Mining of Mineral Deposits
Volume 17 (2023), Issue 3, 42-48

JOURNAL / MINING.IN.UA

https://doi.org/10.33271/mining17.03.042

Automatic characterization and quantitative analysis of seismic facies in naturally fractured reservoir: Case study of Amguid Messaoud field, Algeria

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Abstract

Purpose. Natural fractured reservoirs are a special category of reservoirs due to the effects of porosity and permeability. Optimizing the exploitation of hydrocarbon reserves in this type of reservoir requires a specific study compared to other conventional reservoirs.

Methods. We have focused on the quantitative analysis of seismic traces for the purpose of an automatic seismic facies recognition strategy. The study area, the Amguid-Messaoud Basin, is formed by a series of horsts and grabens bounded by submeridional "North-East and South-West" faults, as well as perpendicular "North-West and South-East" faults with-out outcrops of fractures, which have a great influence on reservoir fracturing. A set of statistical data analysis methods, such as principal component analysis, discriminant factor analysis, and automatic classification, have been tested on real data from geophysical seismic data interpretation, in particular the stratigraphic interpretation.

Findings. The results obtained show a better use of data, which, however, are of a different nature, leading to a reliable interpretation of the geological environment.

Originality. The methodology proved to be useful for constructing a reservoir model and predicting the geological properties of the reservoir along a field.

Practical implications. The results obtained clearly demonstrate the best use of data, which, however, are of a different nature, which leads to a reliable interpretation of the geological environment. These methods have proved to be very useful for constructing a reservoir model and predicting the geological properties of the latter along a field.

Keywords: *statistical data analysis method, reservoir model, seismic facies, geophysical and stratigraphic interpretation*

1. Introduction

Statistical data analysis methods are increasingly being used to complement deterministic approaches to highlight data interdependencies. They are all the more effective because the observed measurements are multiple and varied [1]-[5] and have the advantage of integrating a multidimensional data representation, including factor analysis, classification method and discriminant analysis [6]. They have discovered very interesting field of application, especially in the domain of seismic technology, since seismic data, due to their good spatial coverage, is an important source of information for geological, structural and stratigraphic interpretation. They are completed by a finer lithological interpretation, which is of interest at the reservoir-level of trace portions, where the morphology of seismic traces is quantitatively analyzed [2], [7].

Lithological interpretation of seismic data seeks to establish links between reservoir geological properties and seismic response [8], [9]. This interpretation is based on the concept of seismic facies, which is defined as a set of identical traces of viewpoint characteristics (attributes) derived from various calculations of seismic traces [10], [11]. Pattern recognition methods are then applied to traces characterized by seismic attributes to obtain a better description of the reservoir.

The work presented in this study is part of a stratigraphic interpretation of seismic data. More specifically, we intend to test the methodology for automatic recognition of seismic facies in the time window of analysis based on statistical data analysis methods. The data preparation for this analysis was discussed, such as seismic sequence determination, pointing and interpretations of geological horizons. Based on a manual analysis of seismic facies and stating that their analysis was a fundamental multivariate approach [12]-[15], several seismic parameters (apparent frequencies and reflection energy) are taken into account simultaneously when determining homogeneous zones of seismic facies. In addition, the characteristics of seismic traces in the vicinity of wells with available geological information were used in order to find similar ones in terms of lithological and petrophysical characteristics.

1.1. Theoretical background

The statistical analysis of the seismic facies approach is based on numerical data coding, which is considered as the

Received: 31 January 2023. Accepted: 17 July 2023. Available online: 30 September 2023

Mining of Mineral Deposits. ISSN 2415-3443 (Online) | ISSN 2415-3435 (Print)

starting point for the whole multidimensional analysis, and the results obtained will be interpreted according to this coding. The flowchart considered in our methodology for automatic classification and seismic facies maps is illustrated in Figure 1. The seismic traces are considered as individuals and will be represented by points in multidimensional space generated by the seismic attributes [10]. The statistical methods used are to organize individuals into well-separated homogeneous groups by highlighting the indirect links between the seismic data and the geological structure that represents the seismic response [14]. Statistical analysis can be controlled by incorporating geological knowledge into the analysis, while unsupervised analysis uses only seismic information. Attribute methods will be applied at the preliminary stage of data preparation, i.e. Principal Component Analysis (PCA) and Discriminant Analysis, which are applied to filter and remove redundancies, as well as to provide new usable attributes instead of the original ones [6], [9], [15].

