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LITHOLOGY CHARACTERIZATION AND GAS VOLUME PREDICTION USING NEURAL NETWORK IN WEST DELTA DEEP MARINE, NILE DELTA, EGYPT

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تمييز الصخور وحساب خاصية حجم الغاز باستخدام تحليل الشبكة العصبية بمنطقة غرب الدلتا البحرية العميقة، دلتا النيل، مصر

الخلاصة: هناك العديد من الطرق والمفاهيم المتنوعة لمحاولة استكشاف وتطوير المكامن الهيدروكربونية. وهذه الدراسة تهدف إلى حساب مكعب احتمالى عن حجم الغاز، والمقصود به هنا هو خاصية حسابية تنتج من حاصل ضرب المسامية الصخرية المتصلة فى نسبة الهيدروكربونات بالصخر. وحساب ذلك المكعب الاحتمالى عن حجم الغاز بعيداً عن الآبار أى فى أماكن لا يوجد بها آبار مهمة بها تحديات كثيرة وذلك لعدم وجود علاقات معينة يمكن من خلالها الربط بين تلك الخاصية المراد حسابها مع البيانات والسمات السيزمية وغير أن العلاقات تكون غير خطية. ولذا فإن ضم مجموعة من السمات السيزمية التى يتم تحديدها بدقة عن طريق تقنية الانحدار المتعدد الخطية مع تقنية الشبكة العصبية الاصطناعية من الممكن أن يستغلوا لتطوير وتحقيق ذلك الهدف لاستكشاف المكامن وتقييمها من وجود هيدروكربونات من عدمه. وقلة الآبار المستخدمة فى الدراسة كانت الهدف لتطوير سير عمل آخر يهدف إلى تصنيف الخصائص الصخرية وذلك لزيادة درجة الثقة للتنبؤ بالمكعب الاحتمالى لحجم الغاز. تغطى منطقة الدراسة حوالى ٦٦٠ كيلومتر مربع ومعظم المكامن المستهدفة بها من نوع القنوات المنحدرة من العصر البليوسيني التى تتكون من تتابعات من أحجار رملية وطينية وتتسم الحبيبات بصغر حجمها كلما رسبت إلى أعلى. وبمطابقة وجود حجم الغاز من المكعب الأول فى الطبقات الرملية من المكعب الثانى تأتى مع احتمالية تقييم وجود المكامن داخل أى مكان بالمكعب السيزمى الثلاثى الأبعاد. وتشير النتائج إلى أن تطبيق طريقة الشبكة العصبية المقترحة تؤدى إلى استنتاجات يمكن الاعتماد عليها ولها تأثير إيجابى على عمليات الاستكشاف والتنمية فى منطقة الدراسة.

ABSTRACT: *There are many approaches and concepts for the exploration and development of the hydrocarbon reservoirs. In this study, the aim is predicting the gas volume which is a multiplication of the effective porosity with hydrocarbon saturation. Predicting the gas volume away from the wells is a challenging task because of the non-uniqueness in its relationship with the conventional seismic attributes. A conjunction of a set of seismic attributes obtained from multi-linear regression technique with the non-linearity of artificial neural networks techniques can be utilized to develop effective workflows to explore the reservoirs and evaluate hydrocarbon presence. Insufficient wells in the studied area led us to develop lithology classification workflow to increase the reliability of predicting gas volume probability cube over the studied area. Within the studied area, which covers around 660 square km, reservoirs are mainly Pliocene slope channel system and consist of a succession of sandstones and mudstones organized into a composite upward finning profile. The matching in the presence of gas volume in the sand classes comes up with a possibility of prospect evaluation at each location inside the 3D seismic coverage. Results suggest that the application of the proposed neural network method leads to reliable inferences and has a positive impact on the exploration or development over the area of study.*

INTRODUCTION

Hydrocarbon exploration of the deep-water Tertiary basins in the studied area have three problems: (1) reducing the risk of finding productive sands, (2) delineating the boundaries of these gas-bearing sandstone reservoirs and (3) well wrap-up the Pliocene development plan before/and success the exploration of the un-drilled Messinian system, which is more differ than the Pliocene concept. Neural-network analysis can perform an effective role to derive a non-linear relationship between the seismic data and its various seismic attributes with the target gas volume (Russell et al, 2001). This method can circumvent the general nonlinearity among the seismic-log relationships and, do not require a deterministic model algorithm. Neural networks are adaptive systems, which can map the input seismic attributes directly into corresponding output log properties. The applicability of the Gas Volume predicted using this method is found to be quite effective for further reservoir characterization and production planning operations. We applied this approach to the 3D seismic-amplitude data sets of the offshore Nile Delta, Egypt. Results show that, the probabilistic neural network estimation of reservoir properties has proven to be effective in significantly improving the accuracy and vertical resolution in the interpretation of the reservoir (Carmen, 2015).

The studied area:

The West Delta Deep Marine (WDDM) concession lies 50-100 km offshore in the deep water of the present-day Nile Delta, covering 1850 km^2 of the northwestern margin of the Nile cone, in water depths ranging between 500 and 1500 m (Figure 1).

