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Gas Chimney Delineation and Prospect Identification from Seismic Data Using Artificial Neural Networks in an Area of North Sea, Netherlands

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Abstract

The study intends to boost the definition of the target volume in the F3 block, southern North Sea, Netherlands by applying artificial neural networks (ANNs), multi-attribute seismic analysis, and the geological framework from the Paleo-Cambrian to the Cenozoic periods, by identifying pertinent horizons for HC deposits. To gain a greater understanding of subsurface geology, seismic parameters comprising signal breadth, amplitude, and spectral attributes are calculated. Here, we used artificial neural networks (ANNs) to model gas chimneys, creating a 'chimney cube.' Quantitative evaluation of seismic data was done using RMS amplitude and similarity measures. Techniques like spectral decomposition and RGB blending modes were introduced. After examination, it is recommended to drill three vertical wells. Besides, the application of seismic attributes and ANNs in mapping gas chimneys, in addition to the contribution made in the understanding of identification of the hydrocarbon prospects in complex geological domains, forms the major novelty of this research. However, the results enrich the understanding of gas chimney structures and provide useful approaches for subsequent hydrocarbon exploration in similar geological conditions.

Keywords: *Gas chimney; Artificial neural networks; Interpretation; Seismic attributes; Well placement.*

1. Introduction

1.1. Gas chimney

Seismic data show gas chimneys as distinctive vertical features with fragile discontinuous reflectors that affect the recorded data [1]. Seismic interpretation methods including velocity modeling and multi-component seismic analysis allow experts to detect these structures [2]. The discovery of gas chimneys supports drilling safety and petroleum system knowledge but produces disturbances that hide seismic reflections [3]. RMS along with variance are among the traditional seismic attributes used for detection yet identification of gas chimneys versus other geologic features remains elusive [4]. Artificial Neural Networks receive research attention for their ability to improve detection accuracy and minimize drilling risks [5]. The identification process for gas prospects requires studying geological information while performing seismic survey examinations to develop exploration areas through seismic attribute analysis [6]. Multiple scientific methods combine to assess both reservoir hydrocarbon quality and quantity during evaluations [7]. Drilling confirms resource viability. New technology such as machine learning enhances detection systems and promotes cross-discipline teamwork which results in deeper subsurface evaluation [8].

1.2. Geology

Seismic data show gas chimneys as distinctive vertical features with fragile discontinuous reflectors that affect the recorded data [9]. Seismic interpretation methods including velocity modeling and multi-component seismic analysis allow experts to detect these structures [10]. The discovery of gas chimneys supports drilling safety and petroleum system knowledge but produces disturbances that hide seismic reflections [11]. RMS along with variance are among the traditional seismic attributes used for detection yet identification of gas chimneys versus other geologic features remains elusive [12]. Artificial Neural Networks receive research attention for their ability to improve detection accuracy and minimize drilling risks [13]. The identification process for gas prospects requires studying geological information while performing seismic survey examinations to develop exploration areas through seismic attribute analysis. Multiple scientific methods combine to assess both reservoir hydrocarbon quality and quantity during evaluations [14]. Drilling confirms resource viability. New technology such as machine learning enhances detection systems and promotes cross-discipline teamwork which results in deeper subsurface evaluation [15].

1.3. Data

One important geological dataset obtained in 1987 is the seismic data of the F3 block in the North Sea, which is located offshore of the Netherlands. It is situated at N 54°52'0.86" / E 4°48'47.07". Nederlandse Aardolie Maatschappij (NAM) was the first to obtain this information. The data was originally taken and then processed in the same year. In 2023, the seismic dataset was upgraded with the help of advanced data processing techniques. The side view and top view of the F3 block are viewed in Figure 1 and 2 respectively.

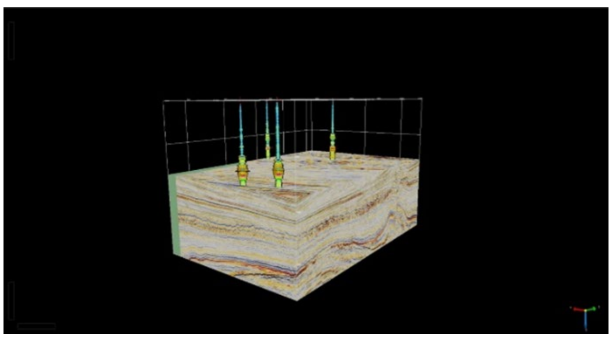

Figure 1. Side view of F3 Block with vertical wells.

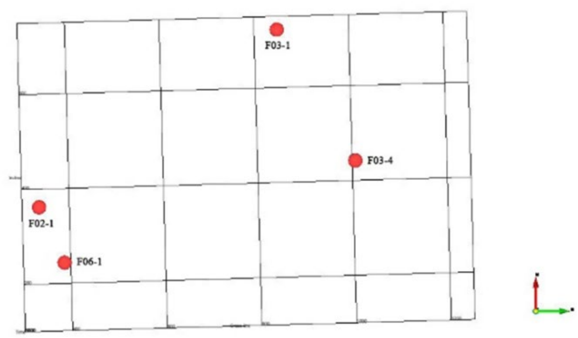

Figure 2. Top view of F3 Block with vertical wells.

