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ENHANCING SEISMIC DATA FOR CHIMNEY GAS PREDICTION USING STEERING CUBE TECHNIQUE, META-ATTRIBUTES, AND ARTIFICIAL NEURAL NETWORKS (ANN) IN F3 DEMO OILFIELD, NETHERLANDS

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Abstract

The accurate identification of chimney structures is crucial for understanding hydrocarbon migration paths and evaluating seal integrity, thereby reducing drilling risks. Effective assessment of hydrocarbon seepage relies on knowledge of migration routes and the source/reservoir. This study uses Artificial Neural Networks (ANN) to predict the occurrence of gas chimneys, leveraging seismic data processed with the OpendTect platform. Seismic data conditioning plays a key role in building the machine learning model, involving the creation of two types of steering cubes: a background steering cube for dip median filtering (DSMF) and a detailed steering cube for generating meta-attributes. Two labels, Chimney-Yes (1) and Chimney-No (0), are used for training, with a 70%/30% split between training and testing datasets. The ANN model comprises an input layer with eight nodes, four hidden layers, and two output nodes. The resulting Chimney Probability Cube (CPC) combines the seismic meta-attributes optimally using the ANN method. Model evaluation shows excellent performance, with a Root Mean Square (RMS) error between 0.25 and 0.3 and zero misclassification. This method provides a reliable approach to identifying gas chimneys, which is essential for determining migration directions, spill spots, mud volcanoes, gas seepages, and hydrocarbon origins. The proposed method has significant potential for global applications in geological hazard assessment, subsurface storage characterization, and petroleum exploration.

Keywords: Seismic data enhancement; Chimney gas; Artificial Neural Networks; Model Evaluation.

1. Introduction

Oil and gas migration plays an important role in the accumulation process of hydrocarbons. Its migration characteristics and migration patterns control the formation and distribution of

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oil and gas reservoirs. Therefore, the study and prediction of migration pathways have always been the focus of oil and gas exploration. Chimneys typically disperse seismic waves and have a poor appearance; detectingئ them from seismic data is time-consuming and challenging (Heggland, 2002; Ligtenberg, 2005). According to Heggland (2005), there are significant discontinuities among the reflectors and decreased reflection amplitudes in gas chimneys.

In the research process, scholars primarily base their studies on geological structures, integrating geophysical data and existing oil and gas distribution patterns. They propose various potential pathways for hydrocarbon migration, including faults, unconformities, ancient buried hills, microcracks, diapir structures, inversion structures, and high-porosity and high-permeability sand bodies. Among these pathways, diapir structures in (Figure 1) exhibit unique formation environments characterized by abnormally high pressure, playing a crucial role in hydrocarbon accumulation by providing vertical migration channels and acting as both conduits and traps for oil and gas (Heggland, 1998; Meldahl et al., 1999; Meldahl, Heggland, & Bril, 2001). The concept of a gas chimney was originally developed from a fluid diapir structure, see (Figure 1). Gas chimneys are a special associated structure formed by the action of active hot fluids (Davison et al., 2000).

The importance of gas chimney studies: They are direct evidence of the existence of shallow oil and gas reservoirs and have attracted much attention in recent years. As a special associated structure, gas chimneys will become a special channel for oil and gas migration after they are formed. They become an important bridge connecting source rocks and traps, affecting the migration and accumulation of oil and gas.

Gas chimneys are important in predicting fault activity and trap integrity, identifying oil and gas seepage points and shallow gas anomalies, and determining hydrocarbon types and geological disasters (Aminzadeh et al., 2002; Tingdahl et al., 2001). The detailed interpretation of gas chimneys can reveal the hydrocarbon generation history of oil and gas basins. It is a new solution for comprehensive analysis of oil and gas systems and exploration of oil and gas prospecting areas (Heggland, 1998).

Using a set of criteria to emphasise distinctions between chimneys and surrounding features, skilled geoscientists must spend a significant amount of time and effort manually delineating gas chimneys in seismic data. However, the identification of gas chimneys by hand is not always consistent and can change over time for a single interpreter as well as between interpreters. Utilising automated technologies, on the other hand, is quite desirable since it offers the possibility of reproducible and time-saving outcomes with equivalent precision (Zibar et al., 2015).

By using multi-trace properties including energy, similarity, and signal-to-noise ratio, among others, it is possible to efficiently identify gas chimney paths with deeper depth information, overcoming the aforementioned difficulties, there are two main problems with seismic interpretation that rely on a single or principal attribute: 1) it could not be able to identify the aim of interest, and 2) it might only outline a portion of the aim's information (F. C. G. Brouwer et al., 2011; Meldahl, Heggland, Bril, et al., 2001).

Many academics have therefore developed clever and reliable methods for merging numerous qualities using an ANN to produce a meta-attribute, such as the gas (CPC). (Meldahl et al., 1999; Meldahl, Heggland, Bril, et al., 2001; Singh et al., 2016). The supervised ANN and multilayer perceptron (MLP) were among the first machine learning applications for gas chimney recognition (Meldahl et al., 1999; Meldahl, Heggland, Bril, et al., 2001).

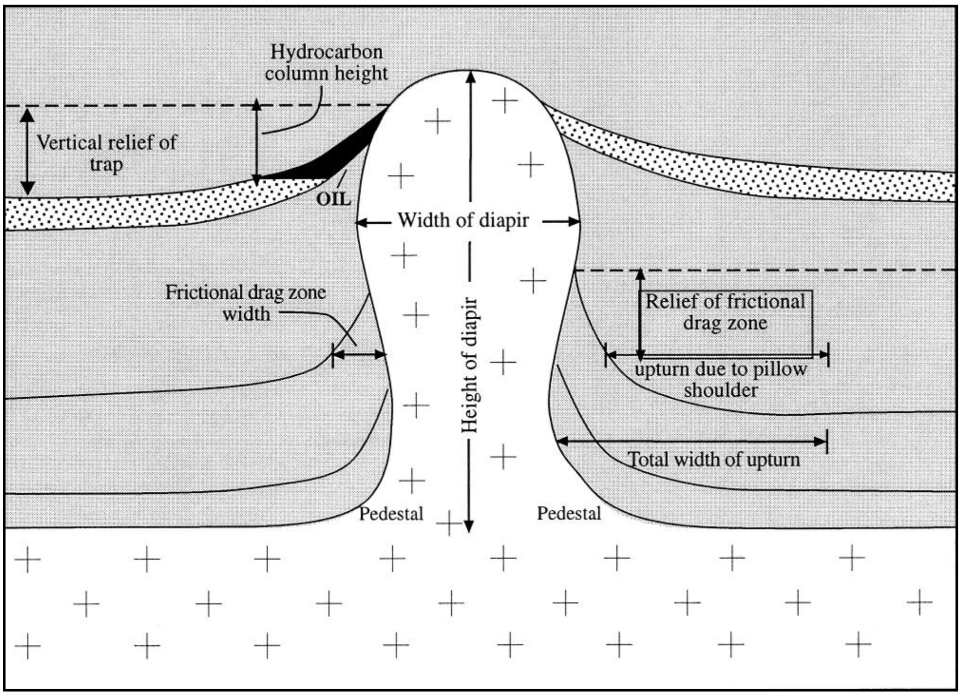

Figure 1. Shows the diaper structures (Davison et al., 2000).

Furthermore, numerous studies (Ebrahimi et al., 2013; Heggland et al., 2000; Singh et al., 2016) have succeeded in applying ANN to identify gas seepage. Meldahl et al. (1999) and Meldahl, Heggland, Bril, et al. (2001) proposed an idea as the foundation for constructing a hybrid characteristic. They suggested using Artificial Intelligence (AI) and ANN to create hybrid or meta characteristics by combining a variety of traits and training them as input under the guidance of an interpreter's experience. The seismic data may exhibit vertical disturbances as a result of the reservoir's stored gas diffusing through faults and fractures.

The conventional gas chimney identification technology was first proposed by Meldahl, Heggland, and Aminzadeh in 1998 (Aminzadeh et al., 2002). Using the feedback mechanism of ANN, a gas chimney attribute set (NN Chimney Cube) consisting of single-channel attributes, such as similarity and energy, was established.