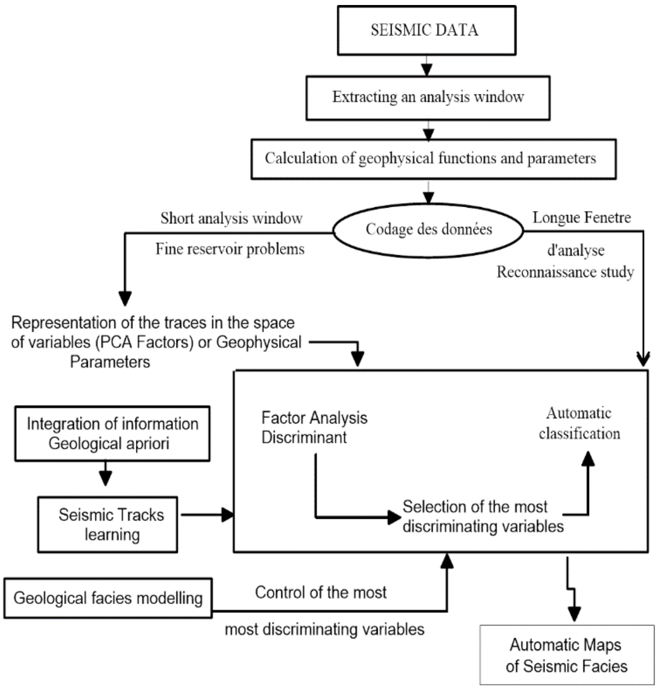

Figure 1. Methodology flowchart

The seismic traces can be analyzed in a time window at the reservoir (target) level, defined by the top and bottom peaks of the target interval. The calculation of the methodology parameters is to take into account all the information contained in the extracted part of the trace, and then to retain the most important elements of this information (Fig. 1). The following sections provide the detailed multidimensional theoretical analysis required for application in this study.

2.1. Seismic data coding

Let n be the number of traces located on the abscissas x_1, x_2, x_3, ... x_n on the data position plane. These traces constitute a 2D seismic section in the time window around the reservoir. Amplitudes corresponding to J time horizons t_1, t_2, t_3, t_j, which are denoted by the values $Z(x_i, t_j)$. For statistical purposes, the sample t_j will be considered as a variable, and $Z_{ij} = Z(x_i, t_j)$ will denote the measurement (seismic attributes) of this variable on individual i (seismic trace x_i). The Z array corresponding to this data has the formed n_J dimension (geological horizon) [16].

2.2. Seismic attributes of traces and time windows for analysis

After selecting a time window, seismic attributes are extracted from each trace, calculated from the temporal or spectral domain. All seismic survey's traces can be represented using their definition as points in the multivariate space created by these attributes (feature space). From the perspective of the considered seismic properties, adjacent traces in this space appear to be comparable [17]-[19].

2.2.1. Calculated geophysical functions and attributes

Taking as a basis the main families of variables characterizing the geological environment, an attempt can be made to characterize the collected seismic traces by a number of seismic attributes, the discriminating ability of which in relation to a priori geological information [20], [21]. The considered geophysical parameters and functions are quantification of trace morphology to measure their similarity (or dissimilarity).

For this purpose, seismic attributes must be calculated from the temporal and frequency representations of the traces. All seismic traces can be considered either in the time domain or in the frequency domain:

– in the time domain, one can consider the trace $y(t)$ and its autocorrelation:

$$E = \left[y(t) \cdot y(t+\tau) \right]; \tag{1}$$

– in the frequency domain, the phase and amplitude spectra are calculated from the FFT of the trace:

$$\left[y(t) = A(t) \sin \alpha (\omega t + \varphi) \right], \tag{2}$$

as well as the analytical signal:

$$S(t) = y(t) + iz(t). \tag{3}$$

Table 1 summarizes all geophysical parameters (statistical population variables) calculated on the seismic traces used for the statistical analysis (quantitative characterization and automatic analysis of seismic facies) [21]-[24].