The F3 survey is the perfect example of a detailed geophysical survey done with both the 2D and 3D survey techniques. It is spread over an area of 386.93 square kilometres. In-line is located in the direction of the main survey, and the range can reach 750 from 100 with a step of 1. The span range is from 300 to 1,250, in steps of 1, vertically portraying the same distance as the in-lines. The Z range covers a range of 0 up to 1848 ms with a sampling rate of 4. The well logs of F02-1, F03-2, F03-4, and F06-1 contain the most comprehensive set of geophysical data that ultimately feed into the evaluation of formations below the surface. These logs collect different parameters including density, sonic, gamma ray, porosity, and lithology that are crucial for rock type identification, determining in-situ conditions such as the overburden pressure, and learning the properties of the rock formation.

2. Methodology

The research identifies prospect locations through seismic data collected from three wells situated in the F3 block of the North Sea. 3D models emerge from processing data acquired from TerraNubis.com which allows observation of subsurface structures. Geological formations at different depths can be defined through aerial visualization by drawing contours onto the images. Artificial Neural Networks detect gas chimneys in the dataset which results in "chimney cube" outputs for assessments. The assessment of hydrocarbons depends on RMS amplitude analysis as well as similarity evaluation and spectral decomposition techniques which include RGB Alpha blending. The particular analysis techniques make it possible to identify unique frequencies for separate horizons which optimizes hydrocarbon detection outcomes.

During the evaluation process, researchers determined three areas with hydrocarbon presence while determining correct drilling depths. ANI organizations proved superior to established seismic interpretation procedures when examining hydrocarbon reservoirs providing better precision along with efficiency. Figure 3 indicates the overall interpretation.

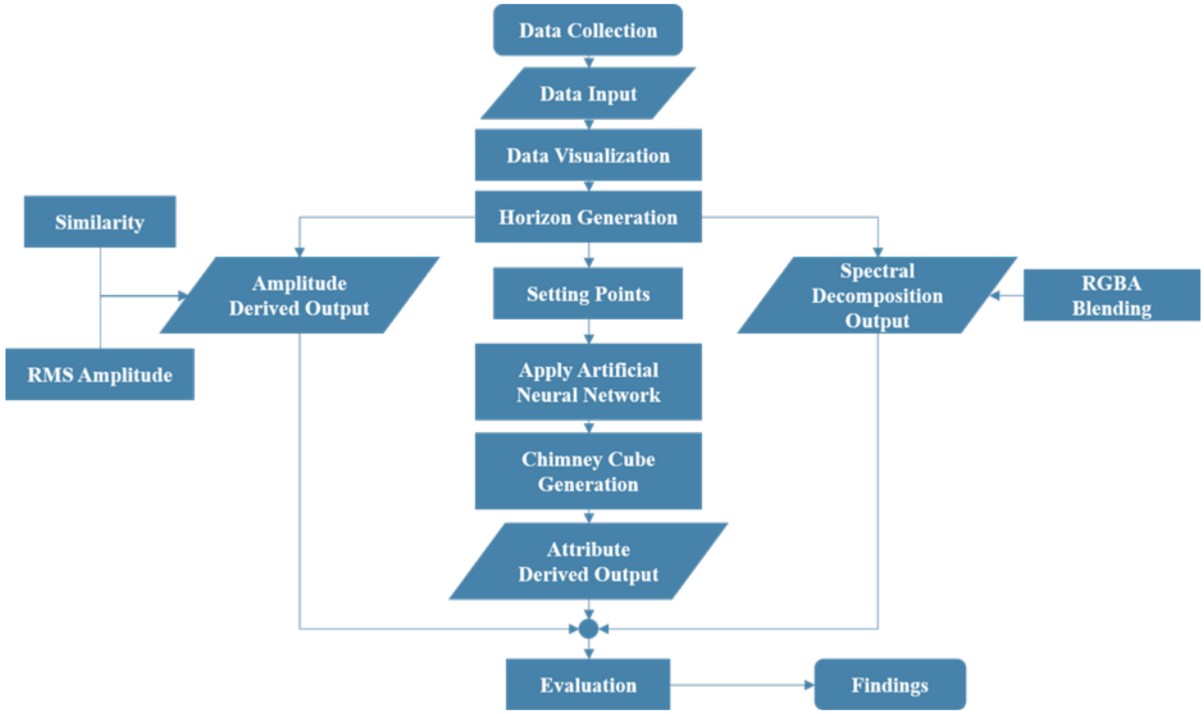

Figure 3. Flow chart of overall interpretation.

