specific logs. The objective function or the optimized goal of the proposed model consists essentially of minimizing the summation of the quadratic error. This difference will be set between the calculated and the observed normalized FZI as mentioned in the equation below:

$$Obj_{func} = minimize\left(\sum_{i=1}^{n}(FZI^{*}_{obs} - FZI^{*}_{calc})^{2}\right) \quad (72)$$

Where:

Obj_{func}: The objective function

FZI^{*}_{obs}: Observed normalized FZI factor

FZI^{*}_{calc}: Calculated normalized FZI factor

n: The number of plugs presented in this study ($n = 42$)

and normalized observed FZI (FZI^*_{obs}) has been calculated by applying Shier, D.E., (2004) formula as:

$$FZI^*_{obs} = \frac{FZI - FZI_{min}}{FZI_{max} - FZI_{min}} \quad (73)$$

Where FZI, FZI_{min} and FZI_{max} are considered from core data.

Noting that FZI^* is constrained by the rock lithofacies (Shaly-Sandstone and Sandstone & clean Sandstone subzones). According to this categorisation, each lithofacies has a specific mathematical model.

In this study, in order to solve the nonlinear optimization problem and compute the optimal model parameters based on the chosen subject function, the Generalized Reduced Gradient (GRG) method was performed (Maia A. et al., 2017). The mathematical models of normalized FZI (FZI^*_{calc}) for shaly-sandstone and sandstone & clean sandstone subzones were developed. They were performed on the basis of several scenarios carried out on the observed normalized FZI issues from plugs and normalized FZI estimated from normalized well logs, RHOB* and DT*. NPHI* has been used as a parameter, but it has not led to reliable results. Thus, the mathematical models deduced for the two subzones are corresponding:

- ***Shaly-Sandstone;***

$$FZI^*_{calc} = 0.312739 * \ln(RHOB^* + 1.163084) + 1.105386 * \ln(DT^* + 0.789186) \quad (74)$$

- ***Sandstone & clean Sandstone;***

$$FZI^*_{calc} = \frac{1.342524}{-1.00692 + 1.408993 * e^{4.16757 * RHOB^*}} \quad (75)$$

Where $RHOB^*$and DT^* are normalized parameters and are calculated by Shier, D.E., (2004):

$$Normalized_{log} = \frac{Reading\ Value - Min\ Value}{Max\ value - Min\ Value} \quad (76)$$

Based on equation 73, the FZI log is calculated from the normalized FZI and stated as follows:

$$FZI_{log} = FZI^*_{calc} * (FZI_{max} - FZI_{min}) + FZI_{min} \quad (77)$$

For the permeability calculation, reservoir rock types were classified based on the FZI values, in which a permeability model was defined for each rock type (Table 3-2). The results presented

in the figure 4-9 indicate a relative fine comparative correlation between the calculated and observed parameters (FZI and permeability). Therefore, these deduced models can be used to calculate permeability in non-cored wells.

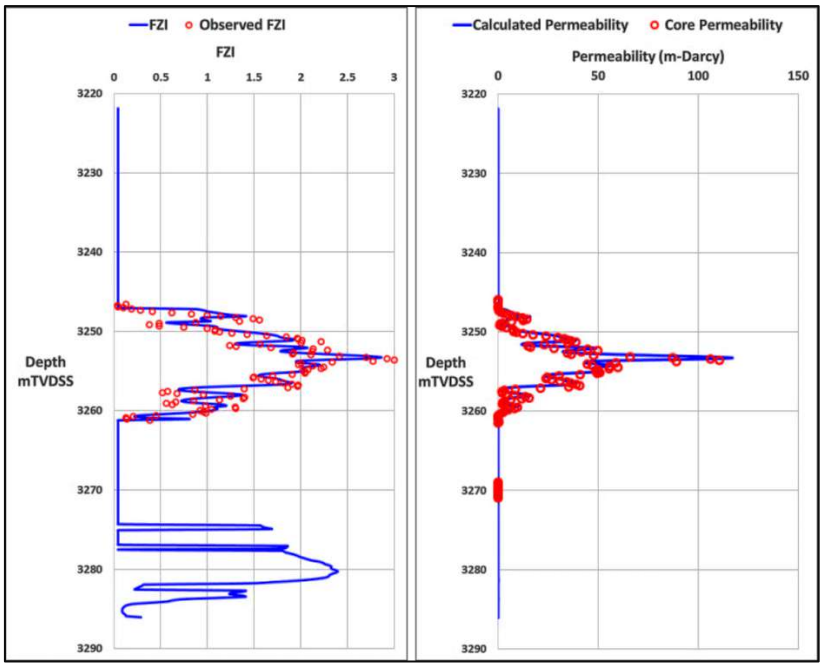

Figure 4-9: FZI and Permeability profiles calculated from well logs data

The application of these mathematical models (equations 74 and 75) to newly drilled wells (developed wells) where new data is available allows the FZI* prediction. The graphical analysis of the cross plot of the FZI* core versus the calculated FZI* has shown a very low correlation coefficient (0.0928), which directly affects the prediction of the FZI and the permeability (Figure 4-10). On this basis, the search for an alternative mathematical model was necessary. Noting that the use of new data extracted from newly drilled wells is needed to give more support for the improvement and development of the model.

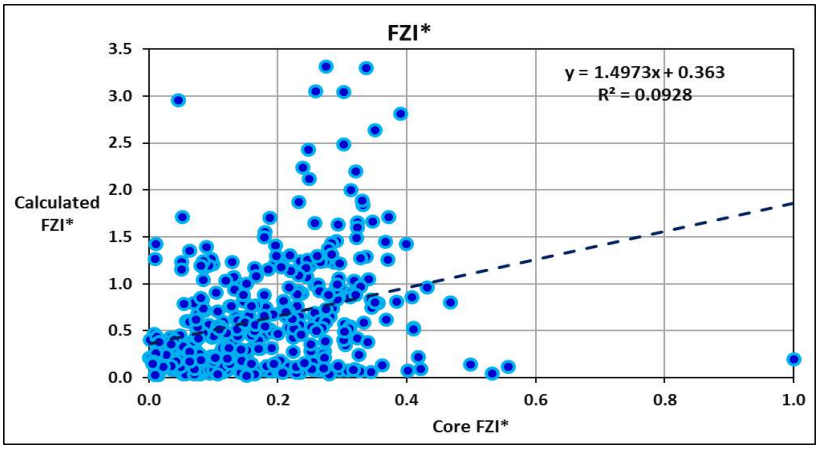

Figure 4-10: Calculated normalized FZI* from equations 74 and 75 versus core normalized FZI*