ANN supervised methods were used in this study. This study's objective is to present a novel workflow that uses amplitude, a single seismic parameter, to detect and extract gas chimneys from 3D seismic reflection data. Ultimately, the quality of the seismic data, the effectiveness of the ANN's training, and the interpretation accuracy all play a significant role in how confidently this process can be used.

2. Geological structure of chimneys

Gas chimneys are generated in pressure storage boxes and are formed by the action of active hot fluids. They serve as pressure relief channels for former fluids. They not only look like chimneys, but also have chimney effects. On conventional seismic sections of high quality, gas chimneys appear as seismic fuzzy zones with low coherence, low energy, and chaotic emission (Figure 2) (Arntsen et al., 2007).

This phenomenon is the result of the combined effect of multiple factors: when the fluid migrates upward along the gas chimney, it causes a sudden pressure drop, resulting in a large amount of dissolved gas being released, changing the acoustic wave characteristics of the rock, causing low-speed anomalies and reflection shielding; at the same time, the formation's natural gas will absorb a significant quantity of seismic energy, significantly decreasing the reflected wave's signal-to-noise ratio and decreasing its amplitude, in addition, when the natural gas migrates upward from the reservoir along the structural weak zone, when the migration is more intense, it may destroy the original sedimentary stratification of the formation, causing the profile to suddenly appear chaotic reflection phenomenon.

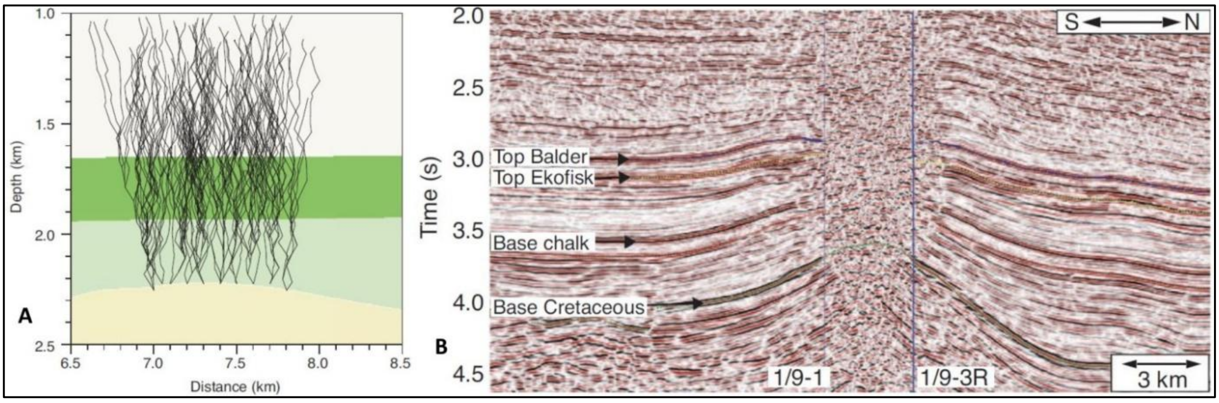

Figure 2: A) Geological model and the seismic response of gas chimney (Arntsen et al., 2007), B) Seismic response of gas chimney (Granli et al., 1999).

In addition, when the natural gas migrates upward from the reservoir along the structural weak zone, when the migration is more intense, it may destroy the original sedimentary stratification of the formation, causing the profile to suddenly appear a chaotic reflection phenomenon (Aminzadeh et al., 2002).

3. Methodology

The methodology adopted for this study consists of four main steps, which have been presented as a workflow in Figure 3. The 1st step: the dataset is a seismic dataset composed of a high resolution of 3D post-stack seismic data. The 2nd step: The goal of the seismic data conditioning technique is to improve structural objects, such as chimney gas, from the seismic data by reducing noise that makes it difficult to recognise them by using a dip steern median filter and several meta-attributes. The 3rd step: a supervised ANN approach was used to identify faults based on a trained points dataset of chimney-yes and chimney-no. Finally, the 4th model evaluation: in this phase, a confusion matrix was used for the assessment of the ANN during training and testing (Bijan and Al-Rahim, 2024). The best method for more accurately reading these disturbed aspects from seismic data is to combine several meta-attributes using a non-linear neural network. (Meldahl et al., 1999); (Heggland et al., 2000);(Meldahl, Heggland, Bril, et al., 2001).

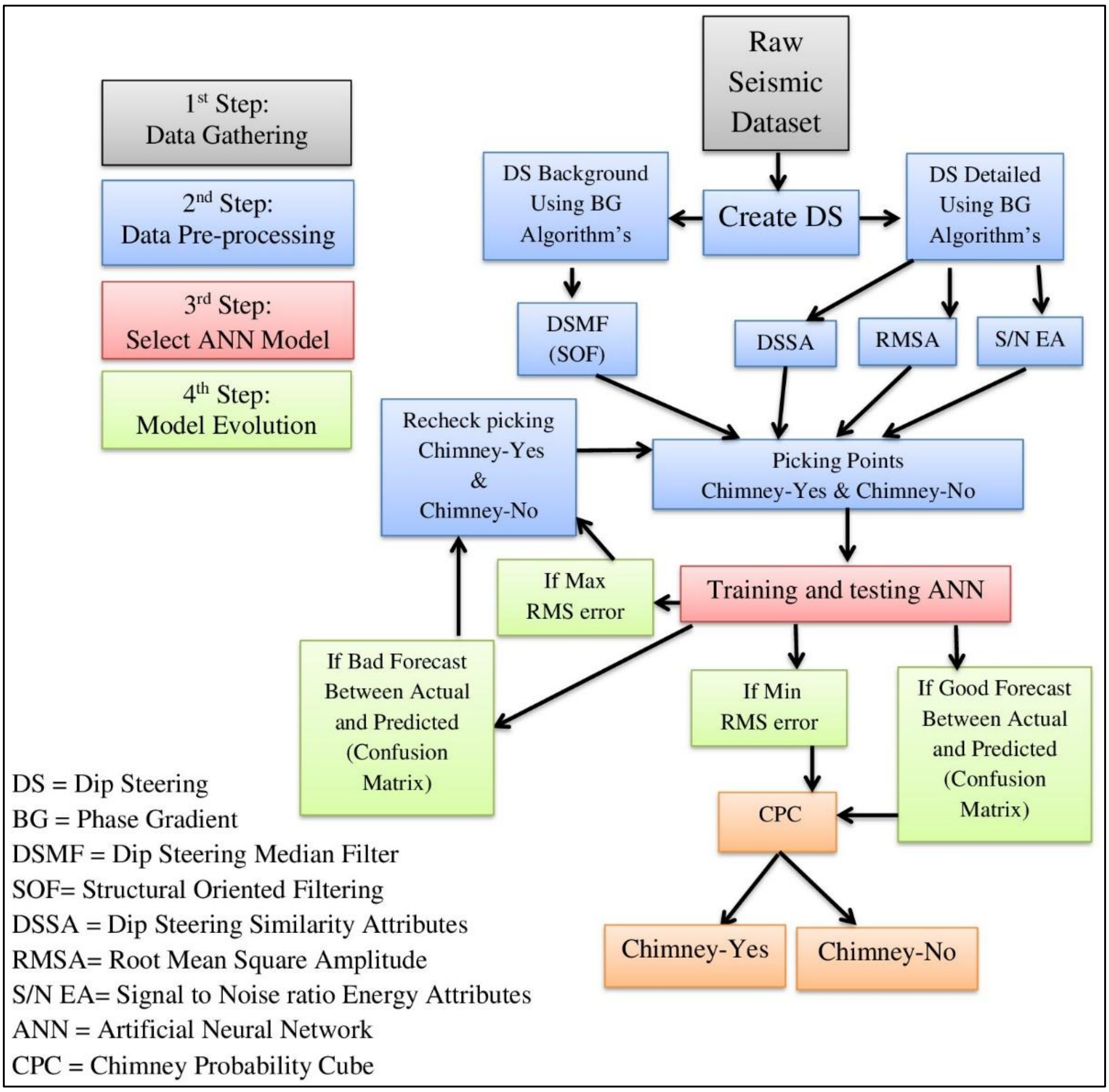

Figure 3. The workflow classification of the current study.