3. Results and discussions

3.1. Artificial neural networks

ANNs based on McCulloch and Pitts (1943) operate through weighted inputs that pass through a non-linear activation function to generate a definitive output [16]. By adjusting weight values predictions become more accurate thus making ANNs valuable for seismic processing operations when detecting gas chimneys. The supervised classification training of ANNs allows them to enhance contrast between discontinuities and low-amplitude regions which leads to gas chimney probability cube creation [17]. The workflow begins by preparing data and then calculates attributes and applies ANN analysis to seismic volumes which leads to gas chimney detection and characterization. ANNs succeed in gas chimney interpretation because they identify particular seismic indicators which help overcome the interpretive difficulties of complex structures and noise [18]. Modern techniques have enabled automatic precise identification of gas chimneys which enhances the opportunity to detect hydrocarbons and research complex geological structures.

3.2. Seismic attributes

Seismic attributes serve as vital tools during seismic data analysis since they supply an advanced understanding of underground geological features that regular methods usually miss [19]. The depiction of geological formations along with stratigraphy and geomorphology becomes clearer through seismic attributes as opposed to traditional methods using seismic amplitudes and 3D seismic techniques [20]. In Sheriff classification, these subsurface properties fall under the Sheriff approach with members envelope, amplitude, phase, polarization, dip and phase azimuth [21]. These attributes give both qualitative and quantitative information which enhances subsurface imaging capabilities while allowing the identification of lithology and fluid content assessment needed for reservoir characterization [22]. 3D seismic data improvements have made seismic geomorphology an essential technology for geological mapping when well control is scarce [23].

3.3. Spectral decomposition

The analysis method known as spectral decomposition transforms waveforms to show basic frequency elements which reveal underlying geologic subsurface features. The interpretation method aids analysts in examining frequency shifts while measuring sedimentary rock layer thicknesses and spotting horizontal breaks which aid raw material discovery. The method proves useful whenever normal seismic approaches fall short of solving the interpretation problems below the resolution level and estimating sand thickness. The procedure relies on two essential computing methods consisting of Fast Fourier Transform (FFT) together with Continuous Wavelet Transform (CWT). The speed accuracy combination of FFT exists alongside CWT's wavelet-based analysis flexibility which improves through various wavelet selection options including Morlet Mexican Hat and Gaussian functions.

3.4. Similarity

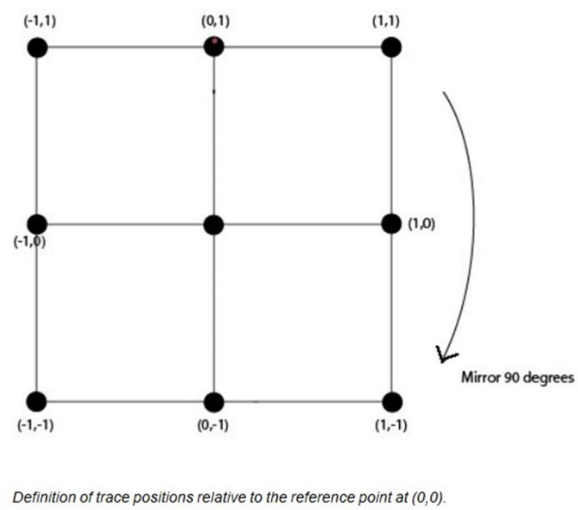

Figure 4. Similarity.

Similarity is a metric that is used to calculate the degree of resemblance between various parts of a feature. This algorithm finds the level of "correlation" between two or more traces by identifying their waveforms and the level of their amplitude. A full match is represented by several 1s, whilst no similarity at all is indicated by a value of 0. We start by defining trace segments using relative coordinates to ascertain their positions and a time-gate in milliseconds. In the case of 2D data inputs, the trace positions are determined solely by a trace step-out, without considering inline and crossline. The extension parameter is a crucial factor that determines the number of trace pairs included in the computation. Figure 4 shows an example of similarity.

The similarity function is a vector product of two N-dimensional vectors in which N represents the length of the vertical running window for the similarity attribute which is in samples. The length of the vertical running window equation is:

$$\mathrm{N} = \frac{\text{timegate\_max} - \text{timegate\_min}}{\text{sample interval}} + 1 \qquad (1)$$

The similarity is calculated by dividing the Euclidean distance between the vectors by the sum of the length of both vectors, which is then subtracted from 1. The similarity equation is:

$$\mathrm{sim} = 1 - \frac{\sqrt{\sum_{i=1}^{N}(X_i - Y_i)^2}}{\sqrt{\sum_{i=1}^{N} X_i^{\,2}} + \sqrt{\sum_{i=1}^{N} Y_i^{\,2}}} \qquad (2)$$

3.5. Energy

Energy in seismic data analysis refers to the reflectivity strength of a particular data section. The calculation of this measure involves squaring the sum of sample values within the time window followed by normalization with sample count. The calculation method yields trustworthy data about reflected energy strength across the analyzed time interval. The strength of seismic reflections along with their amplitudes increase when energy values rise thus making energy a fundamental attribute for identifying gas chimneys and detecting lateral variations and characterizing rock properties and bed thicknesses. The method improves interpretation of geological subsurface structures because it helps analyze their petroleum exploration potential.