In this context, the same strategy applied previously was executed to find a model capable of calculating the FZI. Several mathematical models have been evaluated based on the combination of mathematical functions such as; linear, exponential, logarithmic, power, and rational functions using conventional well logs such as Gamma rays, NPHI, RHOB, and DT. These models are generally characterized by the unknown parameters, the independent variables, the dependent variables and the error terms. To estimate these parameters, a nonlinear regression method should be applied. According to (Maia A. et al., 2017), The Generalized Reduced Gradient (GRG) method has been employed to solve nonlinear optimization problems, requiring that the objective function be differentiable. The selection of the optimal model could be related to this objective function defined previously (equation 72). Thus, the mathematical model obtained is given by:

$$FZI^* = \frac{a}{b + c * \exp(d * GR^*)} + \frac{e}{f + g * \exp(h * GR^*)} + \frac{i}{j + k * \exp(l * GR^*)} + \frac{m}{n + o * \exp(p * GR^*)} + q \quad (78)$$

Where a, b, c, d, e, f, g, h, i, j, k, l, m, n, o, p, and q are fitted for each rock type (shaly sandstone, sandstone, and clean sandstone) using the Generalized Reduced Gradient (GRG) method. The results are well expressed in table 4-4 underneath:

Fitting parameters	Shaly Sandstone	Sandstone	Clean sandstone
a	1.082473	2.289359	0.994504
b	3.392247	1.984179	0.121264
c	1.25E-10	1.82E-06	3.05E-05
d	44.21345	32.69867	24.33081
e	0.353465	0.030151	0.121167
f	3.283898	-2.77224	1.359092
g	-2.38049	2.892795	2.92E-05
h	-4.87558	0.308805	64.31746
i	-1.52904	-0.02456	-12.5166
j	1.482987	-0.01731	1.619119
k	0.007797	0.03771	0.063542
l	4.987003	0.067782	0.557722
m	0.045324	0.457354	3.090263
n	-9.61968	1.987036	24.1681
o	7.701637	0.009967	0.007561
p	2.976596	29.77806	26.92022
q	0.669686	0.073777	-0.59068

Table 4-4: Table presenting the fitting parameters used in the mathematical model (equation 78) for shaly-sandstone, sandstone and clean Sandstone facies

The application of this model makes it possible to improve the correlation coefficient from 0.0928 to 0.3417 (Figure 4-11), but the latter is still weak. Thus, this outcome proves the

limitation of nonlinear regression methods when facing big data. This thought is well supported by (Kraus, M. et Al., 2019). Accordingly, machine learning methods must be called upon to improve the determination of FZI. Among these methods for solving this kind of identification problem are neural network techniques.

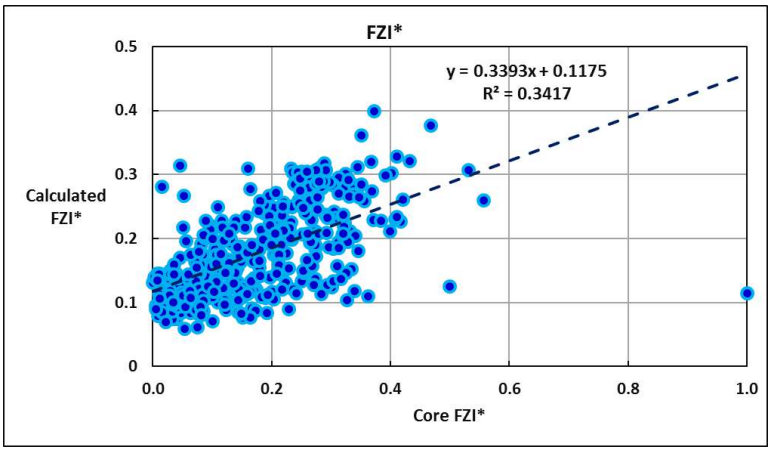

Figure 4-11: Calculated normalized FZI* from the mathematical model presented in the equation 78 versus core normalized FZI*

4-3-2 Neural Network approach

Due to the difficulty of creating the mathematical model and the limitation of regression methods to determine its parameters against big data, machine-learning concepts are introduced. They are aimed to find a solution for this type of issue. Several machine-learning methods have been published in the literature for making predictions, recommendations, classifications, and decision tasks. Based on chapter 2, where the various methods of machine learning were presented, one of these methods, applied in many studies and which gave excellent results in this research, remains the neural network technique. As mentioned earlier, this technique is focused on creating a mathematical model that works by finding a logical relationship between the inputs and the outputs. In our case, radial neural networks have been applied to extract a mathematical model that allows the prediction of normalized core FZI* based on normalized conventional well logs (GR*, RHOB*, NPHI* & DT*). The same procedure has been applied; it will start with the normalization of the inputs and outputs using equation 71, followed by the execution of the radial neural network. The typical scheme of this network is well illustrated in the figure 4-12.

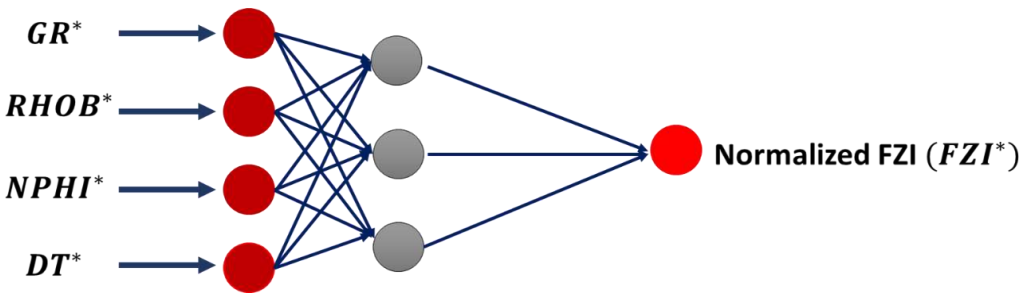

Figure 4-12: ANN representation for normalized FZI prediction

The same procedure was performed; 75% of the data has been used as training data, 10% is used for validation, and 15% for prediction. These Neural Networks (RBNNs) have been executed on Matlab. In the first instance, the model has been run to minimize the objective function to 0.0000001. The execution of the latter allows for improving the correlation coefficient from 0.3417 (estimated by regression methods) to 1 ($R^2 = 1$) and accordingly, the main objective is achieved (Figure 4-13.a). The number of hidden neurons for this execution is 350 neurons, and the mean squared error (MSE) reached 3.19154 e-06. The denormalization of the flow zone indicator (FZI) has been intended using equation 79. The plot of this calculated parameter versus the core FZI shows a good correlation coefficient around 1 ($R^2 = 1$). The results are well shown in the figure 4-13b.

$$FZI = FZI^* * (\max FZI - \min FZI) + \min FZI \qquad (79)$$

Where;

FZI: flow zone indicator (de-normalised FZI).