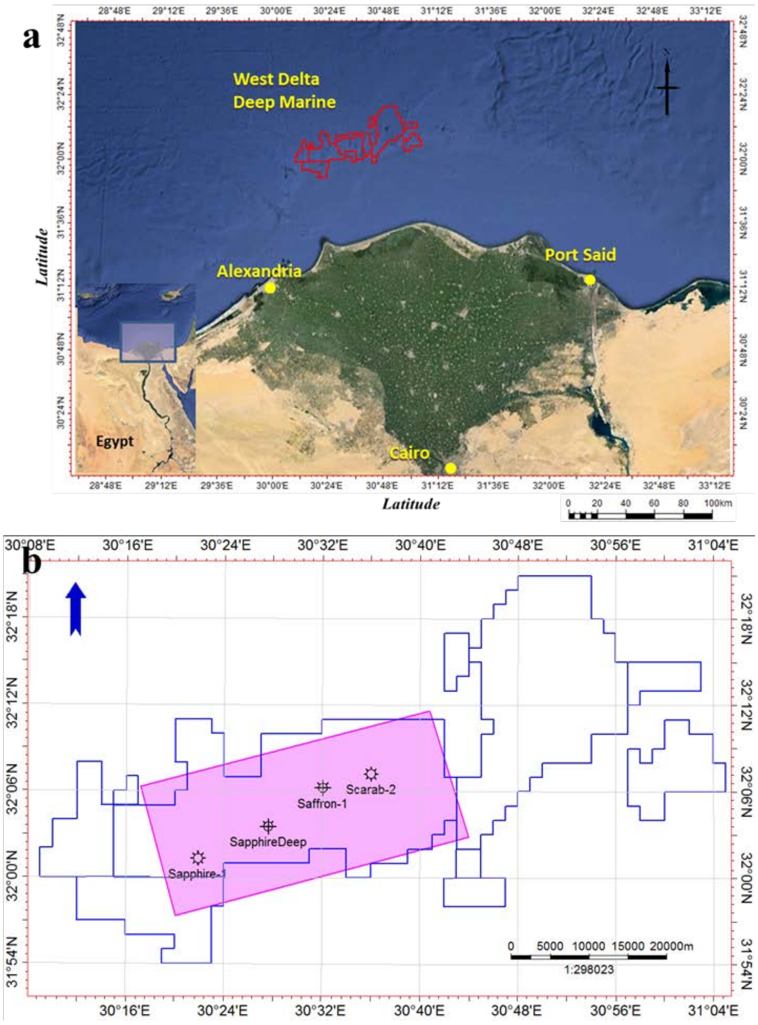

Figure (1): (a) A map showing the location of West Delta Deep Marine concession, modified from Google Earth, and (b) The studied area location map.

The study are attains around 660square km and covers most of the WDDM's important fields; from West to East: Sequoia, Sapphire, Scarab, Saffron and Serpent fields. In 2010, the U.S. Geological Survey (USGS) estimated means of 1.8 billion barrels of recoverable oil, 223 trillion cubic feet of recoverable gas, and 6 billion barrels of natural gas liquids in the Nile Delta basin (Kirschbaum, 2010).

The reservoir consists of a succession of sandstones and mudstones organized into a composite upward-finning profile. Sand bodies include e laterally amalgamated channels, sinuous pattern, channels with frontal splays and leveed channels, and are interpreted to be the products of deep-water gravity-flow processes. Above a major basal incision surface, the reservoir is highly sand prone and made up of laterally amalgamated channels. The medial section of the reservoir is more a gradational and exhibits laterally isolated and sinuous channels. Within the upper part of the reservoir, and channels are smaller, straighter and built of individual channels, associated with frontal splay elements and less common leveed channels. The main channel system is buried by a prograding slope succession, that includes lobate sand-sheet elements (Nigel et al., 2009).

The major structures within the WDDM concession are the northeast-southwest trending Rosetta fault, the east northeast–west northwest trending Nile Delta offshore anticline (NDOA) and the rotated fault blocks to the Northeast (Abdel Aal et al., 2001). All have been active at various periods during the Pliocene and Pleistocene, but have not had a major impact on the depositional geometries of the Upper Pliocene channels, which can be traced in the map and seismic sections, without significant thickening or change in the sedimentation style across these features (Samuel et al., 2003).

Lithology Characterization and Gas Volume Prediction:

Four exploratory wells are used from the channel-fill sandstone reservoirs. All the wells are vertical and have a full suite of wire line logs over the reservoir interval. Figure (2) shows an example of the well logs and reservoir stratigraphy at Scarab-2 well.

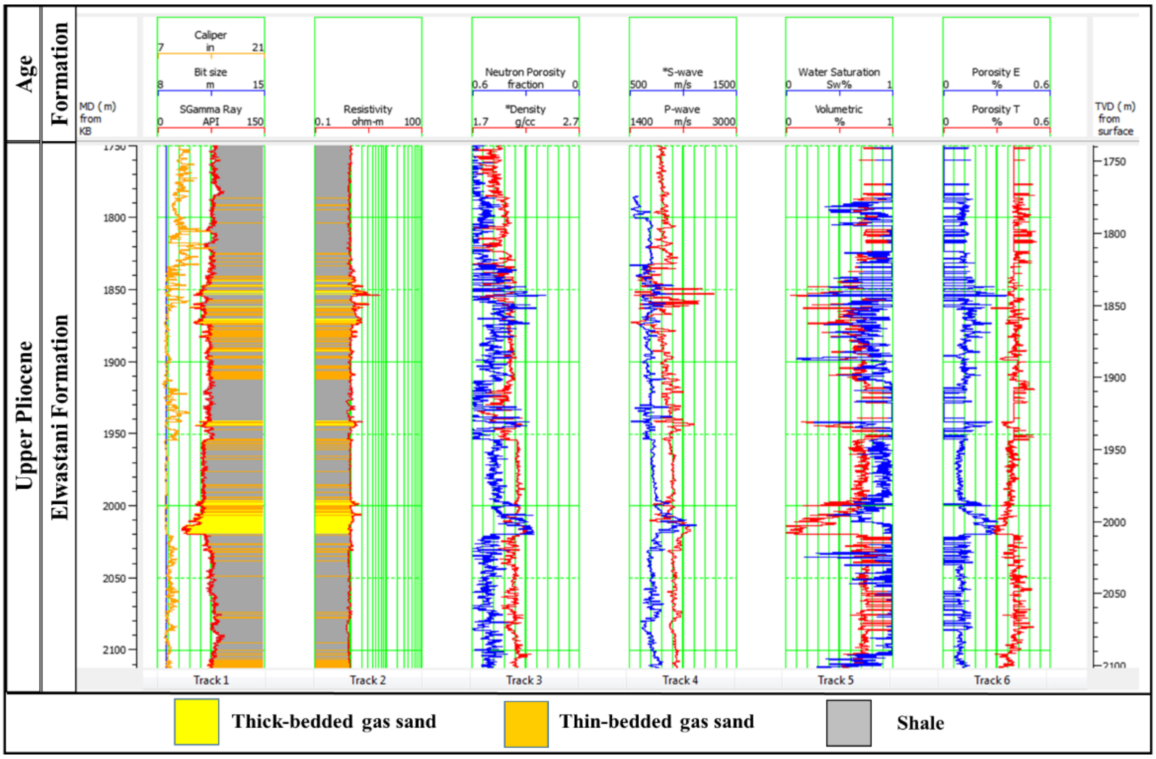

Figure (2): Stratigraphy and representative well logs of El Wastani Formation at the Scarab-2 well location.