3.6. Horizon generation

Through its horizon generation process, OpendTect generates detailed subsurface models from seismic data which helps find hydrocarbons while spotting geological anomalies. The goal is achieved by evaluating RMS Amplitude through multiple horizons with spectral decomposition methods that combine RGB Alpha blending between different frequencies per horizon for hydrocarbon verification. PLQ Glomar Exxonmoor Exploration Limited confirmed three distinct zones with hydrocarbon presence during their evaluation stage which resulted in locating proper drilling depths for three different wells. Systematic exploration procedures provide accurate hydrocarbon assessment which enables better profitability in exploration activities. In the horizon generation process in OpendTect, the data collected from seismic surveys are interpreted to develop a model of the subsurface [24]. It assists in defining different geological formations and their contacts and therefore offers a realistic perspective of the sub-surface environment that can be used for actual geology and geo-physics assessment. The structural map of all three horizons with the contour is shown in Figure 5-7. The RMS amplitude of channels 1 and 2 are shown in Figure 8 and 9 respectively.

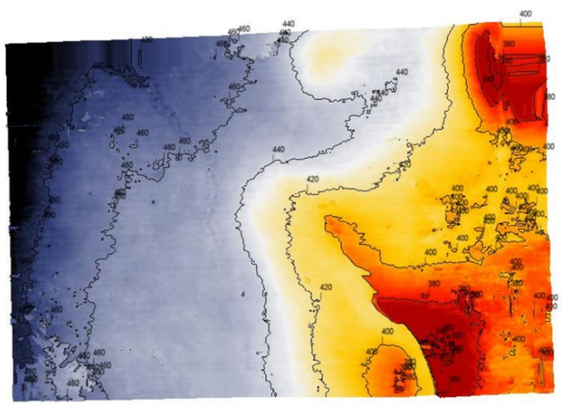

Figure 5. Structural map of horizon 1 with contour.

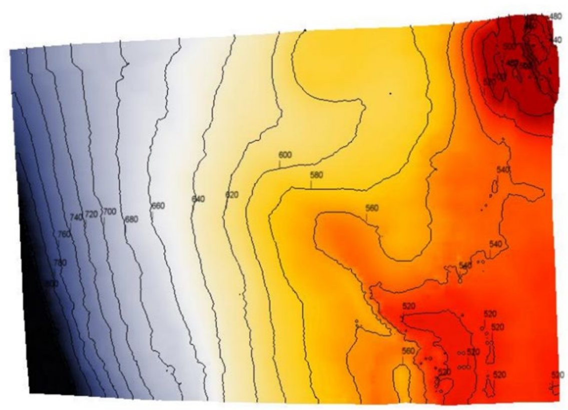

Figure 6. Structural map of horizon 2 with contour.

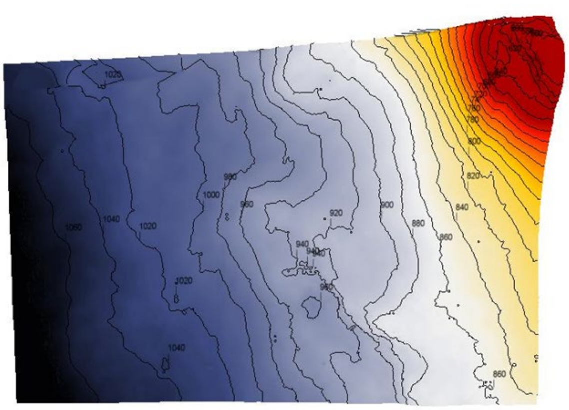

Figure 7. Structural map of horizon 3 with contour.

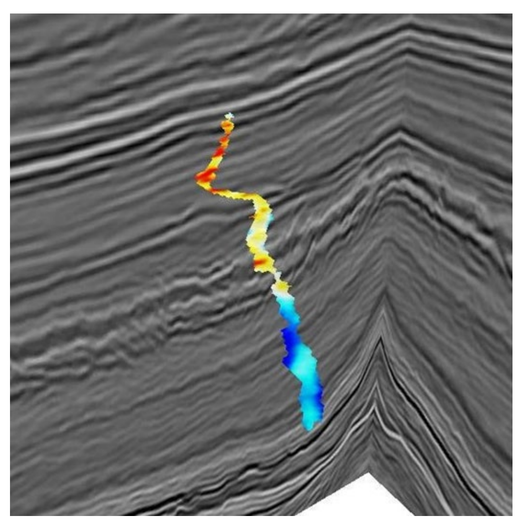

Figure 8. RMS amplitude of channel 1.