FZI^*: Normalized FZI.

$\max FZI$: maximum FZI value.

$\min FZI$: minimum FZI value.

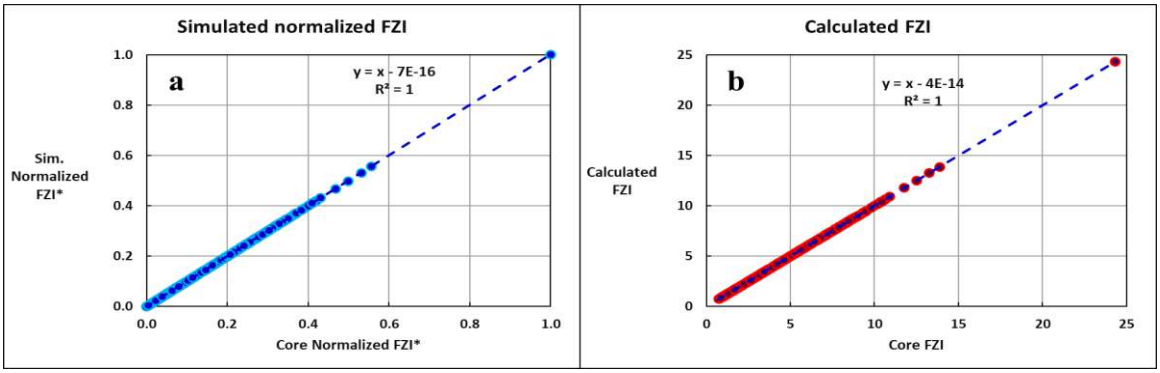

Figure 4-13: Normalized and Calculated FZI

Before validating the neural network model, it is necessary first to check the response quality of the model when predicting normal FZI in the non-cored areas. The execution of this model shows the presence of out-of-range values (more than one and less than zero), which means that the spread must be worked on until the model improves the prediction results, which must be between 0 and 1. To achieve this goal, the spread will be reduced to 0.04. Once the model is confirmed, the log FZI can be calculated using equation 79, and the results are presented in figures 4-14 and 4-15.

The graphical analysis shows a good correspondence between the log FZI and the experimental FZI data, which indicates the efficiency of this type of neural network (RBNN) to identify relationships between a large number of input data and a large number of output data.

According to the results expressed in the rock typing section, the FZI method can be considered the best method for calculating permeability as a function of porosity (Figure 3-7c). This method has a high correlation coefficient of 0.9746 (Figure 3-7d). The mathematical models inferred from this method are well summarized in Table 3-2. The execution of these models allows the prediction of permeability in non-cored sections and wells. The results are well presented in the figures 4-16 and 4-17. Graphical analysis shows a very good match between calculated and observed permeability.