Table 1. Summarized geophysical parameters

Family	Description	Symbol
Auto-correlation	Main rebounds of auto-correlation, ranked by decreasing amplitude	$A_{mi} \cdot i = 1, ..., n$
	Time corresponds to the main rebounds	$TAM_i \cdot i = 1, ..., n$
	Time of the first crossings to zero	$TPZ_i \cdot i = 1, ..., n + 1$
Spectrum	Frequency corresponding to the amplitude peak of the amplitude spectrum	FM
	Frequency corresponding to deciles of amplitude distribution	$Q_i \cdot i = 1, ..., m$
	Frequency corresponding to deciles of distribution of frequency-weighted amplitudes	$QW_i \cdot i = 1, ..., m$
Analytical signal module or real trace	Area under the module curve	$ETNT$
	Time corresponding to deciles of distribution of the standardized module amplitudes	$E_i \cdot i = 1, ..., m$
	Time corresponding to deciles of distribution of absolute values of trace amplitudes	$T_i \cdot i = 1, ..., m$

The autocorrelation of the trace is related to the cyclicity of sedimentation, the amplitude spectrum is related to the average thickness of the banks. The frequency spectrum is related to the distribution of sedimentation in a given interval. The third family of variables is related to the energy distribution of the trace, which can be quantified either directly on the trace or using an analytical signal module.

3. Statistical methods used and data coding

In this section, we drew inspiration from the basic source data of statistical methods, depending on their distance [2], [3], [7]. They organize points into an n-dimensional vector space where they define various trace classes or groups. By creating a new vector p-dimensional space with a lower dimension than the original n-dimensional space ($p < n$) by linearly combining the initial variables, factor analysis attempts to efficiently summarize the basic data. Then, the points are transferred from the original *n*-dimensional space (variables) to the new *p*-dimensional space (factors). The goal of Principle Component Analysis is to determine the number of *p* or orthogonal axes needed to project x_i points onto the new space in a manner comparable to their initial placement. When discriminant factor analysis is performed, it is necessary to arrange the points into classes to minimize the distortion inevitably created by the projection [25]. The feature used to choose new axes is that group projections should be as far apart as possible, and projected points within the same group should be as close to each other as possible. The property used to set the new axes is that projected points from the same group should be as close together as possible, and the group projections should be as far apart as possible. The fundamental distinction between the two procedures is that in discriminant factor analysis, the spatial distortion of the data can be enhanced to reveal a priori differences between groups.

3.1. Methodological steps

Discriminant factor analysis and clustering techniques are used to characterize and distinguish traces related to particular geological environments [2], [7].

The used methodology has two distinct stages, one training stage and then a prediction stage.

At the training stage, it is possible to determine the discrimination between traces and calibrate the studied seismic data with data from nearby wells. Due to the high seismic data heterogeneity, caused by geographic seismic data variability and processing, this step becomes necessary. When using data from nearby wells with available geological information, or, compared with stratigraphic survey, training or reference seismic traces are determined for each seismic facies representing a specific seismic facies.

The second step is to apply discriminant factor analysis to the training traces. In this study, the technique used is based on stepwise discriminant analysis by stepwise selection of variables useful for determining among a priori classes, assumed to be multivariate normal, with a common covariance matrix. Variables are chosen to enter or exit the model according to the F-test significance level from an analysis of covariance, where already chosen variables act as covariances and the variable considered is a dependent variable [26]. A modelling stage to check whether the chosen discrimination parameters are linked with the characteristic geological variations is included in the prediction stage [14]. At this stage, the classification of unknown seismic traces, where we calculate the traces whose facies we want to determine, the discrimination parameters previously chosen, and classify the traces with respect to the training traces.