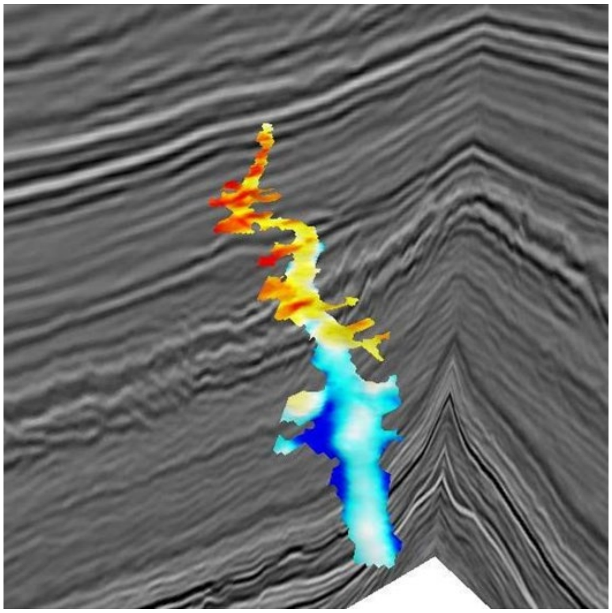

Figure 9. RMS amplitude of channel 2.

3.7. Attribute derived output

Vertical seismic anomalies known as gas chimneys reveal how gas moves while forming in the subsurface [25]. The strategic identification of chimney features relies on the seismic cube which serves the ANN system as training data to enhance accuracy [26]. The seismic study achieves thorough analysis through ANN software utilizing inline and cross-line evaluation to generate the Chimney Cube command [27]. The software produces a 3D model known as a chimney cube that provides visualization of gas storage regions alongside separate subsurface areas. Further exploration attempts benefit from the chimney cube system which helps discover potential energy resources. Points set for presence, absence and both chimneys are shown in Figure 10-12. And chimney cube is viewed in Figure 13. Here is the chimney cube for the three-horizon output is depicted in the following Figure 14-16.

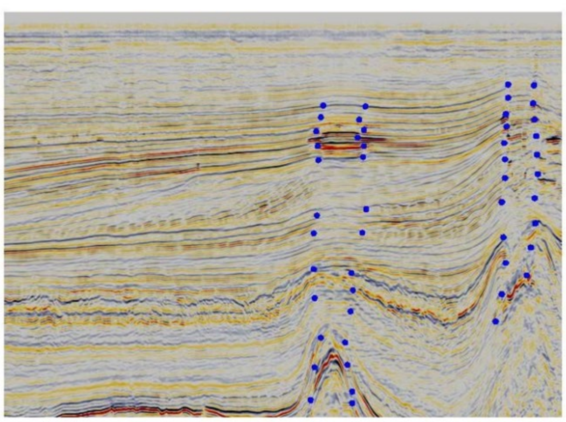

Figure 10. Point set for presence of chimney.

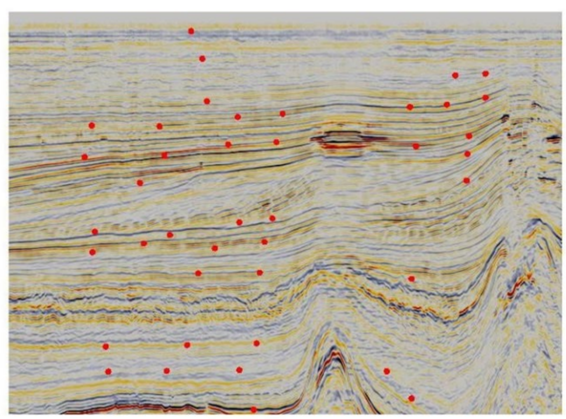

Figure 11. Point set for absence of chimney.

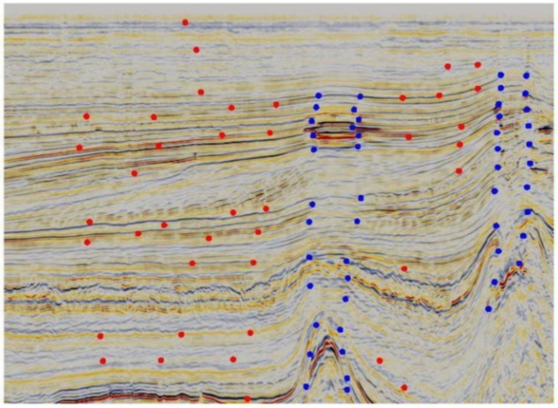

Figure 12 Point set for both presence and absence of chimney.

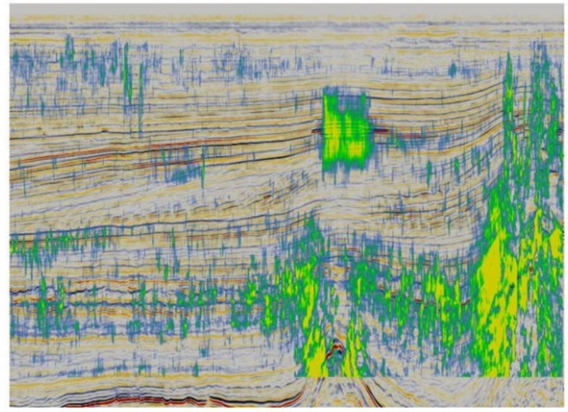

Figure 13. Chimney cube.