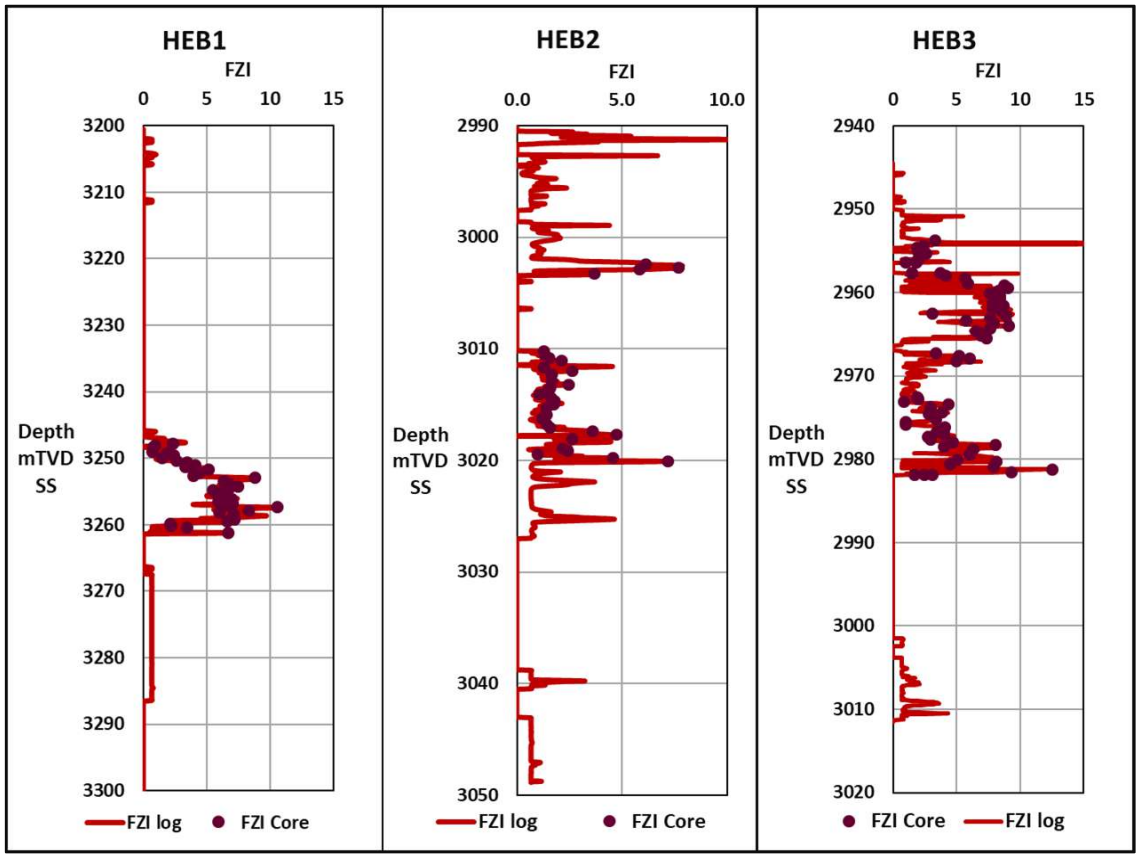

Figure 4-14: FZI log prediction for HEB1, HEB2 and HEB3 wells

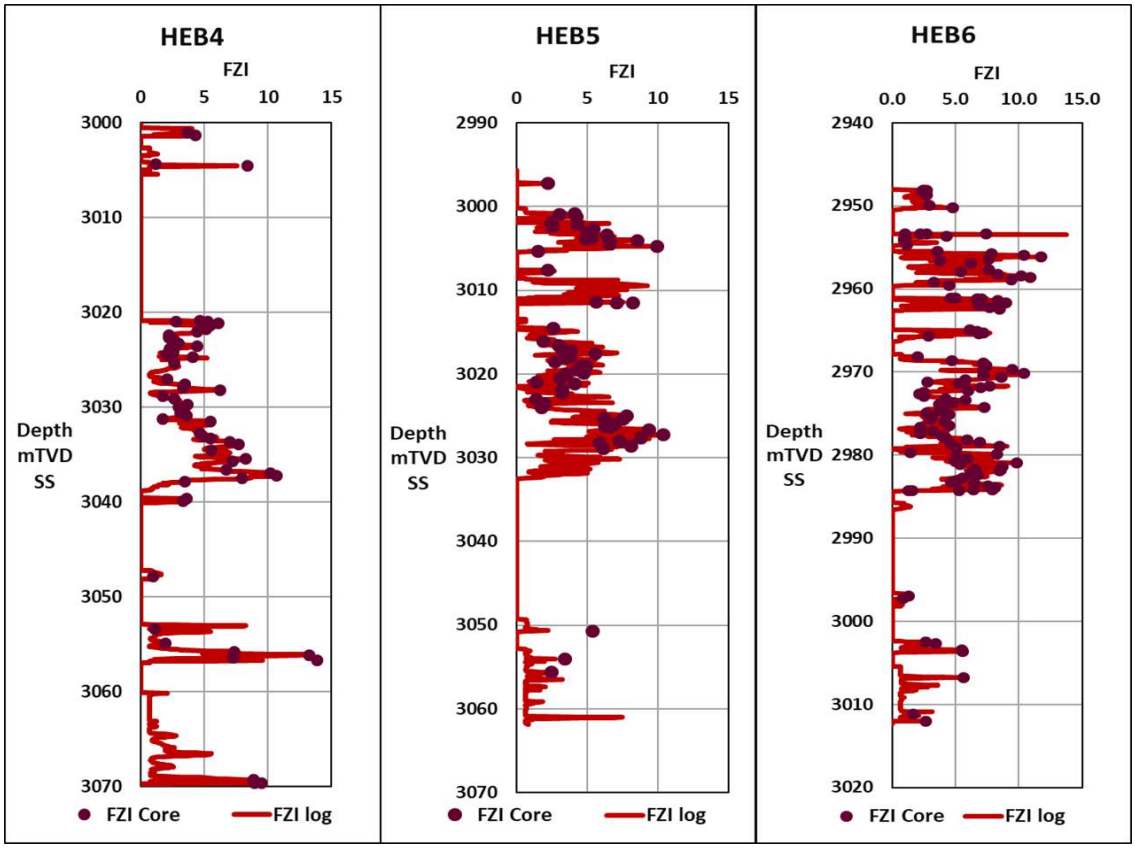

Figure 4-15: FZI log prediction for HEB4, HEB5 and HEB6 wells

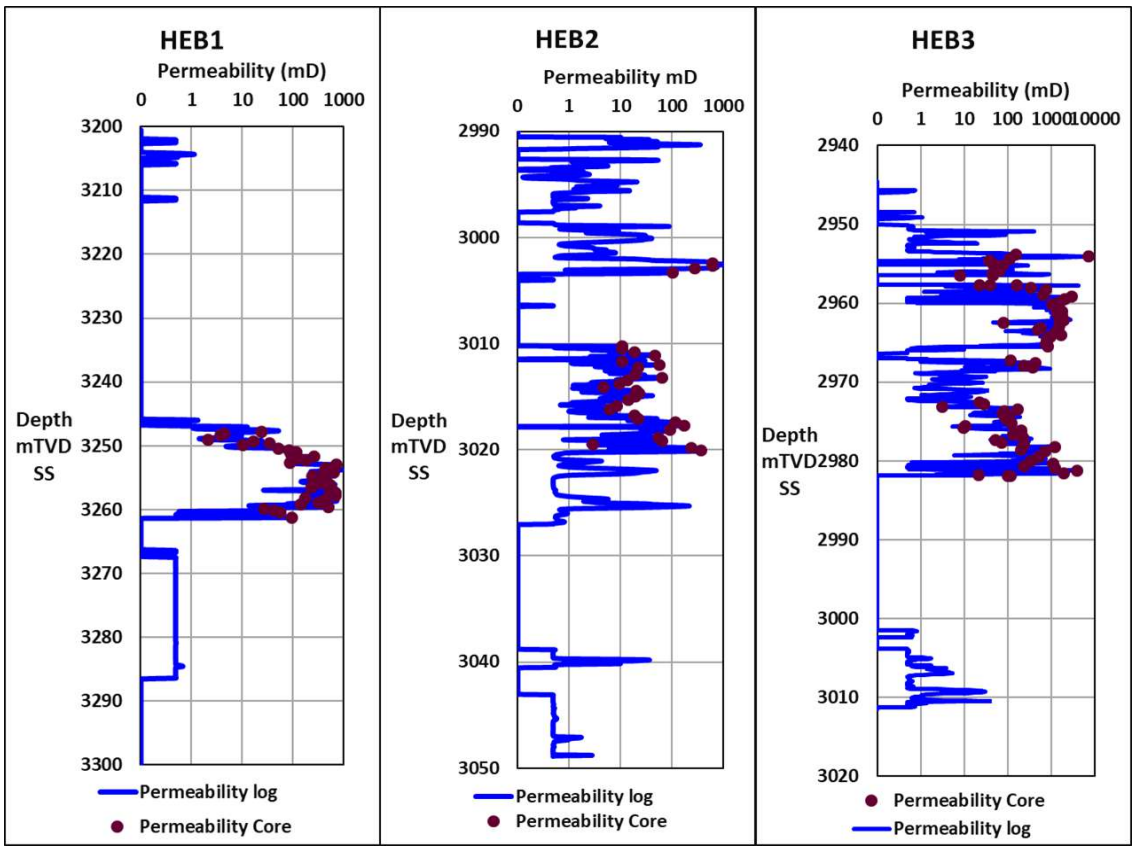

Figure 4-16: Permeability log prediction for HEB1, HEB2 and HEB3 wells

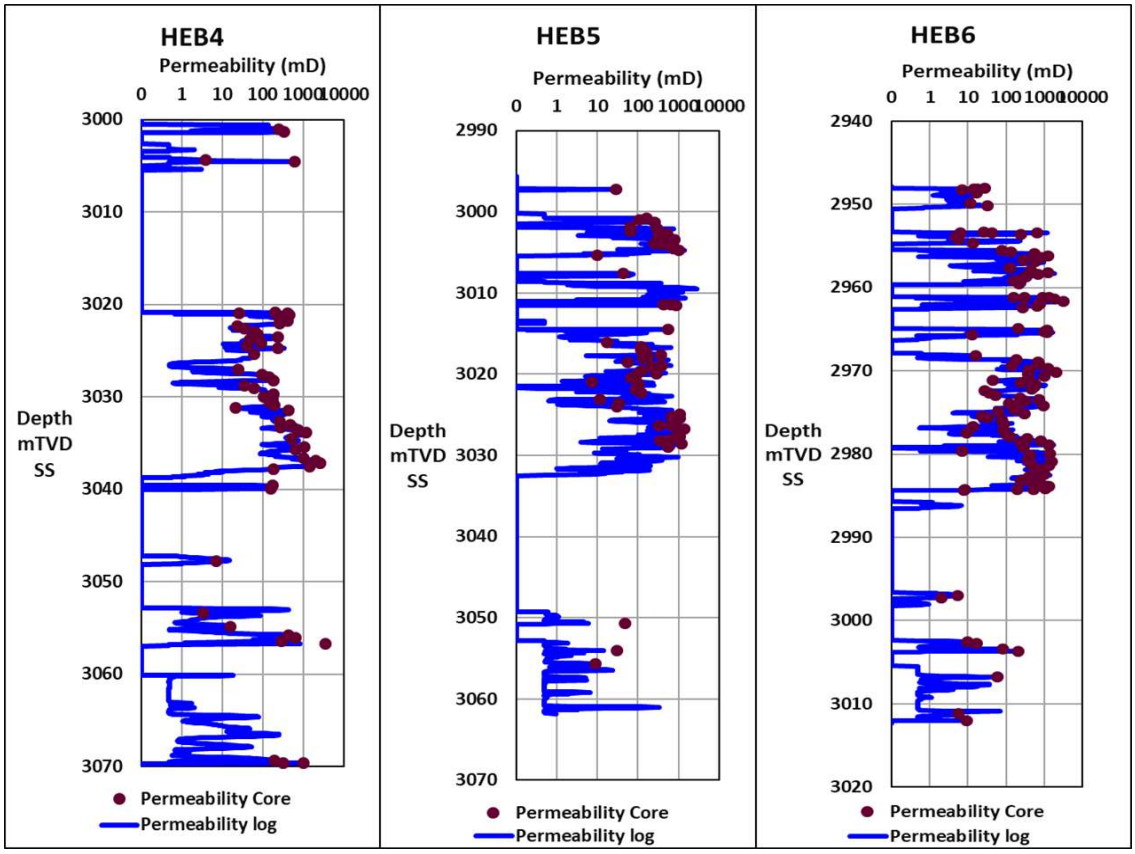

Figure 4-17: Permeability log prediction for HEB4, HEB4 and HEB10 wells

4-4 Water Saturation prediction

Water saturation is defined by the volume of water compared to the pore volume. This is the most important and fundamental factor in determining the amount of oil in place. Similarly, the accurate estimation of this property also plays a key role in economic evaluations of oil reservoirs. However, their determination is very difficult due to the presence of several approaches, where each of them can provide several saturation values that directly affect water saturation distribution throughout the reservoir, both vertically and horizontally. This parameter can be measured directly from laboratory core analysis, estimated from well logs or seismic attributes, or can be assessed from an intermediate parameter such as the volume of shale in sandstone reservoirs. Support is from (Wan Bakar, W.Z., Mohd Saaid,I., Ahmad, M.R. et Al., 2021).

In the past few years, extensive research has been conducted to define a mathematical model that allows finding an empirical relationship between water saturation from well logs and water saturation measured in the laboratory in order to predict the water saturation in the non-core areas. Archie proposed the first of these techniques in 1942. This method is based effectively on water saturation determination from resistivity logs and porosity derived from porosity logs. Archie's model parameters, such as cementing factor, tortuosity factor, and saturation exponent, are computed from laboratory core analysis. However, these parameters are variable, and their values should be calculated for different homogenous reservoirs. Therefore, the accuracy of the Archie equation is extremely dependent on these parameters. Moreover, these

methods are still limited facing the shales and heterogeneous formations (Muskat M and Bots H.G., 1931), (George Asquith and Charles Gibson, 1982) (Schlumberger, 1984).