4. Study area presentation

The study area, the Amguid-Messaoud mole, is located in the central part of the Algerian Sahara (Fig. 2) and is known for its oil producing wells, mainly in Cambrian reservoirs and Ordovician sandstone units (Hamra Quartzite) [27]-[31].

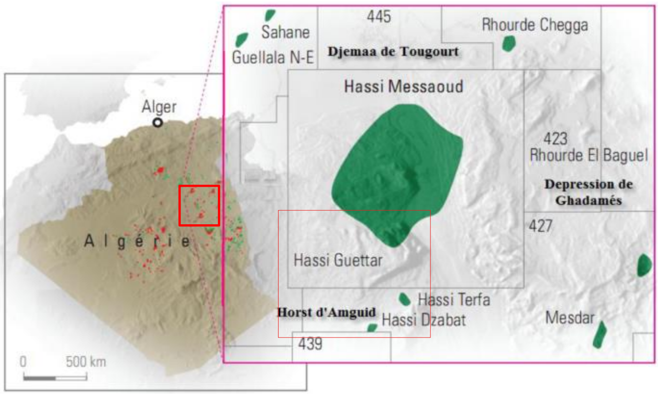

Figure 2. Location map of the study area, Amguid-Messaoud Field (Algeria) in right red rectangle

The reservoirs occur at an average depth of 3200-3400 m and are characterized by a very high variability in the physical petroleum properties. Its up-dip location in relation to the Hassi Messaoud Basin and the Silurian bedrock, as well as the diversity of Cambrian petroleum objects (R1 + R2) and Ordovician sandstone units (Hamra Quartzite) makes it a subject of great interest in Algiers hydrocarbon field [27]-[31]. Oil results recorded in wells of this region confirm not only the existence of an Ordovician wedge around the Hassi Messaoud [29], [31].

4.1. Structural aspect and stratigraphy

The sedimentary cover has a total thickness of about 4200 m and is represented by two transgressive and discordant sets, Meso-Cenozoic at the top and Paleozoic at the base, overlying the Precambrian basement. Under the clay-salt formations of the Tiras, the Paleozoic series (Ordovician-Cambrian) was folded during the Caledonian and Hercynian eras, transgressive and discordant on the Precambrian basement, which is represented by a thick series of detrital rocks [31], [32]. The Ordovician is marked by micro-conglomerate clays, Oued Saret sandstones, Azzel clays, Ouargla sandstones, El Hamra quartzites, El Atchan sandstones, and El Gassi clays, defined by an alternation zone between Cambrian Ri (isometric) and Cambrian Ra (anisometric) (Fig. 3).

The Silurian, the main potential source rock of the Triassic province, is totally absent in the wells of the study area, which is associated with Hercynian erosion, but it is present in the adjacent wells. In the Meso-Cenozoic series, the average thickness of the deposits is about 3500 m. In general, they are transgressive and discordant with the Paleozoic series, represented primarily by continental and lagoon deposits. They are composed of the Triassic sediment resting on the Hercynian unconformity, constituted in its basal part by clayey-sandstone deposits of continental fluvial origin and by volcanic flows. They are surmounted by a clayey-saliferous series of regional strike, constituting a good reservoir cover.