Figure 14. Chimney cube of horizon 1.

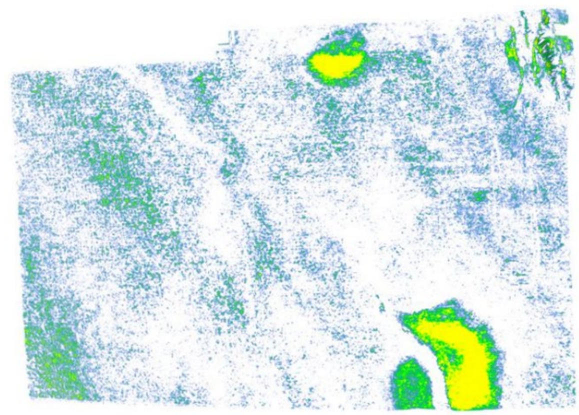

Figure 15. Chimney cube of horizon 2.

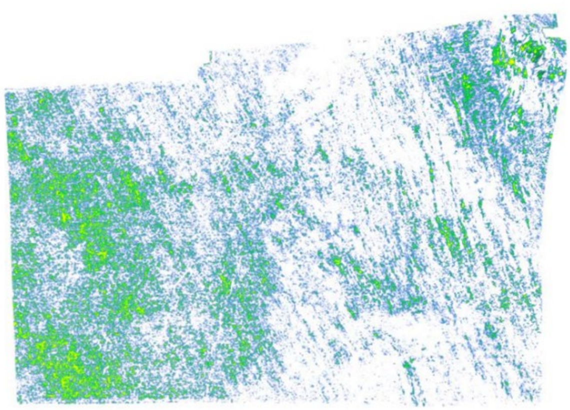

Figure 16. Chimney cube of horizon 3.

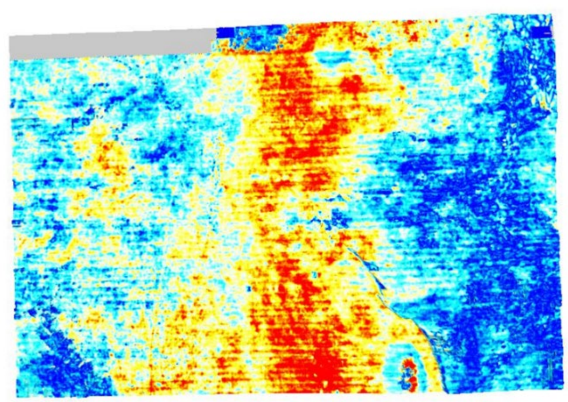

Figure 17. RMS amplitude of horizon 1.

3.8. Amplitude derived output

Finding possible hydrocarbon sources requires interpreting geological data, and attribute-derived interpretation is a critical stage in this process. The presence of hydrocarbons was evaluated in this investigation by processing the Root Mean Square (RMS) amplitude across each horizon [28]. To obtain a better visual representation of measured amplitudes, a Z offset value of 10 was fixed to determine the range of the shaded area. This parameter defines how far from the horizon up it goes and down and what the final output looks like. The shaded areas defined in red colour on RMS amplitude figures (refer to Figure 17, 19, and 21), reveal the possible reservoir area because of its high amplitudes. Their corresponding similarity of horizons is referred to Figure 18, 20, and 22.

Figure 18. Similarity of horizon 1,

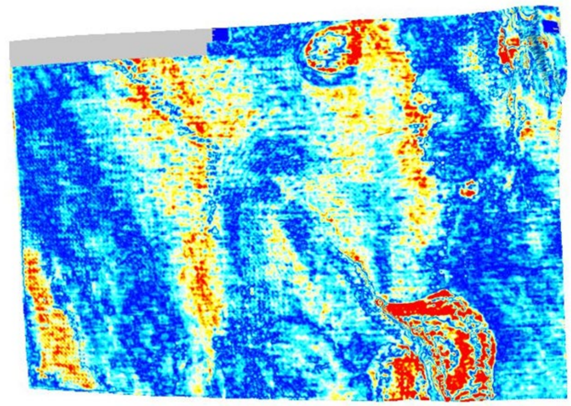

Figure 19. RMS amplitude of horizon 2.

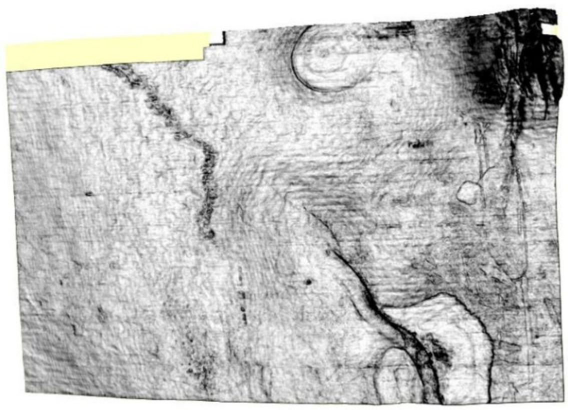

Figure 20. Similarity of horizon 2.