To overcome this problem, rock physics properties should be integrated to determine shale volume in shaly sands using a combination of wireline logging tool data, and their use for water saturation calculation and prediction in the considered type of lithology. More recently, a new approach has been integrated to directly estimate water saturation values from seismic attributes (Rafael Souza and David Lumley, 2015), (Fadlan Ardinda and Agus Riyanto, 2020). These methods are effectively based on the application of artificial intelligence methods such as fuzzy logic, genetic algorithms, and neural networks to identify non-linear relationships between different attributes.

According to the accurate predictions of the porosity and flow zone indicators, a radial basis function neural network (RBF) technique has been developed for water saturation determination from well logs. The final network was created by 3 input layers, including deep resistivity, shallow resistivity, and porosity logs (RHOB, NPHI, and DT), and an output layer, which is our target (water saturation). All the input and output data have been normalized using equation 65 (values range between 0 and 1). For that purpose, 183 samples of logging and coring data from the HEB field were used. These datasets were divided into three groups: training data (75%), validation data (10%), and test data (15%). Thus, these subsets are used respectively to fit the model, provide an unbiased evaluation of a model fit on the training dataset while tuning model hyperparameters, and provide an unbiased evaluation of a final model fit on the training dataset. Figure 4-18 shows the structure model of the RBF neural network model.

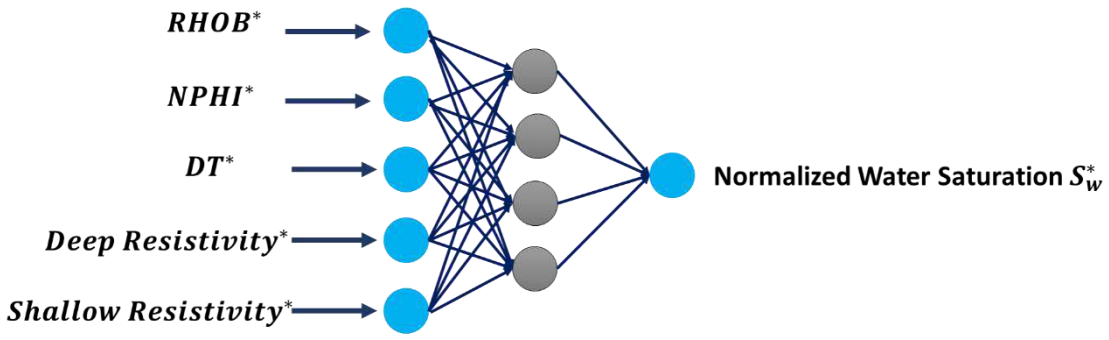

Figure 4-18: ANN representation for normalized water saturation prediction

Once the neural network model is run, it will reach the desired root mean square error (0.000001). The normalized water saturation was estimated and compared to the normalized water saturation associated with the core data (Figure 4-19a). Graphical analysis shows a line with a slope of 45° and a good correlation coefficient, which indicates an absolute match between the observed and simulated data. The final number of hidden neurons needed is 150, and the mean squared error (MSE) attained is 4.56063e-05. For water saturation determination, the equation below (80) was applied. The plot of this latter as a function of core water saturation shows a good correspondence with a correlation coefficient around 1. The results are well illustrated in the figure 4.19b.

$$S_w = S_w^* * (\max S_w - \min S_w) + \min S_w \quad (80)$$

Where;

S_w: water saturation (de-normalised water saturation).