The present study has been carried out using the ANN and dip-steering (DS) modules of the OpendTect v7.0.0 platform. OpendTect is a seismic attribute processing and pattern recognition software jointly developed by the Dutch dGB Geotechnical Company and the Norwegian Statoil Company.

3.1. Data Gathering

The North Sea Netherlands offshore F3Demo oilfield**,** as shown in Figure 4 in 2015, the Dutch government published 3D seismic reflection data into the public domain [dGB]. About 180 kilometres off the Dutch coast, the F3 is an offshore block in the Southern North Sea Basin's Central Graben.

The F3Demo The seismic reflection dataset comprises 386 km2 of complete stack and time-migrated 3D data in the public domain, including 651 in-lines and 951 cross-lines (Figure 4). In 1987, the 3D seismic volume was obtained with a bin size of 25 m (in-line and cross-line), a time range of 1848 ms, and a sampling rate of 4 ms.

A dip-steered median filter with a radius of two traces was used to process the data in order to eliminate noise. The study's area and interval were defined by the discovery of gas chimneys between cross-lines 950 and 1110 within a 400 – 600 ms time window.

An illustration of 3D visualisation (in-line, cross-line, and time-slice) showing gaschimneys as noticeable features is shown in Figure 4A. In line with the evidence of wave dispersion and loss of continuity seen in the seismic data, direct measurements of this region (such as headspace gas analysis) also show the presence of gas seepage (Schroot et al., 2005).

Where troughs or negative amplitude (blue and white colours) indicate decreasing acoustic impedance and peaks or positive amplitude (red and yellow colours) indicate rising acoustic impedance (Figure 4B).

3.2. Data pre-processing (Seismic data conditioning)

Post-stack seismic data generally include both noise and signal. The seismic signal may relate to continuous or discontinuous reflectors, which may or may not indicate geological features. A fault is often characterized in seismic data by a vertical displacement of a specific seismic reflector. This vertical displacement can be readily observed by multi-trace correlation. Conversely, seismic dispersion, scattering, diffraction, and analogous sounds may affect these correlations and the outcomes (Lee et al., 2017).

The noise obscures structure terminations and diminishes the signal-to-noise ratio, complicating horizon interpretation and structure detection. Conventional image processing of structure patterns may not consistently reflect the actual subsurface structural features.

A standard seismic interpretation is not advisable in this instance (Helal et al., 2015). This phase enhances the efficiency of seismic interpretation by optimizing the performance of seismic multi-trace attributes (Meta-attributes), while structural filtering is executed using a Structure-Oriented Filter (SOF) (Lee et al., 2017).

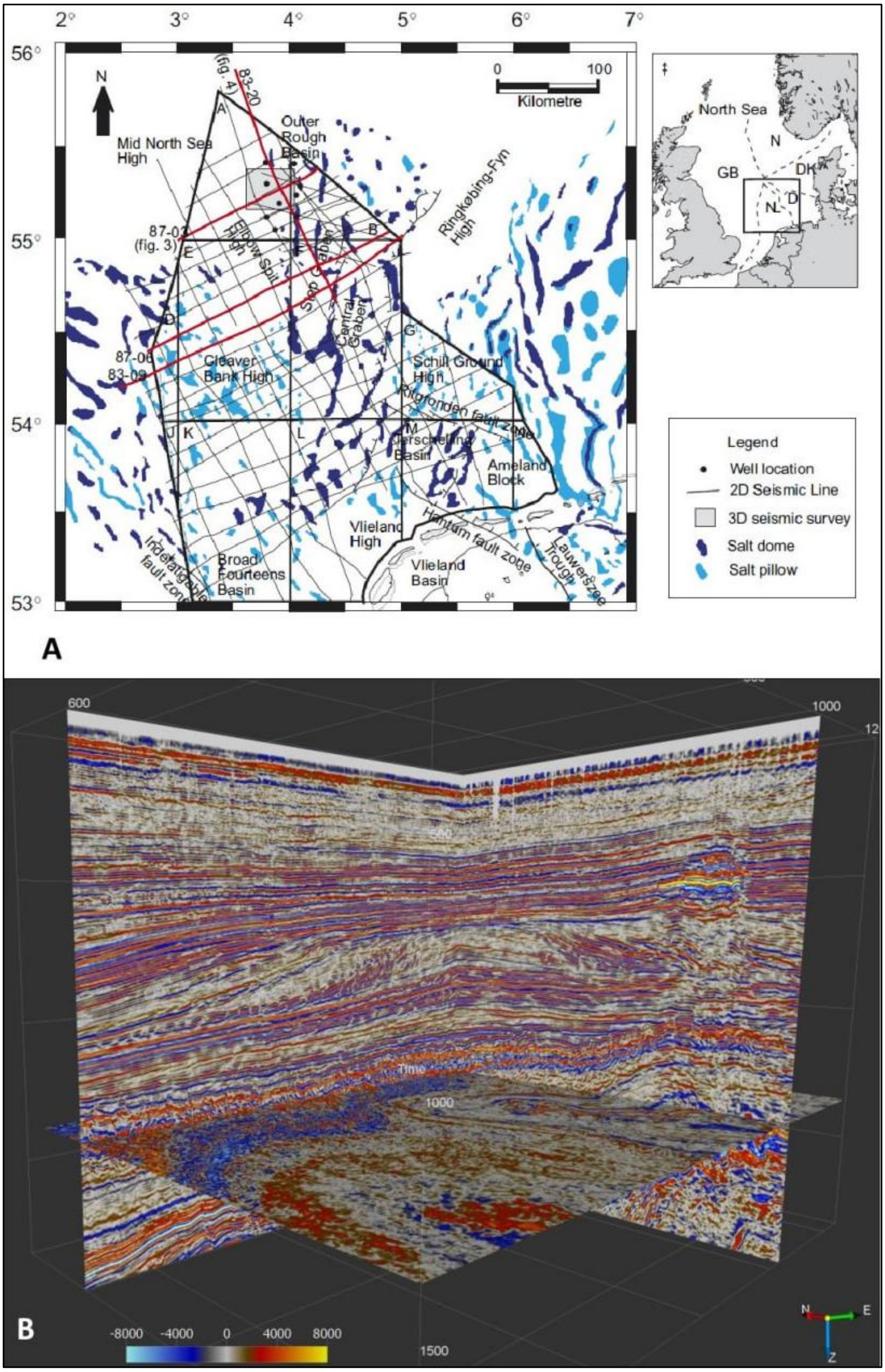

Figure 4. A) Show the location of the study area with seismic line survey; B) Show the 3D section of the seismic dataset (in-line = 603, cross-line = 1030, Z-slice = 1352) of the study area.

3.2.1. A steering cube generation

Steering generation is a critical component of the conditioning workflow, as it significantly impacts the outcomes of structural-oriented filters and seismic multi-attributes (F. G. C. Brouwer et al., 2008).

This study employs a phase-gradient algorithm for steering generation, enabling the extraction of information regarding the azimuth, local dip of reflectors, and discontinuities within the oilfield. Background steering data and detailed steering data were the two types of steering data that were produced.

The background steering data is extensively filtered and contains regional information regarding the dip and azimuth of the structure in the studied area (Figure 5A), employing a filtering step of (inline: crossline: sample) with dimensions of (5×5×0).

Effective filtering of the detailed steering data yields thorough details about the structure and geological aspects, utilizing a filtering step out (inline: crossline: sample) (0×0×5) of the studied area (Figure 5B). Multiple tests were conducted to optimise the dip computation parameters, which were then applied to the whole seismic dataset at each sample position.