The seismic amplitude data, which is used in this study, consist of full offset stack with a recorded duration of 6 second and sampled at 4 ms. No seismic data conditioning required prior the workflow. Special conditioning steps were applied to the well logs, including reconciling sonic logs with check-shot data and re-sampling well logs at the seismic scale.

Neural network (NN) is a mathematical algorithm, which can be trained to solve a problem, which would normally require human intervention (Haykin, 1999). The main advantage of the NN, over most traditional estimation methods, is their ability to determine a nonlinear relationship between seismic properties and well log properties. This can be done by generating seismic attributes, that are physically related to the reservoir properties and combining these attributes to predict the petrophysical properties of the reservoir (Hampson et al., 2001). The combination of the attributes can be done using either multi-linear regression or neural network analysis. Once we have derived a relationship between the attributes and the petrophysical parameters, these log properties can be extrapolated through the seismic volume.

The procedure involves four main steps:

1. The first step involves well data conditioning to make the well data consistent with the seismic data and preserve the relationships between them and prepare the target well logs to supervise the learning of the neural network.
2. In the second step, we find the best set of attributes, which will predict a given reservoir parameter, using the technique of multi-linear regression. The regression is applied between the training values at the wells and the seismic attributes with the lowest prediction error.
3. In the third step, the order and number of attributes are found, using multi-linear regression, are input to a neural network algorithm for further training.
4. In the fourth step, the cross-validation, in which we remove wells from the training stage and then “blindly” predict these wells in the validation stage.

In this study, as can be seen in Figure (3), this procedure had been applied with two different workflows; the first one consists of the seismic and well logs to derive the gas volumes, and the second one is to derive lithology cubes. The lithology log is a calculation from volume of clay log (Vc) and water saturation log (Sw), according to the petrophysical cut-offs Table). Another calculated log is the gas log, which is hydrocarbon saturation times of effective Porosity (Amit, 2012).

In the linear mode, the transform consists of a series of weights, which are derived by least-squares minimization. In the non-linear mode, a neural network is trained, using the selected attributes as inputs. As illustrated before in Figure (3), the multi-attribute linear regression is an essential step to find out the best set of attributes, which can be used by the neural network or otherwise, it can stand alone to produce the desired log volume.

Table (1): Lithology log cut-offs for the volume of clay and water saturation.

Class no.	Class name	Vc	Sw
1	Gas Sand	0-35	0-70
2	Shaly sand	35-60	0-70
3	Water sand	0-60	60-100
4	Shale	70-100	0-100

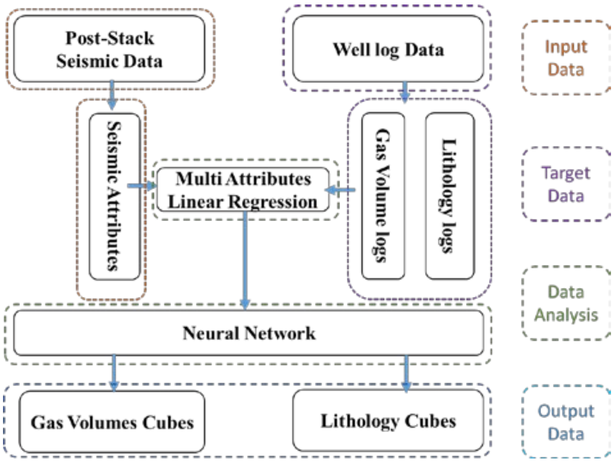

Figure (3): A flow diagram showing the first detailed neural network workflow for the Gas volume and lithology Cube.

To find the combinations of attributes, which are useful for predicting the target log, we use a process called step-wise regression (Russell, 2004): through finding the single best attribute by trial and error and calculating the prediction error then the best attribute is the one with the lowest prediction error. The second step is finding the best pair of attributes, assuming that the first member is a previously chosen attribute. The best set of attributes for the multi-attribute analysis consists of 4 attributes derived from the seismic trace for gas volume log and 6 attributes for lithology log. Some of these attributes were excluded, as they cause incoherent errors and patches in the output volumes. Figure (4) shows the Gas Volume log of Saffron-1 well versus the seismic attributes. Note, an attribute such as the instantaneous phase (zigzag curve, far right) may cause serious errors due to its "nervous" nature.

Another important parameter is the convolutional operator, which is used to overcome the fact that, the frequency content of the target log is typically much larger than the frequency content of the seismic attributes. So, simply the cross plot regression is extended to include the neighboring samples. Each target sample is predicted using a weighted average of a group of samples on each attribute.

This process is equivalent to applying the method to a series of shifted attributes (Hampson et al., 2001). The minimum validation error occurs when a 5point operator is used with 7 attributes. Any other combination results a larger validation error. Figure (5) shows the validation error plot for gas volume log for all the wells. By using this plot, we can determine the best number of attributes and the operator length for each log. Table (2) shows the outcome of the step-wise regression attained, using a 5-point convolution operator. The numbers of the attributes and operator lengths for each target log are calculated and ready to be used by the neural network analysis. These attributes can be used alone without the neural network to produce the reservoir parameters volume.