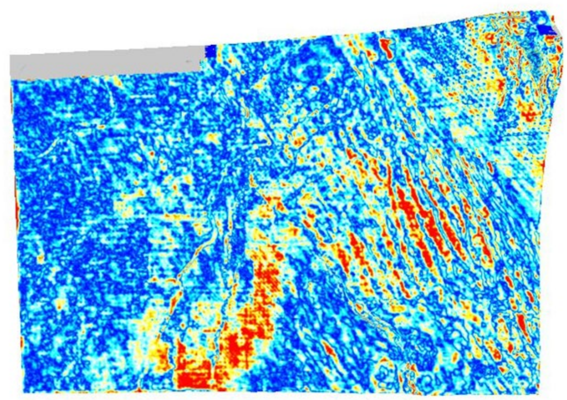

Figure 21. RMS amplitude of horizon 3.

Each horizon obtained its similarity attribute calculation through a -28ms to 28ms time window measurement which detected seismic discontinuities including faults and fractures. Fault zones play an important role in drilling operations through their ability to cause borehole fluid loss and act as migration channels which create prospective oil-bearing rock layers [29]. RMS amplitude analysis together with similarity attribute evaluations on Horizon 2 revealed high amplitudes which indicated possible hydrocarbons. The spatial variations observed in the similarity attribute through its "eye-shaped" behaviour indicate potential reservoir zones which would warrant future exploration activities [30]. Paleontological assessments of Horizon 3 failed to detect hydrocarbons thus making it unsuitable for hydrocarbon production and storage [31]. These discovery results alongside additional geological and geophysical information allow organizations to build clear subsurface pictures which leads to more effective exploration guidance and reduced uncertainties for better decision-making [32].

3.9. Spectral decomposition output

Spectral decomposition operates as the central geophysical method which partitions seismic data signals into frequency domain bands so scientists can examine individual spectral ranges [33]. Geologists use red, green and blue frequencies to evaluate each horizon subsurface layer. The dominant red frequency shows the most important characteristics of the geological stratum [34]. The Alpha attribute allows analysts to determine similarities throughout the horizon to locate both smooth and uneven features. Similarity values rising indicates uniformity in geological formations which proves crucial for oil and gas exploration purposes. The RGB Alpha blending method adds frequency information overlay which shows coherent areas to help detect potential drilling targets. The advanced analysis system enables drilling decisions by helping personnel identify prospects most likely to contain hydrocarbons [35]. The RGB Alpha blending of horizons 1, 2 and 3 are presented in Figure 23, 24 and 25 respectively.

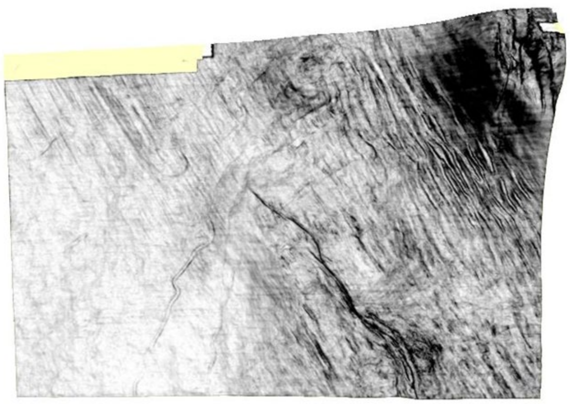

Figure 22. Similarity of horizon 3.

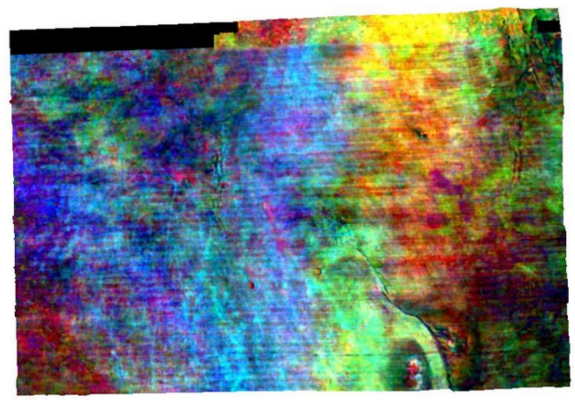

Figure 23. RGB Alpha blending of horizon 1.