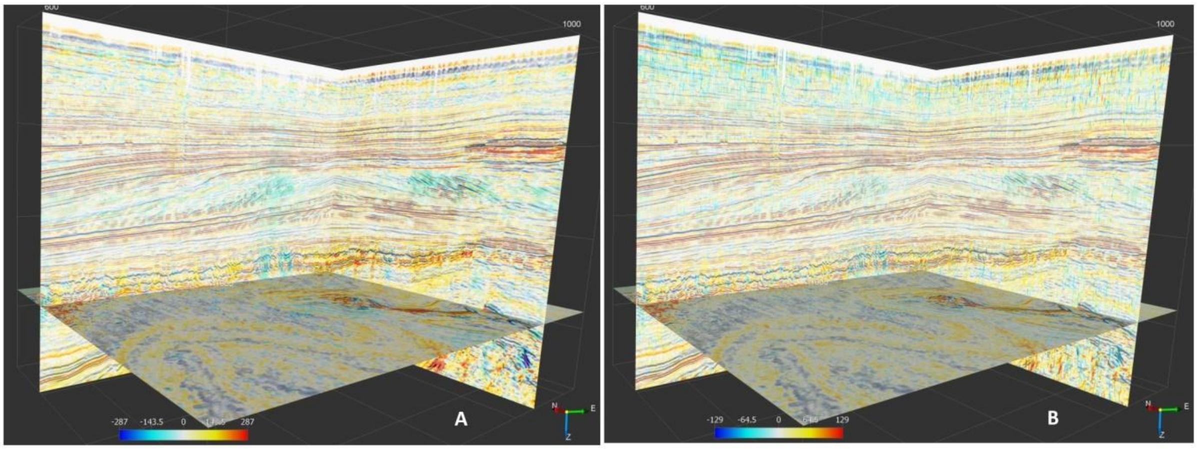

Figure 5. The generated steering cube data are overlaid on the seismic in-line 611, cross-line 1071, Z-slices 1404 ms. The blue color represents the discontinuities, while the red color represents the dip. A) Background B) Detailed.

3.2.1. b Structural Oriented Filtering (SOF)

Starting with seismic data that enables accurate chimney gas structure delineation is essential. The seismic data is methodically pre-processed and conditioned to accomplish this goal. Dip-Steered Median Filter (DSMF) is the most important statistical filter that is applied to the seismic data using a pre-processed Steering Cube.

By tracking the seismic dips, it employs median statistics on the seismic amplitudes (Sain & Kumar, 2022). By eliminating the background random noise, it produces a smoothed seismic volume that improves the continuity of seismic reflectors, as seen in the frequency-wave number cross plot in Figure 6B.

This has improved the vertical and spatial seismic resolutions (Figure 7B). If a gas zone is greater than the median filter size, it is frequently regarded as an edge-preserving smoothing

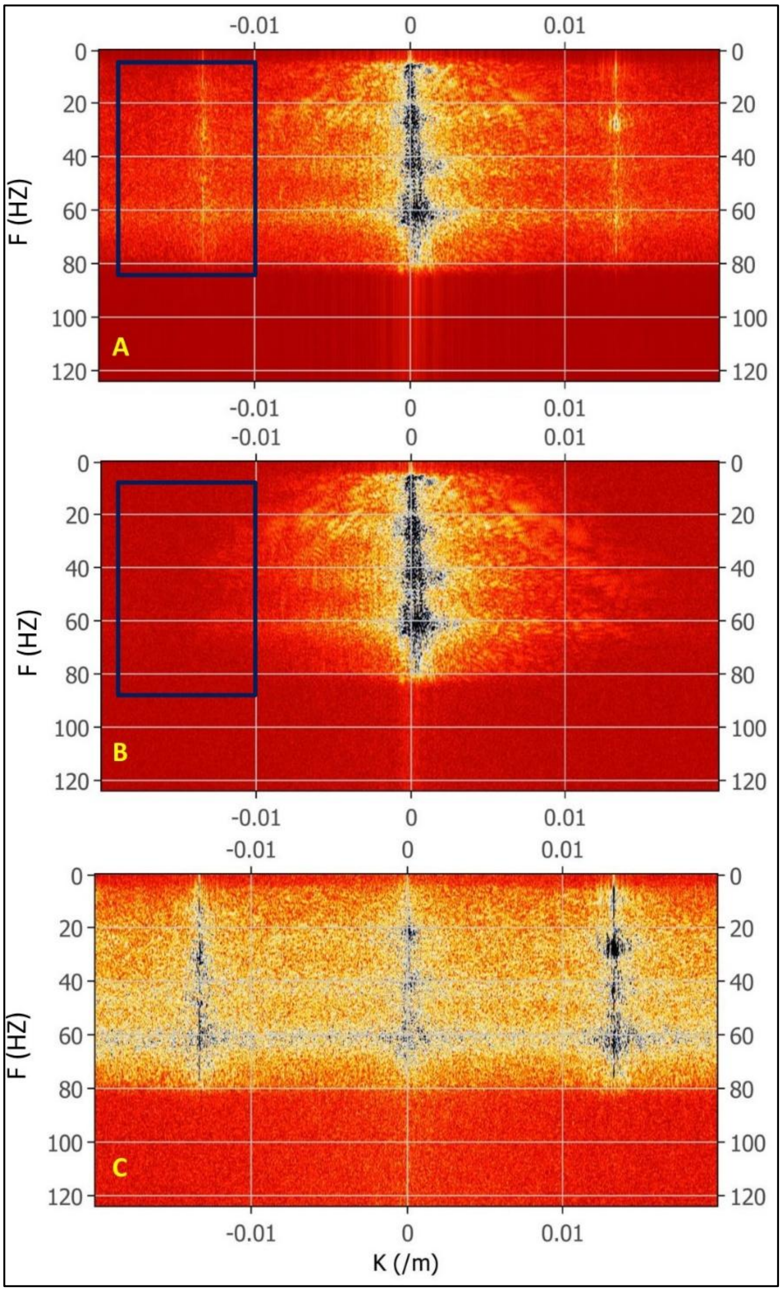

Figure 6. A frequency (F)-wavenumber (K) cross plot for in-line 691: A) before applying the DSMF, B) after applying the DSMF, C) Residual noise that was removed from the original seismic dataset, revealing that the random (higher frequencies) noises are effectively eliminated, as indicated by black rectangles.