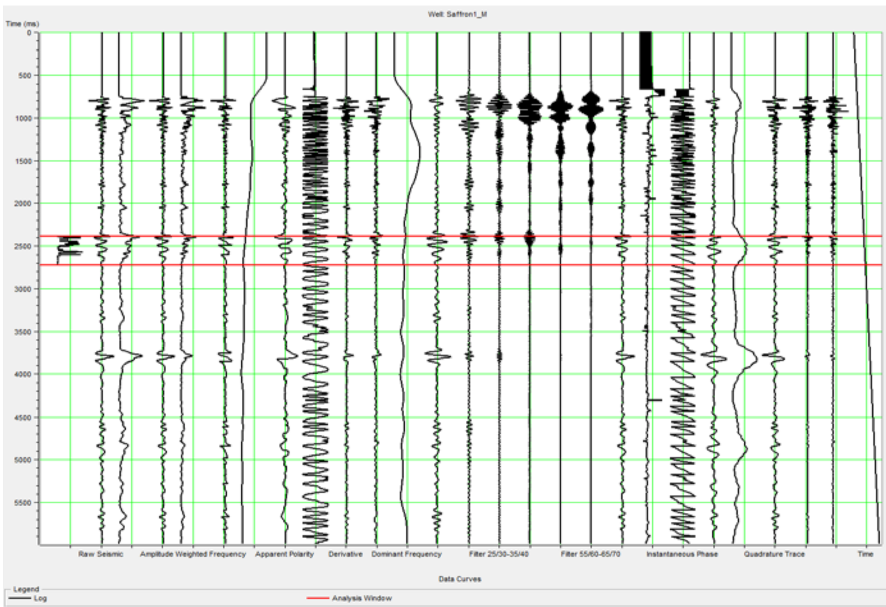

Figure (4): Gas volume log for Saffron-1 well versus examples of seismic attributes, the red lines are showing the reservoir zone.

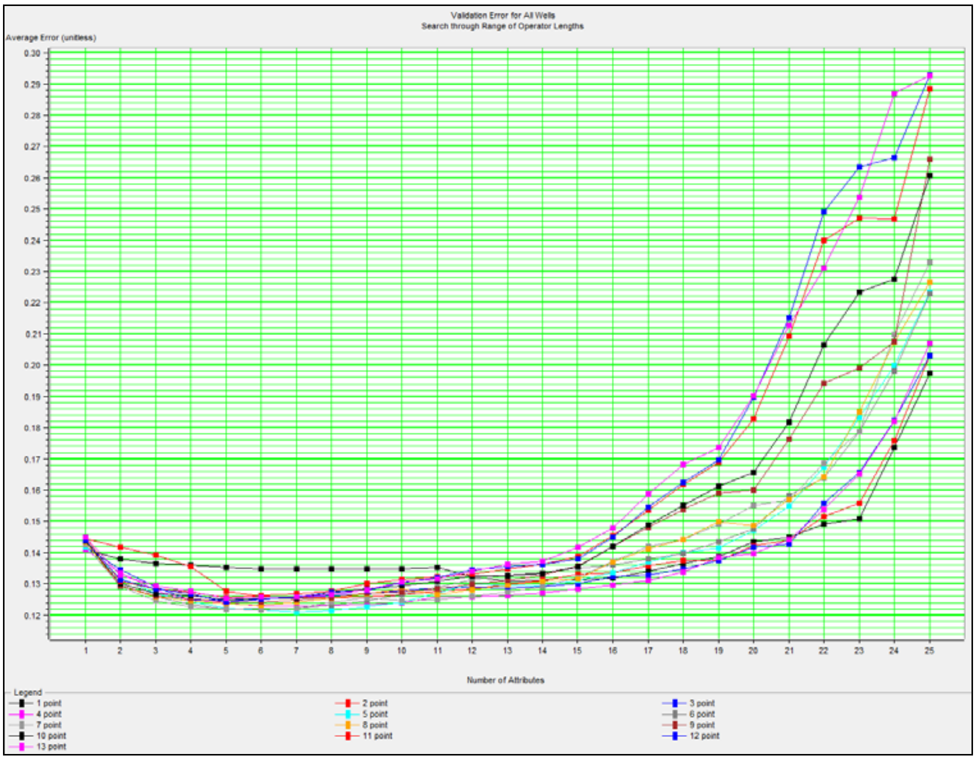

Figure (5): Validation error plot for the different operator lengths. The minimum Validation Error occurs when a 5 point operator (Cyan curve) is used with 7 attributes.

Table (2): Step-wise regression results. The minimum Validation Error occurs with the seventh attribute (Filter 25/30-35/40).

Final Attribute	Training Error	Validation Error
Amplitude Envelope	0.125832	0.141597
Quadrature Trace	0.109750	0.131916
Apparent Polarity	0.102012	0.126947
Integrated Absolute Amplitude	0.098307	0.124366
Instantaneous Phase	0.096238	0.122187
Derivative Instantaneous Amplitude	0.095351	0.121630
Filter 25/30-35/40	0.094254	0.120856
Filter 55/60-65/70	0.094061	0.121409
Cosine Instantaneous Phase	0.093073	0.122543
Second Derivative Instantaneous Amplitude	0.092656	0.124158
Filter 45/50-55/60	0.092346	0.127125
Second Derivative	0.091911	0.129772
Integrate	0.088569	0.129522
Derivative	0.088348	0.129277
Amplitude Weighted Cosine Phase	0.088337	0.131046
Filter 35/40-45/50	0.087293	0.133468
Filter 15/20-25/30	0.085017	0.137040
Average Frequency	0.084544	0.139878
Dominant Frequency	0.083086	0.141542
Amplitude Weighted Phase	0.082767	0.147069
Instantaneous Frequency	0.081372	0.154842
Raw Seismic	0.090900	0.167416
Filter	0.104161	0.183256
Amplitude Weighted Frequency	0.088772	0.199800
Time	0.091608	0.223357

Table (3): show the full results of the Neural Netwok for each target log.