S_w^*: Normalized water saturation.

$\max S_w$: maximum value of water saturation.

$\min S_w$: minimum value of water saturation.

For the model validation, a prediction of normalized water saturation in the non-core zones for the selected wells is required. The simulation results illustrate the presence of values out of range, which leads to changing the dispersion parameter, which is by default 1. Several sensitivities have been implemented to have normalized saturation values in the range [0,1]. The obtained spread value is 0.1. This dispersion makes it possible to validate the RBF model and use it in the water saturation calculation process. Hence, the water saturation log can be calculated by equation 80, and the results are well represented in the figure 4-20.

The results of this work show the successful application of the radial basis neural network (RBF) to the estimation of petrophysical properties, which are porosity, permeability, and water saturation.

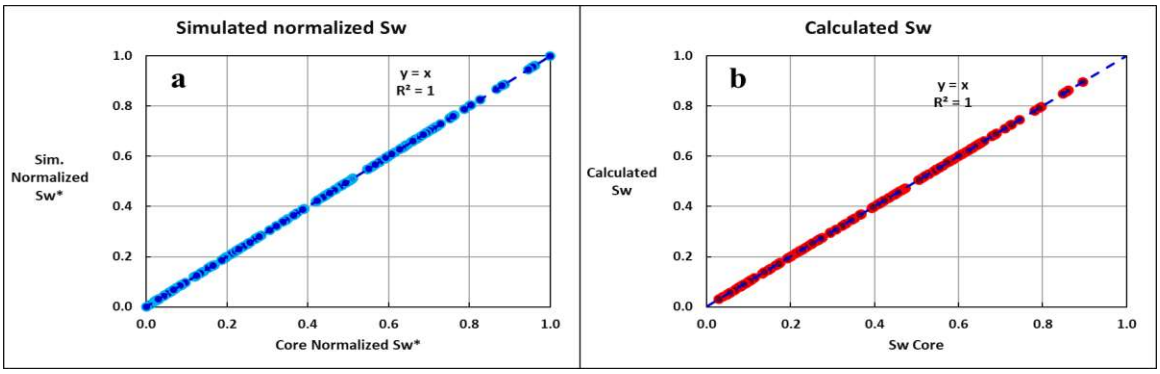

Figure 4-19: Normalized and Calculated water saturation

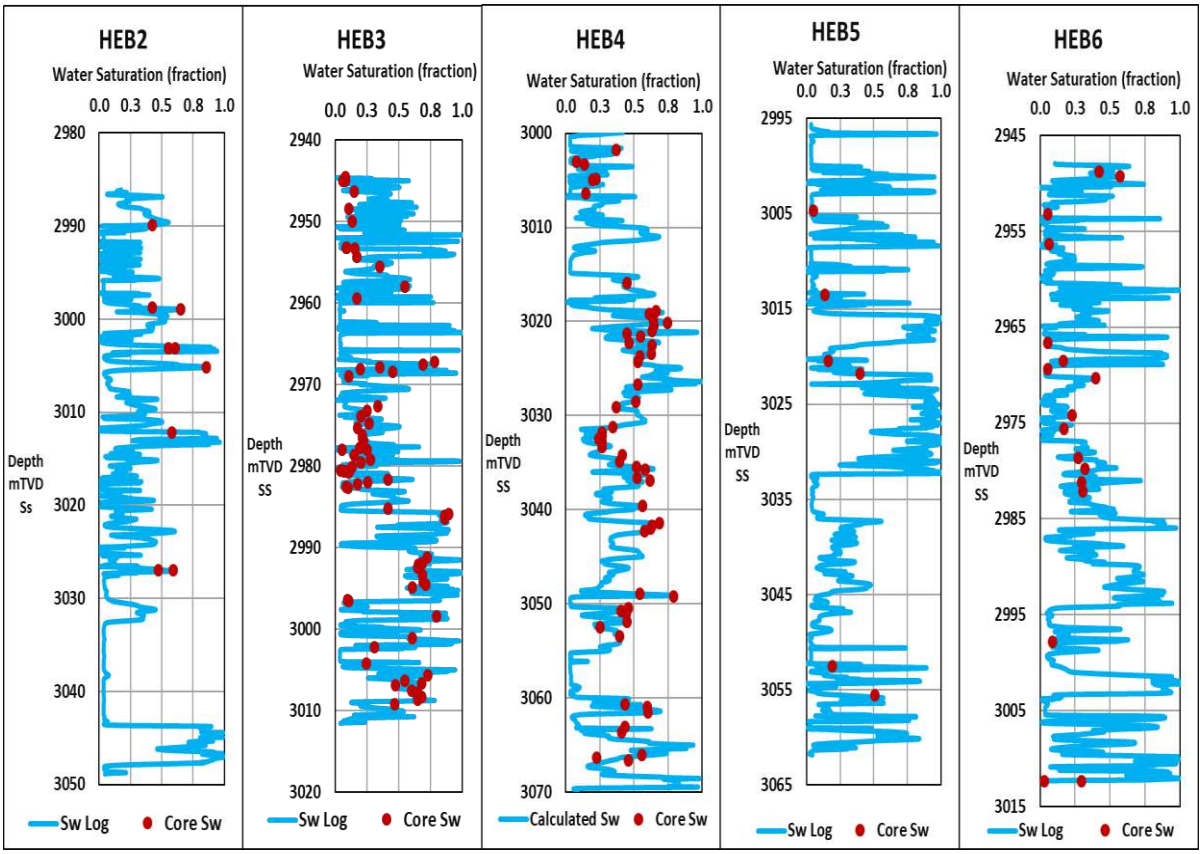

Figure 4-20: Water saturation log prediction for HEB2, HEB3, HEB4, HEB5 and HEB6 wells

4-5 Conclusion

- The absence of a link between lithofacies and petrofacies is not always a solution for predicting petrophysical properties.
- Prediction of petrophysical properties by conventional methods may be the best option for cases where there is a lack of or limited data. The uncertainties resulting from the application of these approaches can have an impact on the expected results, which are highly dependent on the identification of the rock type.
- Identification of mathematical models can be used as an alternative approach to improve petrophysical property prediction and reduce uncertainty. The application of nonlinear regression methods can be a desirable option for developing these mathematical models. These models can be created using conventional logs, which can be found in all core and non-core wells.
- Because of data limitations, the use of the nonlinear regression method is limited, and a switch to the machine learning method is required. The neural network is one of these approaches. This network may be the most effective method for identifying these mathematical patterns and providing a powerful tool for comprehension and prediction.
- The application of this approach enhances the prediction of petrophysical properties such as porosity, permeability, and water saturation in cored areas. Correlation

coefficients of around one are obtained, indicating that these models can be used to forecast petrophysical properties in non-core areas.