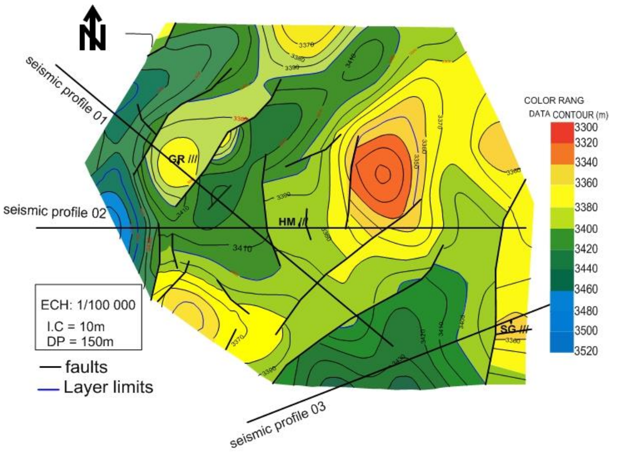

Figure 3. Isobath map of the Hercynian discordance

The detrital Triassic sedimentation is subdivided into three sandstone levels (SI, T1 and T2), which constitute the main petroleum object in the regions bordering the study area. Post-Triassic sedimentation (Lias L1 and L2) is characterized by a clay-evaporitic layer with an average thickness of 900 m [27]-[33]. From a structural point of view, the study area is considered as an anticline controlled by two faults extending North-East-South-West with the top located towards the South-West. The GR///-1 well to the north of HM//-1 is structurally 82 m lower in the Cambrian than the latter, while seismic interpretation predicted a structural gain of 61 m [29]-[33] in the Hercynian unconformity and 90 m in the Cambrian compared to the HM//1 well (Fig. 4).

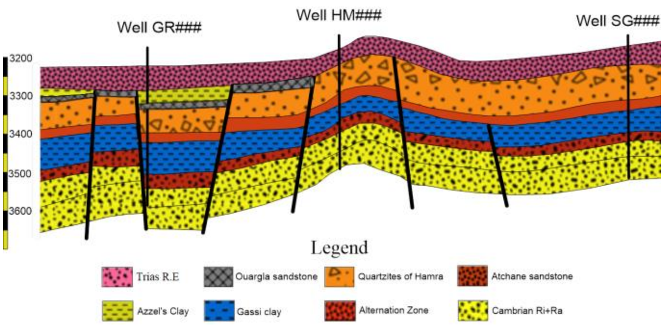

Figure 4. Geological section between the GR, HM, and SG

4.2. Principal oil reservoirs

4.2.1. Cambrian reservoirs

The Cambrian age reservoir is considered the main oil producing reservoir in the Hassi Messaoud field [33] and around is subdivided into two main reservoirs, Ri and Ra. Most of the Ra + Ri units are mainly composed of quartzite sandstone with upward bioturbation. This unit is considered to be transitional facies between continental and shallow marine environments, which has a poorly known and heterogeneous variation of facies compared to other reservoirs. Poor petrophysical characteristics are related to the reservoir facies itself and its very low structural position near the water body. The Hercynian tectonics affects this area, but it has not reached the Ra reservoir [6].

4.2.2. Ordovician reservoirs

From a lithological point of view, the Ordovician formation is considered to be a compact massive, made up of white to grey-white, fine to medium, locally coarse, silico-quartzite to quartzite and dense, hard sandstone with black, silty, and flaky clayey passages. The Hamra Quartzite formation is considered the most important Ordovician formation (Fig. 4). Several wells drilled in the vicinity of the Hassi Messaoud field are producing oil with average petrophysical parameters (porosity ranging from 2 to 10% and permeability ranging from 0.1 to 100 mD), which are controlled by diagenetic effects [27]-[33].

5. Analysis and computation

We have adopted a methodology using both clustering techniques and factor analysis (discriminant factor analysis). We carried out a modelling stage to check whether the selected discrimination parameters are related to the geological variations in order to characterize the predictive stage [8], [13], [34], which provides classification of the unknown seismic traces.

At this stage, we calculated for unknown seismic traces, i.e. traces whose facies we want to determine, the previously selected discrimination parameters. The traces are classified with respect to the training traces. Then, we developed our methodology.

5.1. Statistical characterization of real seismic traces

The statistical method is to analyze small seismic windows within the reservoir [2], [10], [11], [14], [34], [35]. The studied seismic sections (Fig. 5) intersected the paleoenvironment mentioned above and were calibrated and interpreted in terms of the geological formation with data from adjacent wells. The intervals taken from the sections correspond to three distinctly different reservoir facies with the following dual time windows.

The analysis windows of the test samples correspond to the Lias S1-S2 (group 1 G1), Ordovician (group 2 G2), and Cambrian Ri + Ra (group 3 G3). The analysis windows of the reconnaissance samples correspond to the Ordovician and Cambrian Ri + Ra roofs. The main objective is to derive a geological model to determine the special distribution of the target facies (Ordovician: Hamra Quartzite), in the study area and to create a reservoir facies map covering the entire region.