Target Log	**Neural Network**			
Gas volume log	MLFN (Predicting)	training	correlation	0.939
			error	0.055
		validation	correlation	0.338
			error	0.200
	PNN (Predicting)	training	correlation	0.951
			error	0.048
		validation	correlation	0.427
			error	0.143
Lithology log	MLFN (Classification)	training	fractional classification error	0.274
		validation		0.58
	PPN (Classification)	training	fractional classification error	0.240
		validation		0.471

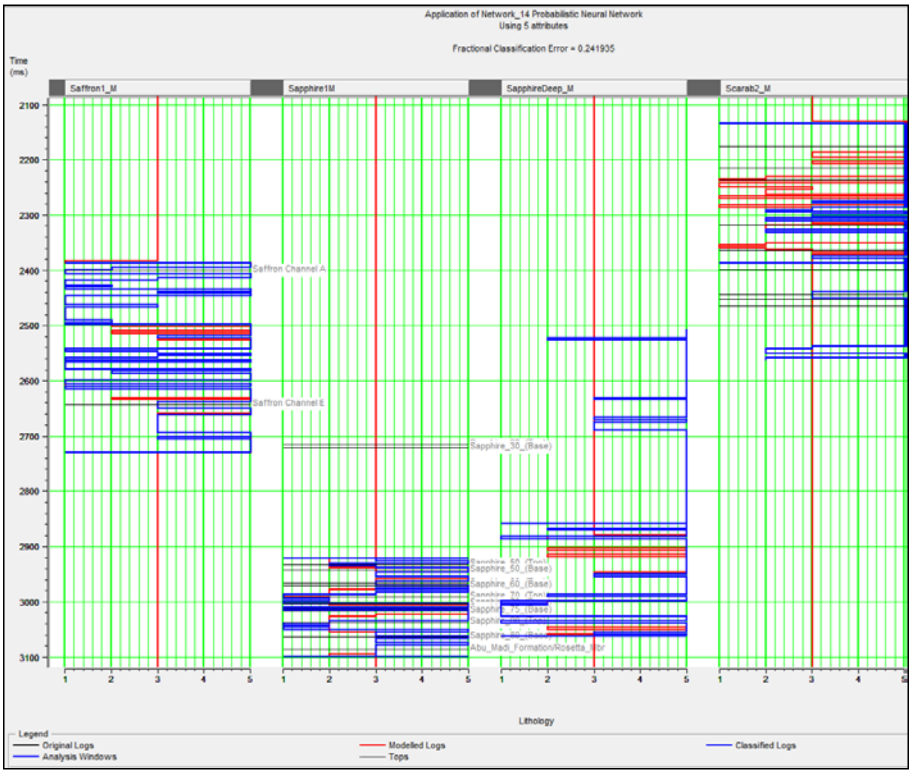

Figure (6): The application of the Probabilistic Neural Network. The classified lithology logs (in blue) and the predicted ones (in red), using all the wells in the training. The average fractional classification error for all the wells is 0.24.

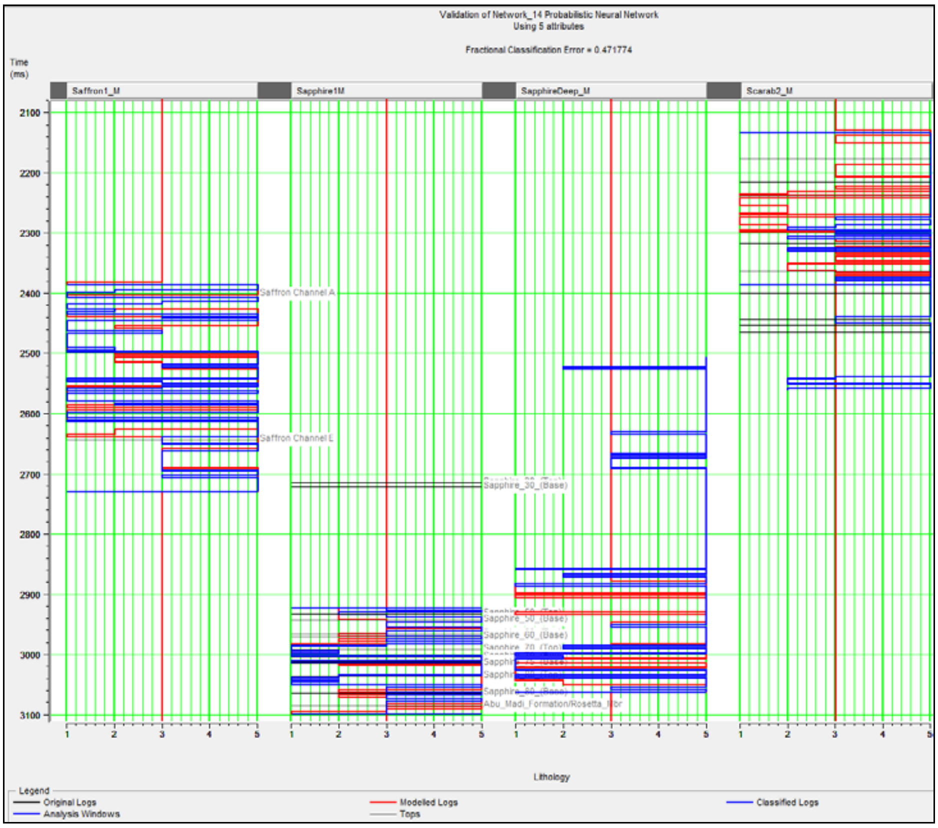

Figure (7): The validation of the Probabilistic Neural Network.The classified lithology logs (in blue) and the classified ones (in red), using all the wells in the training. The average fractional classification error for all wells is 0.47.