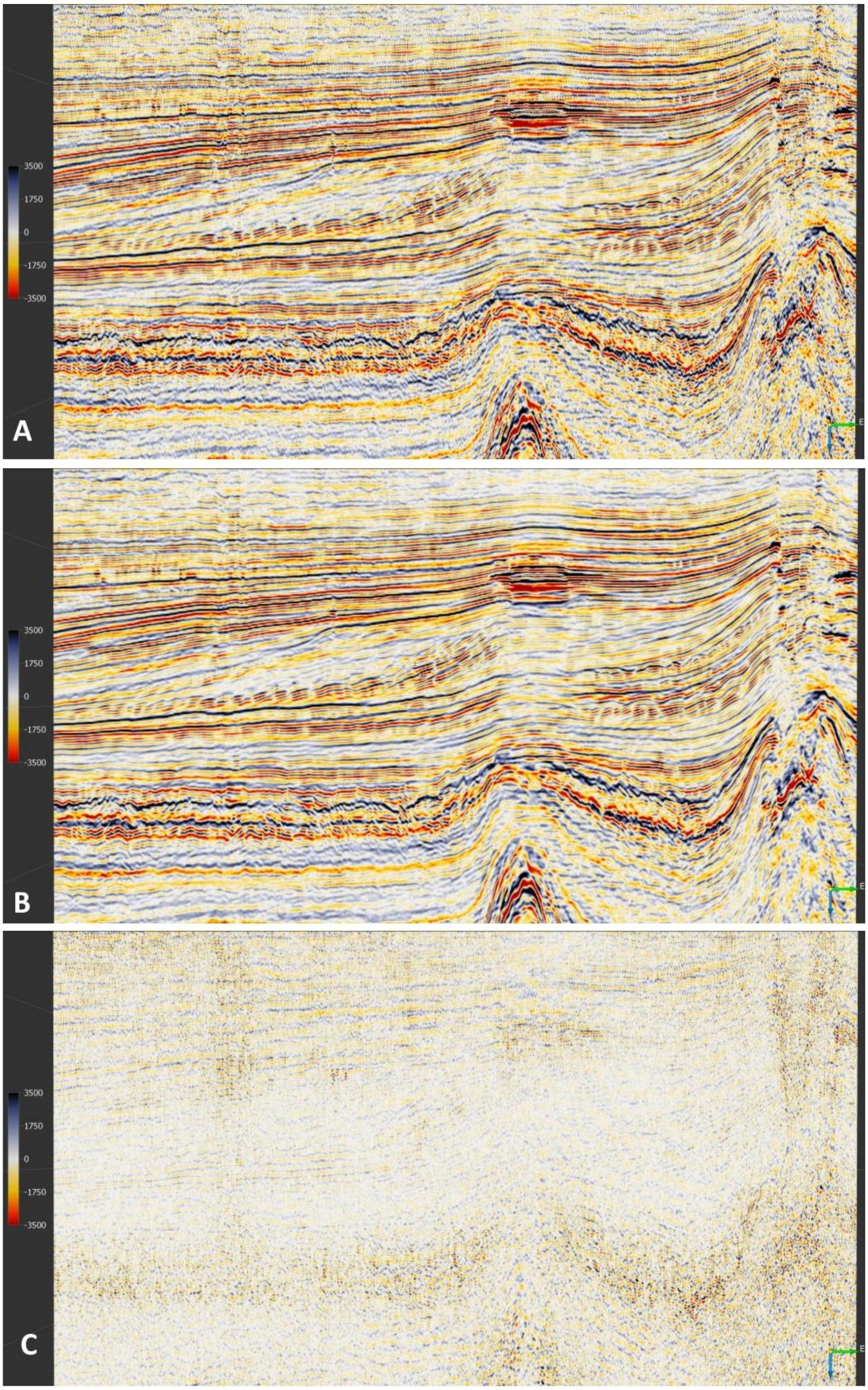

Figure 7. Seismic section inline 691 A) Original seismic data, B) after applying DSMF, C) Residual noise that was removed from seismic cube. The red circle indicates that this weak reflector's lateral continuity has been improved.

Filter. On the other hand, the data will be smoothed out if a fault zone is less than the median filter. Therefore, as explained below, more filters could be needed to sharpen the gas zones.

3.2.2. Multi-Trace Attributes (Meta-Attributes)

Gas chimneys are the routes by which gases and liquids migrate from source rocks and/or hydrocarbon reservoirs (Heggland, 1997). Seismic properties are derived from data through a series of algorithms.

Can an attribute precisely identify a geological target within the full data volume in this scenario? A novel characteristic termed the hybrid- or meta-attribute has been derived by amalgamating a collection of other attributes related to a particular geologic objective (Kumar, Kamal'deen, et al., 2019; Kumar, Omosanya, et al., 2019; Kumar, Sain, et al., 2019; Kumar & Sain, 2018, 2020b, 2020a; Singh et al., 2016).

Consequently, the unique features of gas chimneys in seismic data include vertical zones with chaotic/random texture, low amplitude, low frequency, poor coherence, and low similarity. In order to effectively delineate the gas chimney in the research region, a mixture of relevant variables, such as similarity, signal-to-noise ratio (energy attribute), and RMS (amplitude attribute), is chosen.

To capture chaotic/random texture and verticality, the similarity attribute has been computed in all directions, diagonally, and parallelly with +100 ms (up) and -100 ms (down) from the reference point, as shown in Figure 8A. As seen in (Figure 8B), the amplitude loss signature caused by gas clouds is improved by using the RMS (Root Mean Square) amplitude property in the direction diagonal.

Additionally, S/N (signal-to-noise ratio) energy has been used to identify spatial trend, as shown in Figure 8C. Various parameter settings, including time gates, threshold levels, inline or crossline step outs, etc., are used to extract these chosen features from the seismic data. The next section (training model) may be divided into subheadings (Picking of Points for training and Training ANN model).

3.3. Picking the points and training the ANN

3.3.1. Picking of Points for training

Through the attributes in (Figure 8), the gas chimney can be identified by using the feature that it is a vertical seismic fuzzy zone, and its application effect is relatively ideal. The key to gas chimney identification technology lies in the picking of training points (Figure 9). The quality of the training point picking directly affects the quality of the final gas chimney body. The chimney body generated after the subsequent neural network training has two advantages: picking training points by the manual method.

Firstly, it is highly effective and automatic. Usually, the interpreter does not have time to study the vertical fuzzy band system of the entire work area, and there is no need to pick up training points for the entire work area. It is only necessary to pick points in the typical characteristic areas on one or several sections, and the rest of the work is left to the computer.

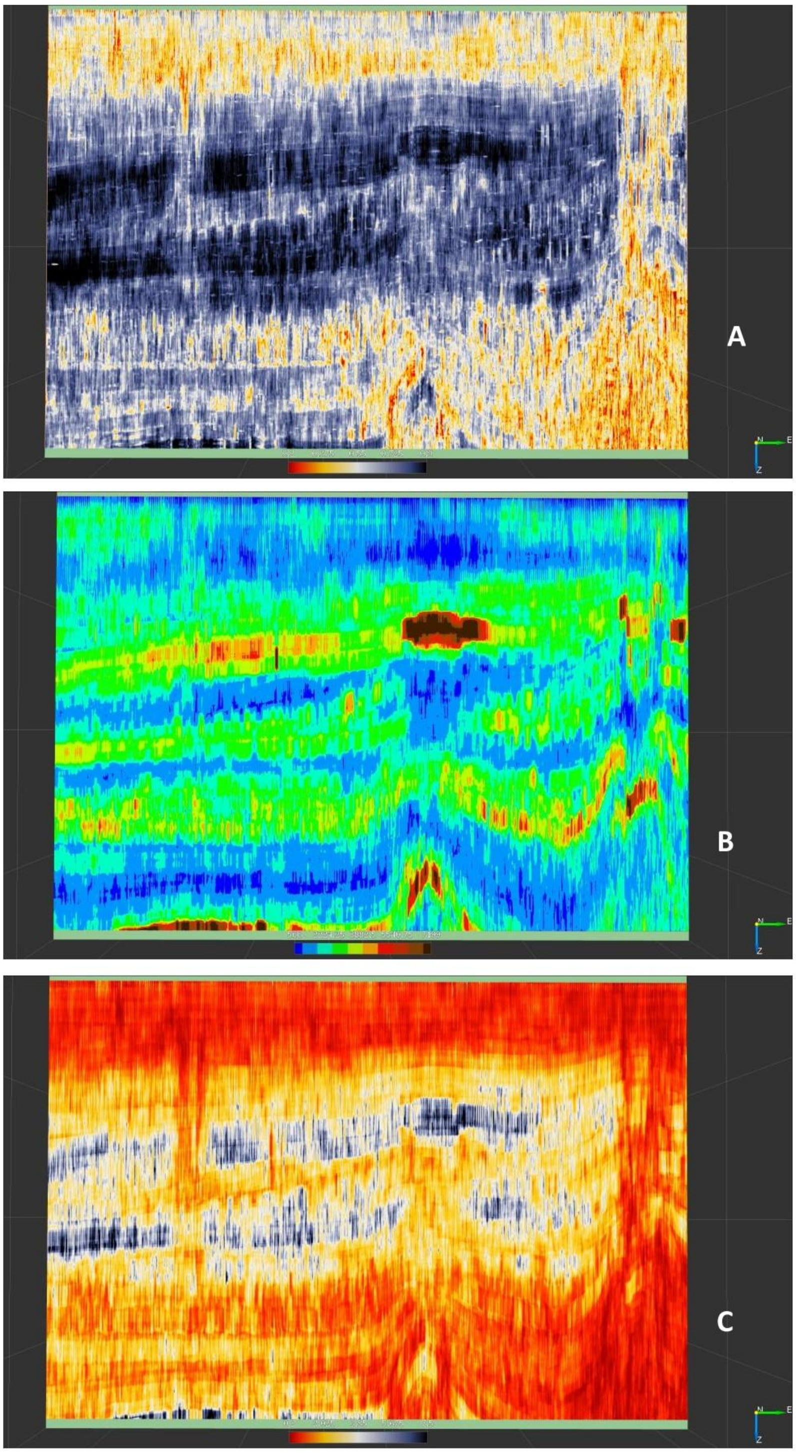

Figure 8. Shows seismic section in in-line 691 A) Similarity attribute, not the red colour is low coherency B) RMS amplitude, not the blue colour is low amplitude C) S/N energy attributes, not the red colour is low in energy. These attributes show the probability gas zone.