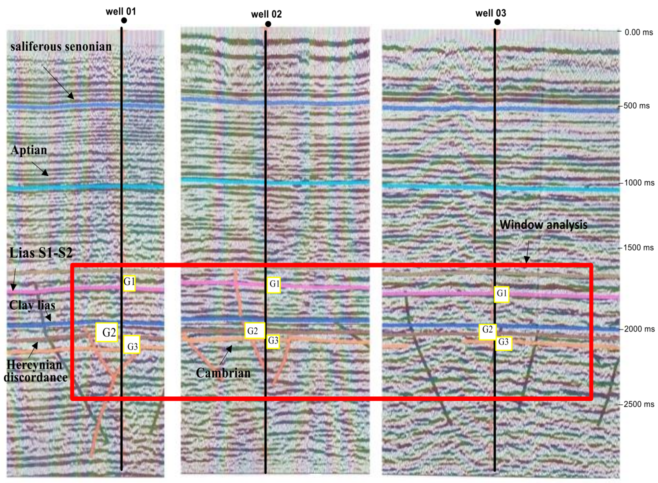

Figure 5. 2D section corresponds to a seismic profile calibrated and stratigraphically interpreted with data from neighboring wells

5.2. Tests for the separating power of variables

The separating power of variables was tested mainly by performing discriminant factor analysis between groups of traces of various geological environments (analysis windows). It was found very quickly that the variables calculated on the "rectified" trace (T_i parameter, in Table 1, quantifying the same information) gave the same result as the variables of the analytical signal module (E_i parameter in Table 1). Taking absolute trace values is also a way of estimating the "trace envelope", but the envelope given by the analytical signal is less sensitive to noise. For this raison, we retained the E_i parameter for quantifying the trace energy and its distribution due to the T_i variables (Table 1).

5.2.1. Discriminant analysis of seismic traces of different seismic groups

First, we tested the discriminatory power of the variables by using only one family at a time [7], [8], [34], [35]. The 19 variables calculated from the autocorrelation amplitude spectrum allow some grouping of individuals according to their facies, but the barycenter of the classes is less close. Therefore, the projected cloud is very compact within the same group. The 10 variables calculated from trace autocorrelation allow for only opposition due to axis 1, whose discriminatory power is very strong between individuals of group 1 facies. Other groups (G2, G3) are also well separated, while axis 2 also provides good discrimination. The 10 variables quantifying energy, total module emergence and deciles of the distribution of module amplitudes, allow practically a weak separation between G2 and G3, but the G1 group is isolated. Classical discriminant factor analysis with variables of three families allows an excellent separation between the three groups of traces G1, G2 and G3.

5.2.2. Search for the most discriminant variables

The reliability of discrimination will be better if we consider a small number of variables compared to the number of individuals. For example, in the case of two groups of individuals, it is easier to identify a separating hyperplane in low-dimensional space. However, for a given number of variables and a given number of groups, there are few studies that define the number of individuals from which the discrimination will be significant (for a given number of variables, the higher the number of groups, the more individuals will be needed to obtain a statistically meaningful discrimination).

5.2.3. Discriminant factor analysis by principal component analysis factors

The population of traces was studied and 39 variables belonging to various families were included. We performed a Varimax Principal Component Analysis and retain the 09 components that account for about 97% of the cloud's total inertia [7], [8]. Discriminant factor analysis, carried out without reduction of new variables with these 09 principal components, gave a fairly satisfactory distribution of individuals on the factorial plane. Axis 1 has a greater discriminatory power (55.42%) than axis 2 (19.86%) and allows for the opposition of all the studied types of facies. Classical principal component analysis with 39 variables allowed the extraction of 10 principal components that account for 98% of the cloud's total inertia. Discriminant factor analysis was then performed on 10 components, with the population divided into three groups. The results obtained are not very satisfactory, because only axis 1 has a significant discriminatory power and allows the separation between the groups of individuals from three groups. We continued these tests on a population of 93 traces, conducting family-by-family principal component analysis of the variables. We have retained 02 components to summarize all the variables calculated on the amplitude spectrum, 04 principal components to summarize that of the autocorrelation, and 02 components to summarize the parameters calculated for the analytical signal. Discriminant factor analysis performed with these 08 principal components allowed for a good separation along two axes.