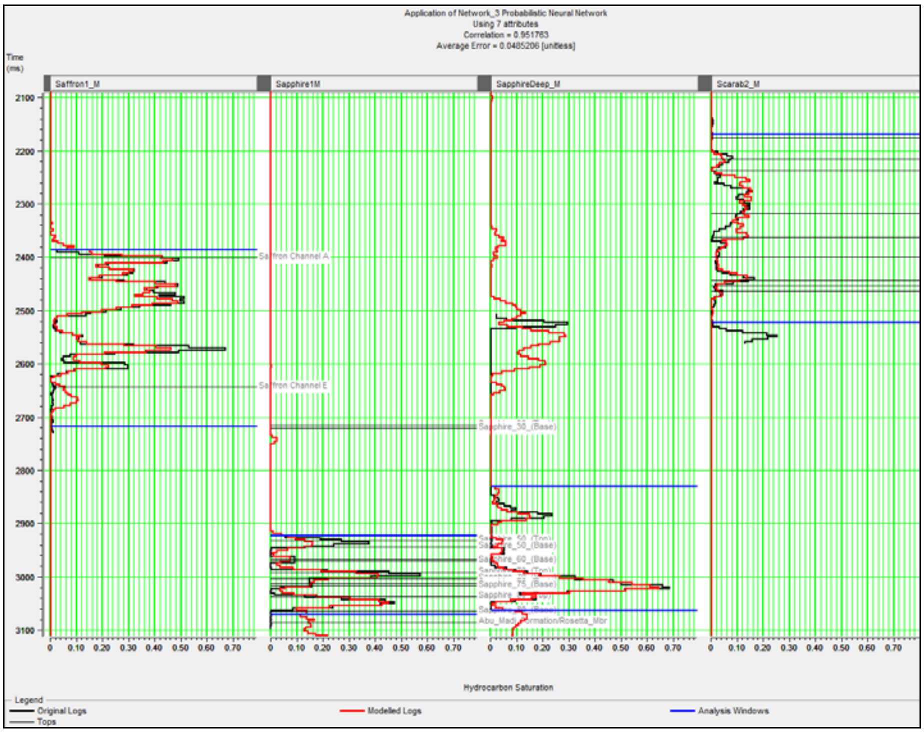

Figure (8): The application of the Probabilistic Neural Network. The calculated Gas volume log (in blue) and the predicted ones (in red), using all the wells in the training. The normalized correlation coefficient for all the wells is 0.95.

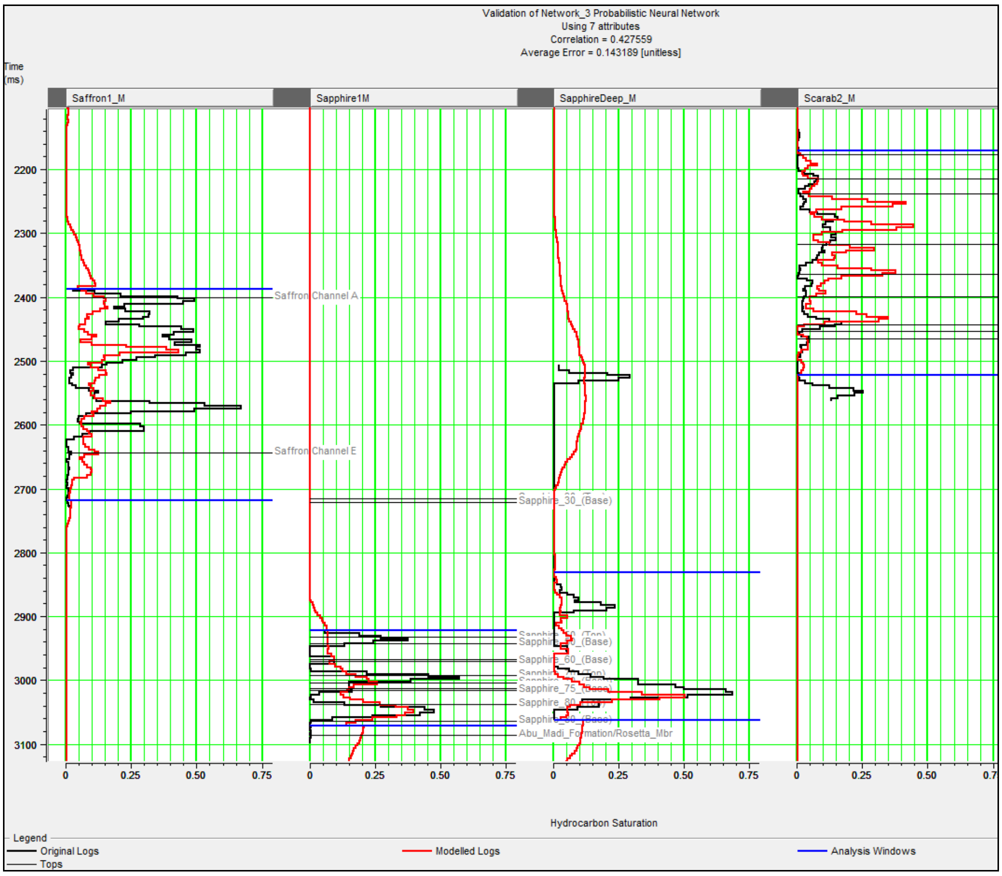

Figure (9): The validation of the Probabilistic Neural Network. The calculated Gas volume log (in blue) and the predicted ones (in red), using all the wells in the training. The normalized correlation coefficient for all the wells is 0.42.