- Uncertainties in data analysis with various obtained mathematical curves can be involved and useful to find out and support the correlation between hydraulic units issued from core data and well logs.
- The use of the classification process can be the main concern for the permeability determination and its anticipation for each rock type.
- Similar reservoir characterization steps can be applied to other non-cored wells, particularly boreholes set in the same structure and with broad-spectrum characteristics.
- The validation of a machine-learning model can be strongly connected to the good correlation coefficient issues from the plot of simulated results versus real data, as well as the prediction results. The output results should be consistent with the input data range. Thus, the normalization process should be used to normalize the input data to a fixed range between 0 and 1.

Synopsis - Conclusion

The led research has permitted to reach the following statements:

1- Reservoir Characterization and Modelling: General view:

Reservoir characterization is the process of identifying and estimating reservoir properties using all types of data that are directly or indirectly related to any parameter introduced in the property specification.

Using a range of data can help determine the type and age of geological formations, as well as deposit environments, reservoir heterogeneity, and hydrocarbon quantities in place.

The gathering of various forms of data, the availability, and the quality check can be considered half of the work of all tasks to be accomplished.

The use of the physical properties of the fluids in relation to the rock-fluid characteristics recorded in boreholes led to the creation of a numerical simulation model.

2- Rock typing as input for reservoir characterization: Approaches and Materials in need

Rock typing is one of the main procedures applied in reservoir characterization to have a more reliable reservoir model.

The application of different reservoir rock typing approaches is necessary to select the best method to ensure the finest estimate of reservoir properties such as lithology, porosity, permeability, and saturation.

The development of the rock typing process is closely related to the type, volume, and quality of the data.

The use of all data related directly or indirectly to the reservoir properties is recommended to have more control over the use of these resources and reduce reservoir modelling uncertainties and convergence problems that can be expected in the numerical simulation.

Thus, machine learning is one of the best practical solutions implemented in the oil and gas industry to elucidate classification, regression, forecasting, and optimization problems.

Accordingly, machine learning is considered one of the most effective ways to develop oil and gas projects, by reducing costs, helping in decision-making, and time-consuming.

3- Reservoir rock type Characterization – A case study of Algerian oil field

The quality of data available for any study has, in general, a direct impact on the results value. Outlooks from the project can skew and thus cause technical, economical, and time-wasting issues.

Preparing the data, ensuring its quality and steering it towards the required objectives, can be considered as a main step towards the proposed guidelines.

For the case study, among the restrictions involved in the control of the reservoir is its shaliness or clay content parameter. It is believed to be an important parameter for identifying lithofacies in TAGI sandstone formations.

Five major lithological facies types have been identified: organic-rich shale, shales, shaly sandstone, sand, and clean sandstone, with shaly sandstone, sand, and clean sandstone being the best reservoir facies.

A lithofacies method is suitable and useful for describing lithology and predicting the net with regard to the gross pay. Recorded well-log column supports this approach. At a similar stage, determining and predicting porosity and permeability can be possible.

Rock types can be identified in a variety of ways based on different methods. It approaches essentially the properties screening, in order to provide some evidences and extra information.

Proceeding on comparison between the following parameters: FZI, DRT, R35, DRT_R35, and GHE unit results were established. Based on the relationship between core permeability and predicted permeability, the FZI method was the best compilation for identifying dynamic reservoir rock types and estimating permeability for the TAGI sandstone formation. This statement is supported by a regression value of 0,97.

A good contest was also met between capillary pressure, saturation height function, relative permeability classification, and FZI classification. Similar results evidence that these methods are among the influencing factors in reservoir rock type classification.

Approach on appropriate categorization achievement by the use of the capillary pressure profile: availability of data is subjected to the same reservoir characterized by the same pressure, temperature, and fluid properties.

The TAGI sandstone formation has fifteen reservoir rock types (RRT) identified using the FZI method. This large number may increase simulation time and cause simulation convergence issues, necessitating the use of the DRT method, which is derived from FZI.

The application of the DRT method has produced a good correlation coefficient around 0,93 with eight dynamic reservoir rock types.

Thus, reservoir rocks from TAGI sandstone formations in the Hassi Berkine oil fields can be classified into four lithofacies and eight petrofacies, with no compatibility between them.

Pore size distribution (PSD) is an alternate method that can be used for identifying the heterogeneity of the TAGI sandstone formations.

4- Petrophysical properties prediction

The absence of a relationship between lithofacies and petrofacies in TAGI sandstone formations is not always a key for predicting petrophysical properties.

Prediction of petrophysical properties by conventional methods may be the best option for cases where a lack of or limited data is occurring The uncertainties resulting from the application of these approaches

may have an impact on the expected results, which are highly dependent on the identification of reservoir rock types.

Identification of established mathematical models can be used as an alternative approach to improve petrophysical property prediction and reduce uncertainty.

Nonlinear regression methods were implemented to develop mathematical models that can link conventional well logs to the core data. However, due to the limitations of regression methods when dealing with big data, a switch to the machine learning method was required.

The radial basis neural network was discovered to be the most effective method for identifying these mathematical patterns, as well as a powerful tool for comprehension and prediction.

Correlation coefficients on cored section parameters may be indicating that obtained network can be a topic in use to forecast petrophysical properties in non-core zones.

Uncertainties in data analysis with various obtained mathematical curves can be involved and useful to find out and support the correlation between hydraulic units issued from core data and well logs.

The usage of the classification process can be the main concern for permeability determination and its anticipation regarding each rock type.

Thus, a similar investigation for the reservoir characterization steps can be applied to other non-cored wells, especially for boreholes set in the same structure and having broad-spectrum characteristics.