5.2.4. Step by step discriminant factor analysis

From the population of 93 real traces, a base sample of 63 individuals and a test sample of 30 individuals were formed. Individuals were divided into three groups and 39 variables representing three families of parameters were used. We obtained 98.60% of wells classified according to the base sample and 62.4% of wells classified according to the test sample. The introduced variables are arranged in order of their discriminatory power in step # 6. The percentage of well-ranked individuals in the test sample may seem low. However, random distribution of individuals into three groups should give only 50.5% of well-ranked individuals. This is quite satisfactory and we believe they are reliable.

6. Results and discussion

Discriminant factor analysis performed using only variables belonging to the same family show that discrimination between groups is possible. Using a set of variables, we obtained a regionalization of the factorial plans into three zones corresponding to the three studied facies groups. This was done with a number of variables less than 10. These tests made it possible not only to confirm that the facies groups are individualized by the parameters calculated from the traces, but also that the partitioning carried out during the analysis had a satisfactory predictive power. Thus, it is possible to predict with good chances of success the facies to which an anonymous individual belongs. The most discriminating variables with respect to the three groups were found to be (E_9, QW_5, QW_8, and E_7) and these variables were introduced first in the various analyses. However, among the variables we always find one or more that describe a trace ($ETNT$ or E_i), sometimes (TPZ_i, TAM, AM_i) or a spectrum (Q_i, QW_i, FM) (Table 1). The fact that no general rule emerges from this study could be a limitation to the implementation of this facies characterization method.

After determining the most discriminating parameters, we calculated for unknown seismic traces and collected seismic profiles passing through the study area, i.e. the traces whose facies we want to determine and classify in relation to already studied traces. At this stage, we decided on the assignment of each section portion and classified these traces in relation to the reference traces studied using AFD and automatic classification.

The assignment analysis results are plotted on isopach map showing the thickness variations of the Hamra quartzite facies reservoirs (Fig. 6). A geometric synthesis can be given to the evolution of reservoir thicknesses (Cambrian Ri + Ra), where Hercynian movements play a major role in structuring the different Saharan platform basins and in the distribution of reservoir rocks, namely the Hassi Messaoud mole.