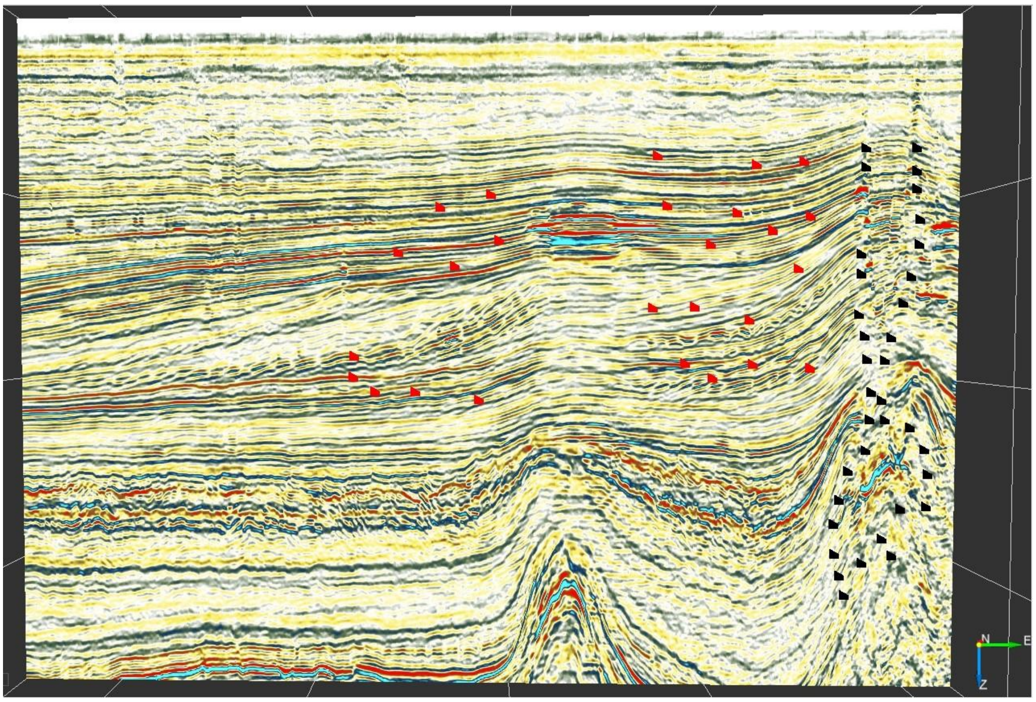

Figure 9. Show pickets for chimney-yes represent by black points, and chimney-no represent by red points.

Secondly, by inferring the unknown from the known, it is easy to immediately discover phenomena that are difficult for the human eye to identify. Some tiny gas chimneys are usually difficult to identify on seismic profiles or are not reflected. However, by training the gas chimney attribute set at the picking point, the mapping relationship between the probability of gas chimney occurrence and each attribute can be obtained, and the presence and intensity of the gas chimney at that location can be determined. In this study, picking 35 points chimney-yes and 26 points chimney-no as shown in (Figure 9), (Table 2) shows the coordinates of every point with values in the seismic section inline 691.

3.3.2. Training ANN mode

A meta-attribute called the CPC is produced in the current study by combining the retrieved qualities further using an ANN (Aminzadeh & de Groot, 2006; Barber & Bishop, 1997; Meldahl et al., 1999; Meldahl, Heggland, Bril, et al., 2001; Singh et al., 2016). As seen in (Figure 10), the ANN is a fully linked non-linear network that typically consists of three layers: an input layer (eight layers), a hidden layer (four layers), and an output layer (two layers). Because of the learning technique it uses for training, it is also known as a "back-propagation" network (Jahani & Mohammadi, 2019; Ligtenberg, 2005; Vaheddoost et al., 2020). It is predicated on supervised categorisation, meaning that it trains itself using user-provided examples (Ligtenberg, 2003). Through random weight initialisation, the learning mechanism, or back-propagation technique, iteratively aims to minimise the difference between the expected and actual output (F. C. G. Brouwer et al., 2011; Hashemi et al., 2008; Le Cun, 1986; Rumelhart et al., 1986).

Table 2. Show the value of every pickset's training and testing for all attributes.

No	Coordinate			Similarity					RMS [-40,40]	Signal to Noise		Chimney-No	Chimney-Yes
	In-line	Cross-lin	Z	[40,40-] Diagonal	Up 100ms [-40,40] Parallel	Down 100ms [-40,40] Diagonal	Up 100ms [-40,40] Diagonal	Up 100ms [-40,40] AllDir		S/N	Up 100ms [S/N]		
1	691	641	0.993419	0.859088	0.8795033	0.6526015	0.8829764	0.8829764	2618.543457	4.2868953	6.2845244	1	0
2	691	642	0.93464	0.900643	0.9135563	0.7145281	0.9135377	0.9135563	1884.203979	4.5928931	4.5908628	1	0
3	691	1129	1.395992	0.349531	0.4332669	0.5095263	0.3731334	0.4332669	1686.06189	0.2948735	0.2737833	0	1
4	691	1131	1.479932	0.4957464	0.598703	0.4026834	0.4617382	0.598703	995.8813477	0.7863055	0.4756316	0	1

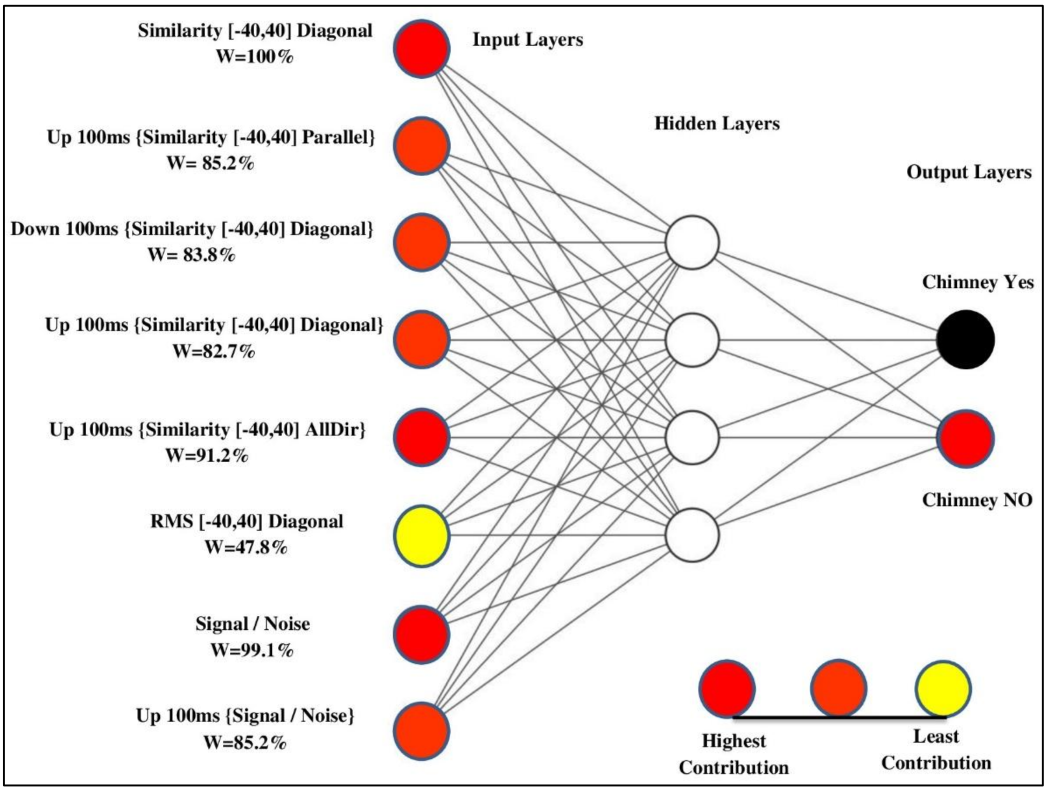

Figure 10. Shows the ANN architecture with contributions to every attribute and weight values (W).

Local minima issues are resolved through iterative training and connection weight updates. (Figure 10) displays the relative contributions of each input attribute for chimney classification. To obtain a meta-attribute in an ANN, the activation function receives the weighted sum of the inputs.

In terms of mathematics, the activation function (A) and weighted sum (W) (F. C. G. Brouwer et al., 2011) are expressed as:

$$W(y) = \sum_{n=0}^{L} W_n y_n \tag{1}$$

$$A(W) = \frac{2}{1 + exp^{(-W)}} - 1 \tag{2}$$

Where A= activation function, y is the input vector, w is the weights, and n = 0, 1, 2 … L.