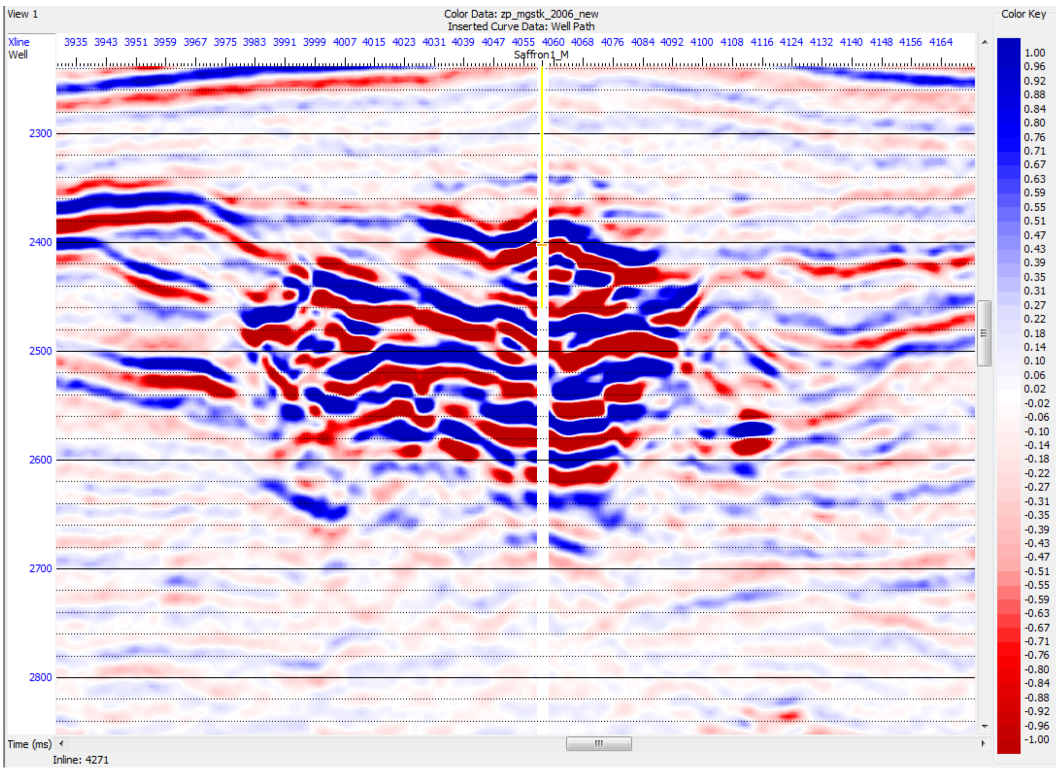

Figure (10): Inline of post-stack seismic cube through saffron-1 well.

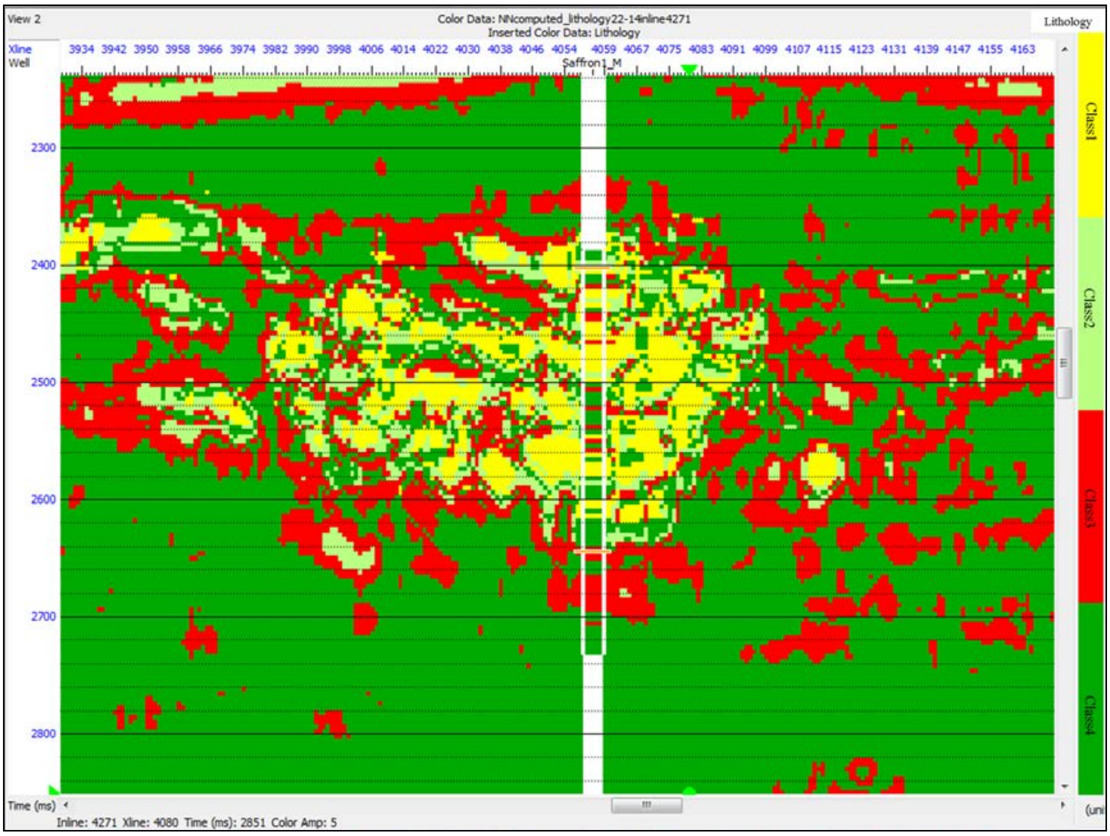

Figure (11): Inline of classes of lithology cube through Saffron-1 well.