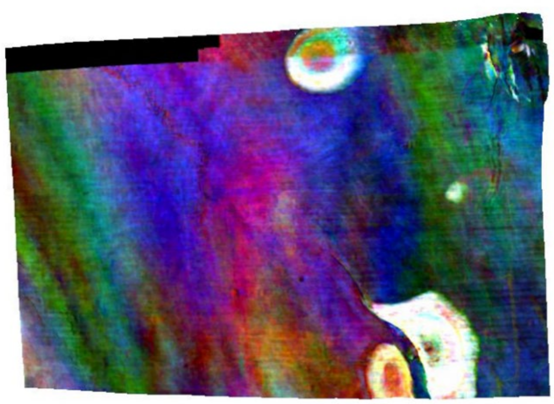

Figure 24. RGB Alpha blending of horizon 2.

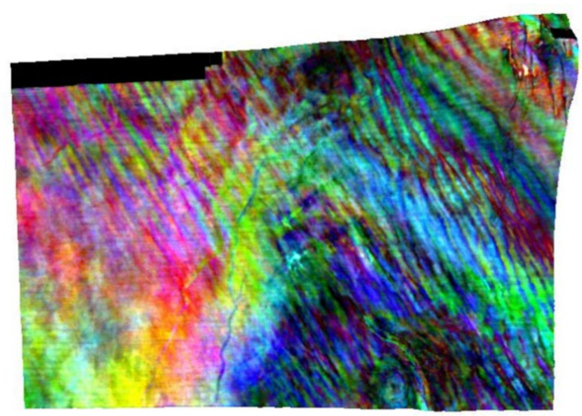

Figure 25. RGB Alpha blending of horizon 3.

3.10. Analysis and interpretation

Having examined three horizons in detail, it is now possible to speak more specifically about the character of the promising zone: three zones were chosen as the most prospective for containing hydrocarbon resources. There are names of three zones namely Prospect X, and Y and these are considered to have exploitable resources. These are the areas that have been assessed and recognizing that drilling in such zones would be the best way to harness the resources as lain the best practices. Subsequent drilling activities will concentrate on these prime areas with a view that they can aid in the efficient search for hydrocarbon deposits [36]. The prospect zone is shown in Figure 26.

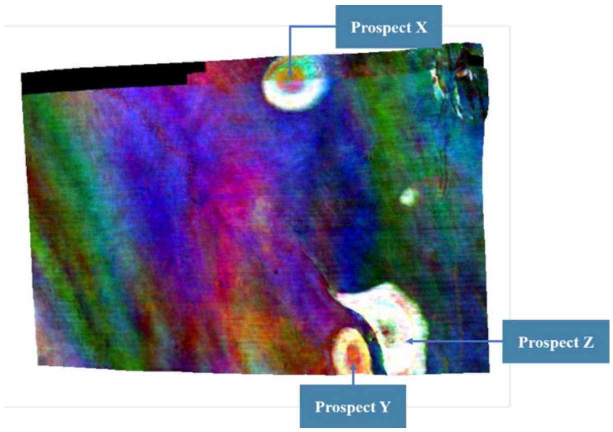

Figure 26. Prospect zone.

Based on the identified areas of prospective zones, we identified that certain coordinates in the prospective zones create the best conditions for the drilling process. Therefore, we are going to find that the wells will be able to gain access the hydrocarbon-rich area of 8.1km2, 3.58 km2 and 12km2 respectively. Our accurate identification of the well locations demonstrates the areas' potential for efficient extraction of hydrocarbons, which offers a promising high return for each point of interest [37]. Table 1 shows the interpreted horizons of hydrocarbon identification.

In Table 2 we can see the used seismic attributes. Lastly, information on proposed well locations is prescribed in Table 3.

Table 1. Interpreted horizons for hydrocarbon identification.

Horizon	Description
X	Top Zechstein
Y	Base Upper North Sea
Z	Intermediate Horizon

Table 2. Seismic attributes used.

Attribute Type	Description
Attribute-derived output	Various seismic attributes derived from the data
Amplitude-derived output	RMS amplitude and similarity measures
Spectral decomposition output	Visualization of frequency content in the data
Chimney cube	Generated using Artificial Neural Networks

Table 3. Information of proposed wells.

Prospect	Well	X (m)	Y (m)	TWT (ms)	Area (km^2)
X	A	619829	6088922	594	8.1
Y	B	622894	6075187	569	3.58
Z	C	625029	6276827	518	12

Rationale:
1) Identified as high potential for hydrocarbons
2) Strategic location based on seismic attributes
3) Optimal drilling site based on ANN analysis

4. Conclusions

Gas chimney identification together with prospect zone assessment proves crucial for prospective hydrocarbon exploration activities. The research used Artificial Neural Networks (ANNs) to properly detect gas chimneys while demonstrating their effectiveness in locating hydrocarbon reservoirs. The research analysis used amplitude-derived and spectral decomposition data to improve the understanding of the geological features in the region. The proposed drilling wells will target the three prospect zones which showed the best potential for exploration. This research confirms how ANNs create efficient exploration processes that advance hydrocarbon studies and help develop new approaches for finding energy resources.

Acknowledgement

The research data used are completely open source and acquired from the available web platform TerraNubis.com. Besides, Opendtect, an open-source and free software which used to interpret the seismic data of this research.

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