According to Tingdahl et al. (2001), the activation function is a non-linear sigmoid function that generates output in two vector classes, a binary classification (1, 0) and (0, 1) corresponding to chimney and non-chimney locations, respectively.

A chimney probability cube, or a volume with probability values roughly between 0 and 1, is then created by applying the trained NN to the entire seismic data. Low probability values indicate a lower likelihood of fluid migration (i.e., chimney-no class), while high values confirm the fluid migration (chimney-yes class). (Figure 11) show the probability of chimney gas in the study area.

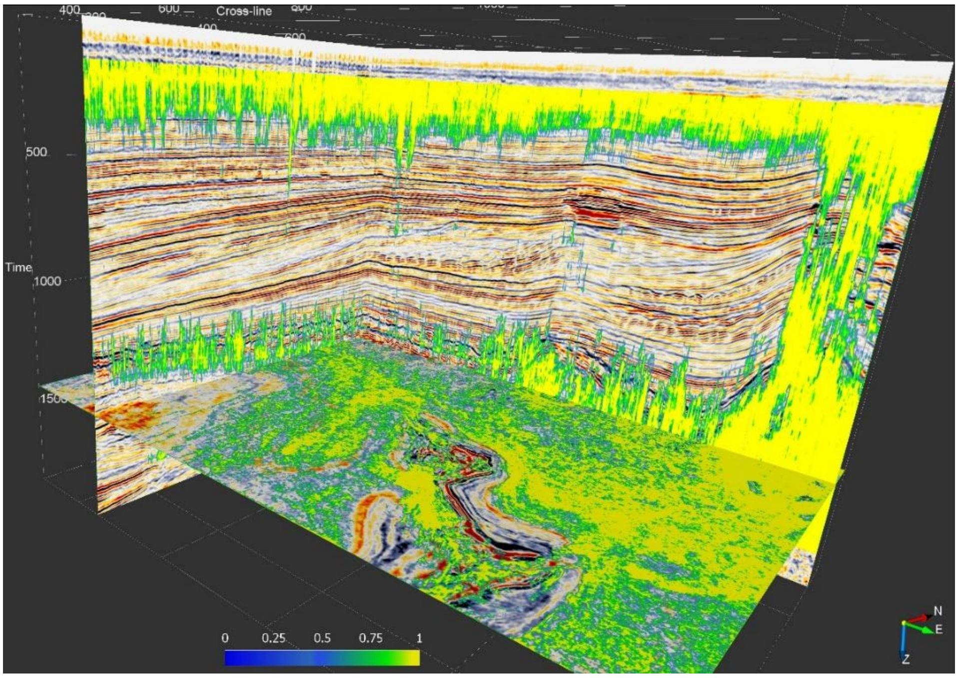

Figure 11. Shows the chimney gas probability in cube section (In-line = 691, Cross-line = 450, Z-slice = 1424), the yellow color represents high probability blue low probability.

3.4. Evaluation Model

A learning model's purpose is to predict class labels for unknown data by using knowledge from a training pickset. The assessment approach is essential in assessing classification performance and leading classifier modeling.

The key to gas chimney identification technology lies in the picking of training points (Figure 9). The number of picking chimney-Yes is 35 points (black points), and chimney-No is 26 points (red points), the sum of these points is 56.

The network divides the data into train and test sets at random to carry out its function. 17 input vectors are used in the testing process, which uses 30% of the data. On the other hand, 39 input vectors and 70% of the data are utilised for training. In both situations, there is a valid input vector.

Through the neural network tool, the training execution can be tracked during training and represented by two indices: the normal RMS curve and the RMS error rate curve. During this phase, the parameters of a classification model are adjusted. The training error measures how well the trained model fits the training data.

The RMS error rate curve represents the total error of the training group (red) and the test group (blue), between 1 (the highest error) and 0 (the lowest error). As you train, both curves should decrease. The network is over-fitted as the test curve rises once again. Training must end before this occurs.

A typical RMS value for training and testing in the range 0.8 is considered reasonable, 0.8 to 0.6 is good, 0.6 to 0.4 is very good, and below 0.4, the RMS error values for training and testing is 0.08 and 0.04, respectively, it isexcellent as show in (Figure 12A) and misclassified was 0 as show in (Figure 12B). In our study, there are two classes of these problems of classification, called binary classification (Chimney-Yes & Chimney-No).

If the model successfully classifies a positive sample as a positive, the result is a correctly classified positive, known as a TP (True Positive), and if the model incorrectly labels a positive sample as negative, then it is known as an FN (False Negative). If the model classifies the negative sample as negative, it is appropriately classified as negative, which is known as TN (True Negative). The error occurs FP (False Positive) when the model incorrectly classifies a negative sample as positive (Bichan & Al-Rahim, 2024).

The elements of a 2x2 confusion matrix or contingency table can be represented by four different outputs, as shown in Figure 13. Correct predictions are shown by the black diagonal, whereas wrong guesses are shown by the red diagonal.

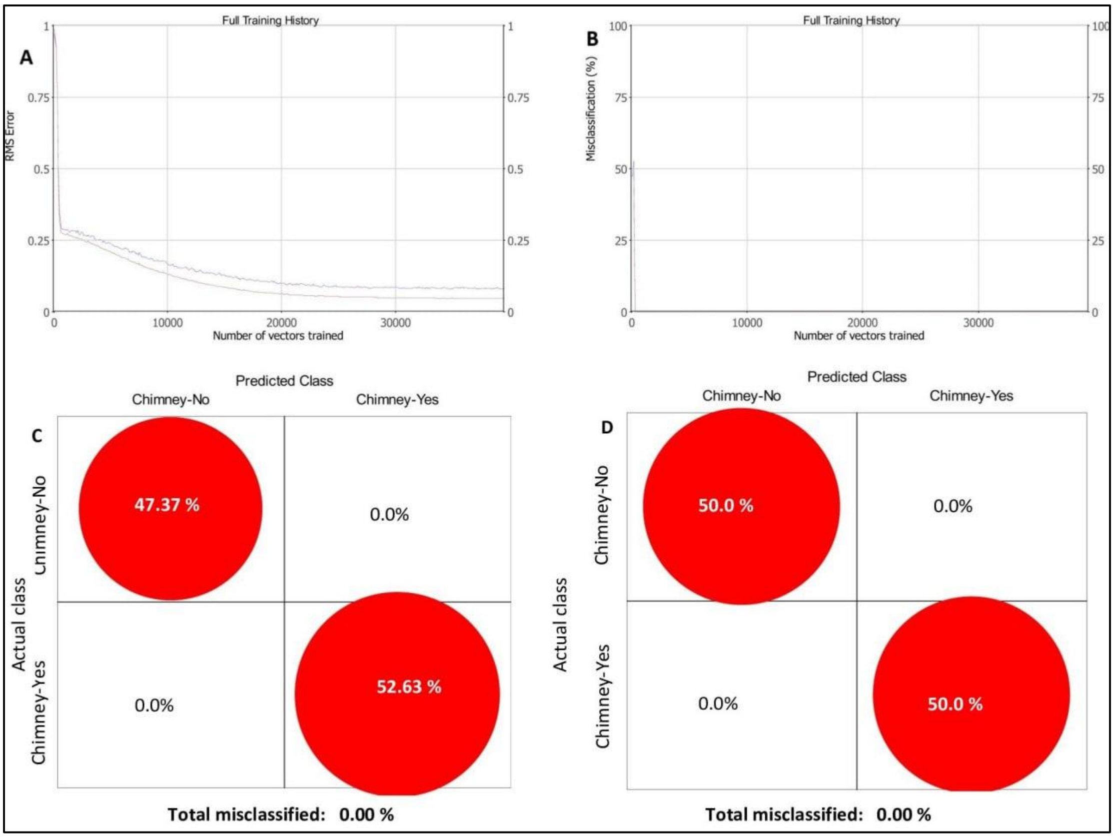

Figure 12. A) RMS error for training; B) Misclassified; C) Confusion matrix for testing; D) Confusion matrix for training.