The validation of a machine-learning model can be strongly connected to the good correlation coefficient issued from the plot of simulated results versus real data as well as the prediction results. However, the output results should be consistent with the input data range.

The normalization strategy is one of the key processes that should be used to normalize the input data to a fixed range between 0 and 1.

The implementation of a radial basis neural network on the TAGI sandstone formation in the Hassi Berkine oil fields improves the prediction of petrophysical properties such as porosity, permeability, and water saturation. The use of the optional data specified for this neural network is required to improve the network's behaviour.

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List of Abbreviations

R_{xx}: Pore radius calculated at saturation of xx % of mercury

τ: Tortuosity

$\emptyset_D$: Porosity calculated from density log

$\emptyset_s$: Porosity calculated from sonic log

$\emptyset_N$: Porosity defined from neutron porosity log

$\emptyset$: Porosity

Q: Flow rate

S_b: a specific internal surface area with reference to bulk volume

A: Area of the reservoir (acres) from map data

$P_{c_{calc}}$: Calculated capillary pressure

FZI^*_{calc}: Calculated normalized FZI factor

S_{gc}: Critical gas saturation

$DRT_{R_{35}}$: Discrete rock type index related to pore throat (R_{35})

$\emptyset_e$: Effective porosity

B_{gi}: Formation volume factor for gas at initial conditions (Res. ft^3/SCF)

B_{oi}: Formation volume factor for oil at initial conditions

h: Height or thickness of pay zone (ft) from log and/or core data

Sw_i: Interstitial water saturation

u: Center of the radial basis function ($u = 0$)

max $Poro$: Maximum porosity

FZI_{max}: Maximum value of FZI

max S_w: Maximum value of water saturation

FZI_{mean}: Mean Flow zone indicator for a rock type

$P_{c_{Obs}}$: Measured capillary pressure

min $Poro$: Minimum porosity

FZI_{min}: Minimum value of FZI

min S_w: Minimum value of water saturation

$Poro^*_{Calculated}$: Normalized calculated porosity data

$Poro^*_{Exprimental}$: Normalized experimental porosity data

Sg_n: Normalized gas saturation

$Poro^*$: Normalized porosity

Kr^*_g: Normalized relative permeability of the gas

Kr^*_o: Normalized relative permeability of the oil

Kr^*_w: Normalized relative permeability of the water

Sw_n: Normalized water saturation

n: Number of plugs

$Pc\_Obj_{function}$: Objective function for capillary pressure

FZI^*_{obs}: Observed normalized FZI factor

y_t: observed value at time t

$Poro$: Porosity

$Poro\_Obj_{func}$: Porosity objective function

$\widehat{y_t}$: Predicted value at time t

$\emptyset_z$: Ration between the pore volume and solid volume

Kr_g: Relative permeability of the gas

Kr_o: Relative permeability of the oil

Kr_w: Relative permeability of the water

σ: represents the radius of the radial basis function

So_r: Residual oil saturation

F_s: Shape factor

S_{gv}: Specific grain surface

Obj_{func}: Objective function

S_w: Water saturation (decimal) from log and/or core data

1D: One dimension

2D: Two dimensions

3D: Three dimensions

4D: Four dimensions

AI: Artificial intelligence

AN: Adaline Networks

ANN: Artificial neural network

BNN: Bayesian neural networks

BPNN: Back propagation neural network

C1: Methane

C2: Ethane

C3: Propane

C4: Butane

CCAL: Conventional core analysis

CCN: Cascade Correlation Networks

CEC: Cross-entropy clustering

CNN: Cascading Neural Networks

cP: Centi poise

CPPNN: Compositional Pattern-producing Neural Networks

CZI: Current zone indicator

DPRT: Dynamic petrophysical rock types

DRT: Discrete rock type

DRT_R35: Discrete pore throats

DST: Drill stem test

DT*: Normalized sonic log

DT: Sonic log

EFU: Electrical flow unit

EM: Empirical Modelling

EOS: Equation of state

ERI: Electrical radius indicator

F: Formation factor

FLN: Functional Link Networks

FZI: Flow zone indictor

G: Thomeer factor

GCN: Gram-Chalier Networks

GHE: Global hydraulic element

GMM: Gaussian mixture model

GR*: Normalized gamma ray log

GR: Gamma ray log

GRG: Generalized Reduced Gradient

Ham: Holographic Associative Memory

HaN: Hetero-associative Networks

HCPV: Hydrocarbon pore volume

HEB: Berkine basin

HFU: Hydraulic flow unit

HFWL: Saturation height function above free water level

Hg: Mercury

HMM: Hidden Markov model

HN: Hybrid Networks

HNN: Hopfield Neural Networks

HU: Hydraulic unit

K: Permeability (m-Darcy)

KN: Kohonen Networks (KN)

KNN: K-nearest neighbor

Kr: Relative permeability

LPNN: Lagrange programming neural network

LVQ: Learning Vector Quantization Network

mD: Milli darcy

MDT: Modular formation dynamics tester

MICP: Mercury injection capillary pressure

MKL: Multiple Kernel Learning

ML: Machine learning

MLP: multilayer perceptron

MNN: Modular Neural Networks

MSE: Mean squared error

NMR: Nuclear magnetic resonance

NPHI*: Normalized neutron porosity log

NPHI: Neutron porosity log

NTG: Net to gross

OGIP: Original gas in place

OOIP: Original oil in place

Pc: Capillary pressure

PEF: Photoelectric factor log

PGS: Pore geometry structure

PLT: Production logging tools

PNN: Probabilistic Neural Networks

PSD: Pore size distribution

PVT: Pressure volume temperature

QA: Quality Assurance

QC: Quality control

R^2: Correlation coefficient

R_{35}: Pore throats

RBF: Radial basis function

RBNN: Radial basis neural network

RCA: Routine core analysis

RCI: Reservoir characterization instrument

RDT: Reservoir description tool

RFN: Rock fabric number

RFT: Repeat formation tester

RHOB*: Normalized density log

RHOB: Density log

RMSE: Root mean square error

RNN: Recurrent neural network

RQI: Rock quality index

RRT: Reservoir rock types

R_t: Resistivity log

RT: Rock type

SCAL: Special core analysis

SNN: Spiking Neural Networks

SPRT: Static petrophysical rock types

SVM: Support vector machine

SVR: Support-vector regression

TAGI L: Lower Triassic Clayey Sandstone lower zone

TAGI M: Lower Triassic Clayey Sandstone middle zone

TAGI U: Lower Triassic Clayey Sandstone Upper zone

TAGI: Lower Triassic Clayey Sandstone

Vsh: Shale volume

WFT: Wireline formation tester

X: Input variable

XPT: Pressure express tool

Y: Output variable