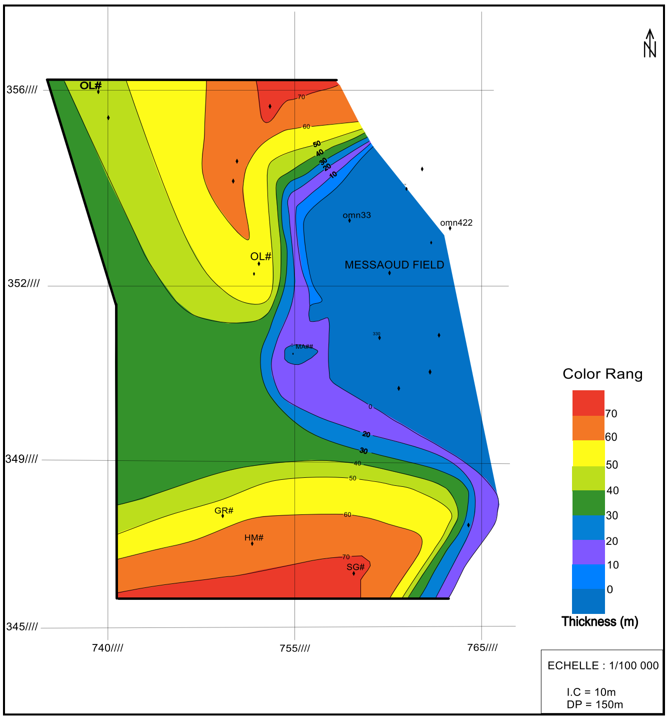

Figure 6. Isopach map from Hamra Quartzite

Analysis of isopach maps below the Hercynian unconformity shows a clear variation in the thickness of the Ordovician reservoirs (Hamra Quartzite). A variation in thickness can be seen between 30 and 70 m, with a distribution of thicknesses from lower in the northern part (10 m) and gradually increasing towards the southern part, reaching about 70 m. This can be explained by the influence of Hercynian erosion. While for the Ra + Ri reservoir, the thickness variation varies from 8 to 30 m, forming a tabular structure that results in a homogeneous reservoir. The most important part of the thicknesses is in the center and in the extreme N-W of the reservoir. The best thickness in this part reaches 13-17 m, while the extreme north and south-eastern part has the smallest thickness of 10 m.

7. Conclusions

The methodology we followed is based on a step for calculating seismic parameters for seismic traces in the vicinity of wells interpreted in terms of seismic facies, followed by a multidimensional analysis step and a step of automatic recognition of seismic facies by assignment. The obtained facies map shows a special distribution of the target facies (Ordovician Hamra Quartzite), and the link between the characterized seismic facies and the geological facies has been established with great success.

The results already found are encouraging, as they confirm in the real case the possibility of discrimination between seismic facies by studying the geophysical characteristics of a portion of a seismic trace crossing a given geological environment. This study led us to the calculation of seismic parameters from temporal and frequency representations of the traces. These variables not only characterize the morphology of the analyzed traces but also allow the discrimination between groups of traces representing various paleo-environments.

Acknowledgements

We would like to express our gratitude to Sonatrach Company for providing the seismic profiles and wells used in this study. I would like to thank Mining of Mineral Deposits for giving me the opportunity to publish this paper.

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Автоматичне визначення характеристик та кількісний аналіз сейсмофацій у природно-тріщинуватому пласті: практичне дослідження родовища Амгуід-Мессауд, Алжир

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Мета. Визначення характеристик та кількісний аналіз сейсмофацій у природно тріщинуватому пласті з урахуванням впливу пористості та проникності для оптимізації використання запасів вуглеводнів.

Методика. Дослідження зосереджено на кількісному аналізі сейсмічних трас з метою стратегії автоматичного розпізнавання сейсмофацій. Досліджуваний район, басейн Амгуід-Мессауд, утворений серією горстів і грабенів, обмежених субмеридіональними Північно-Східним і Південно-Західним розломами, а також перпендикулярними Північно-Західним і Південно-Східним розломами без відслонень тріщинуватості, які мають великий вплив на тріщинуватість пласта. Ряд методів статистичного аналізу даних, таких як аналіз головних компонентів, аналіз дискримінантних факторів і автоматична класифікація, були випробувані на реальних даних геофізичної сейсмічної інтерпретації даних, зокрема стратиграфічної інтерпретації.

Результати. Отримано карту фацій, що показує особливий розподіл цільової фації (ордовикський кварцит Хамра); зв'язок між охарактеризованою сейсмічної фацією та геологічною фацією був встановлений з великим успіхом. Розраховано сейсмічні параметри за часовими та частотними представленнями трас, що характеризують не лише морфологію аналізованих слідів, але також дозволяють розрізняти групи слідів, що представляють різні палеосередовища. Отримані результати свідчать про найкраще використання даних, які, однак, мають інший характер, що призводить до достовірної інтерпретації геологічного середовища.

Наукова новизна. Розроблено нову методологію для побудови моделі пласта та прогнозування геологічних властивостей пласта вздовж родовища.

Практична значимість. Отримані результати чітко демонструють найкраще використання даних, які, однак, мають інший характер, що призводить до надійної інтерпретації геологічного середовища. Ці методи виявилися дуже корисними для побудови моделі пласта та прогнозування його геологічних властивостей вздовж родовища.

Ключові слова: *метод аналізу статистичних даних, модель пласта, сейсмофації, геофізична інтерпретація, стратиграфічна інтерпретація*