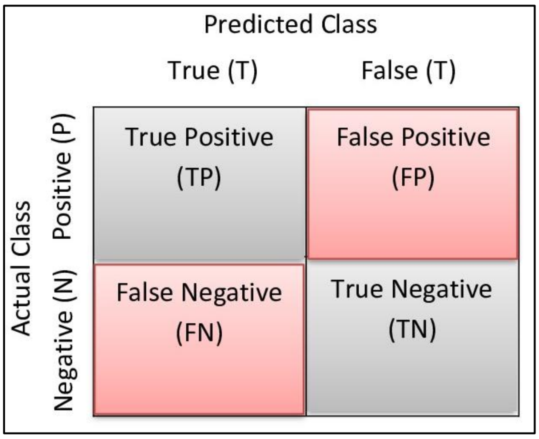

Figure 13. The confusion matrix for binary class classification (Bichan & Al-Rahim, 2024).

4. Result and Discussion

Data conditioning has smoothed the data, which has improved fluid migration that w*as* previously impeded by the acoustic impedance in the seismic data (Figure 6A with B and Figure 7A with B).

The seismic discontinuities associated with the conduit for gas migration have been brought to light by the dip steering cube calculation (Figure 5). The gas chimn**e**y fluid migration features, including amplitude blanking, DHIs, faults, pockmarks, push-downs, frequency wash-out zones, etc., and their continuity have been successfully highlighted using DSMF conditioned data (compare Figure 7 A with B).

4.1. *ANN design training*

By iteratively modifying the weights of the input attributes, the ANN learns from the given samples and builds a relationship between the input and output layers.

Following 7 iterations of training, both the training and testing datasets achieve a minimum misclassification of 0.0% (Figure 12B) and a minimal nRMS error of values between 0.02 and 0.03 (Figure 12A). Confusion plots were utilised to assess the quality of classification following the achievement of the lowest nRMS error and misclassification (Figure 12C and D).

The trained ANN is then applied to the entire seismic volume to obtain the CPC, which is a 3D visualisation of the entire spatial extent of the gas chimney in the area. With values ranging from 0 to 1, this cube effectively caught every little detail of gas movement and the chimney. It also showed the presence of a large gas zone on the right in-line portion (Figures 11 and 14).

4.2. Chimney interpretation

The presence of fault networks that are non-sealing in character and serve as channels for gas migration to the sediments above is suggested by the coincidence of low similarity values with high chimney likelihood (Figure 14A).

Given that gas, a lighter hydrocarbon component, has less capillary resistance, this implies that capillary pressure also plays a role in fluid migration (Ligtenberg, 2003). Furthermore, the majority of fluid migration or gas chimney paths are restricted along faults, which demonstrates a high degree of correspondence with the faults in the research region (Figure 14B and C).

Gas chimneys indicate the discontinuity of seismic data, so their development areas should be places where fractures develop. It is believed that the fault activity in this block was relatively strong, and the large-scale faults controlled the evolution of the structural pattern of the entire depression and the distribution of oil and gas. In local areas, the chimney gas has a dense microfracture structure, which can improve the porosity and permeability of the reservoir.

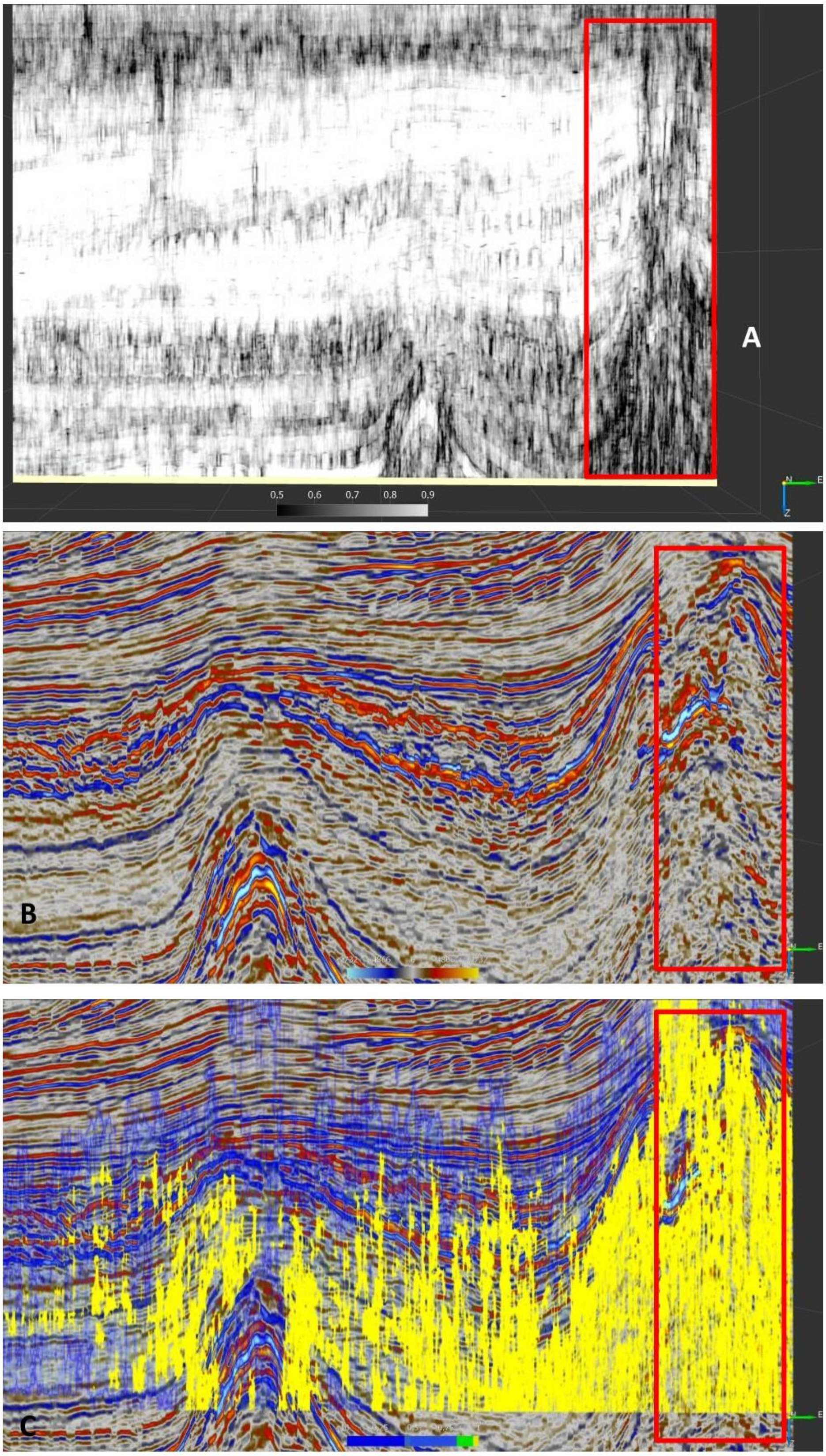

Figure 14. Seismic section in in-line 691 A) Similarity attributes show gas zone red rectangular B) show the high faults and fractures zone C) Gas zone matches with faults and fractures zone.

5. Conclusions

Chimney processing can delineate vertical discontinuities, which are related to hydrocarbon migration. This means that, when geophysicists are incapable of recognizing underground fault systems, chimney assists them to achieve their goal, and the following insights were obtained.

The developed CPC attributes (meta-attributes) based on the 3D steering seismic data and ANN have effectively delineated the gas chimneys, thereby enhancing the understanding of the petroleum system of the F3 demo oilfield prospect. The CPC attributes that the hydrocarbon spillage started from the bottom of the horizon and continued migrating up to the top layers. The fluid migration is mostly confined in the SE direction.

The overlay of CPC attributes and the seabed’s pockmark morphology also indicates the presence of a cold-seep system. ANN methods achieved a gas chimney and a non-chimney by measuring RMS Error 0.1 for training and 0.09 for testing. This superior performance was achieved using only one seismic attribute, which is the seismic amplitude.

This study introduces a new workflow based on ANN algorithms and steering cube seismic data successfully applies them to 3D seismic volumes. The workflow utilized three seismic attributes to delineate and extract gas chimneys with 100% accuracy. Finally, the study provides an innovative strategy by using an ANN; all segments are evaluated trace by trace, which cannot be done by human intelligence, to validate the gas-bearing zones.

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