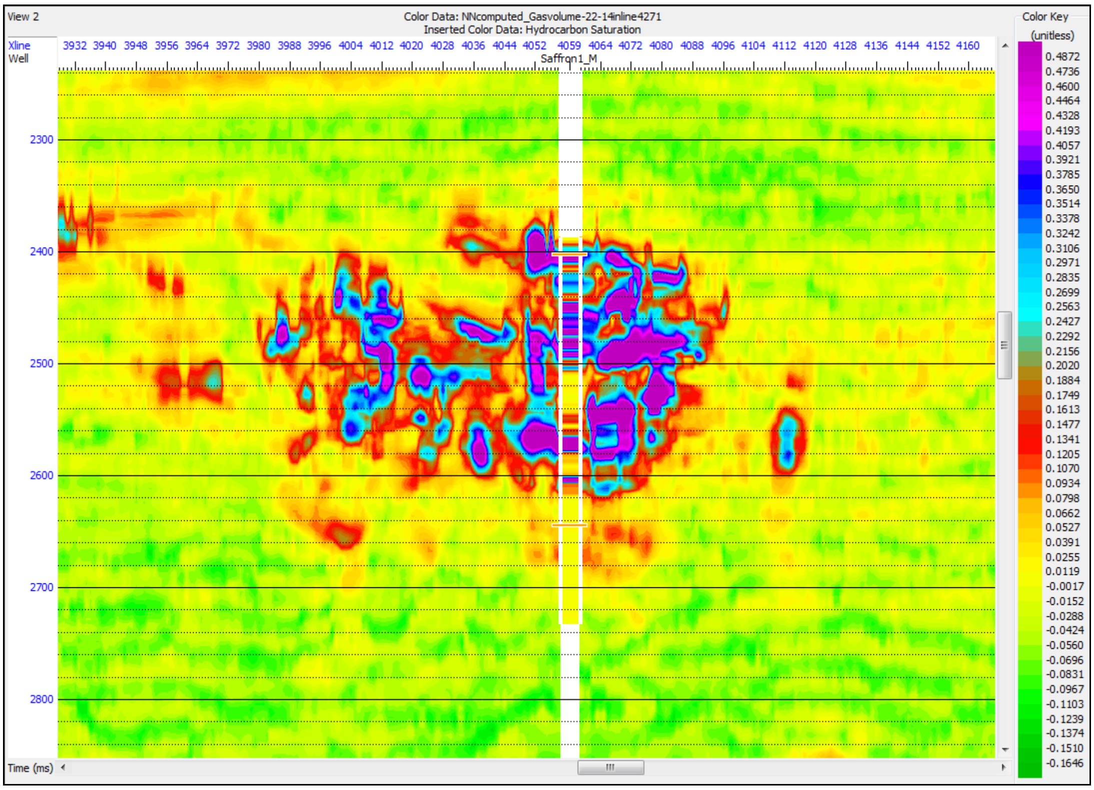

Figure (12): Inline of gas volume cube through saffron-1 well.

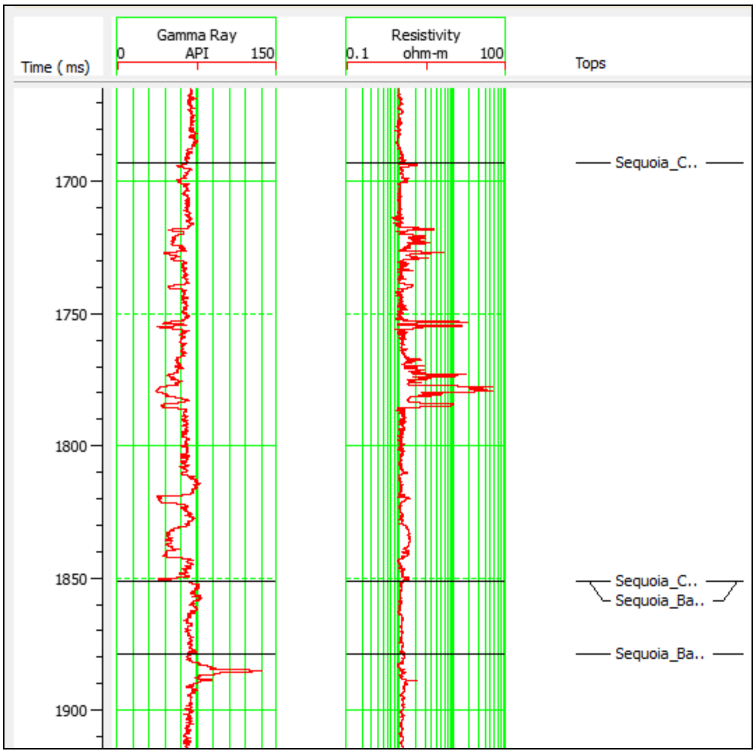

Figure (13): The sequoia tops on Sapphire-1 from 1692.96 to 1851ms.

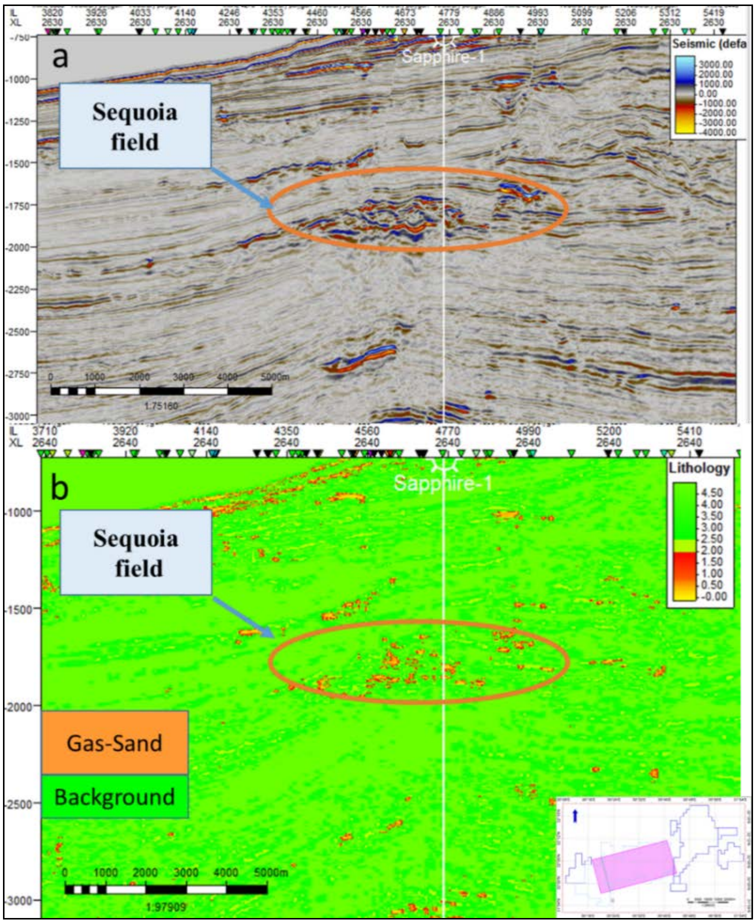

Figure 14: (a) The seismic xline 2630 and (b) the line on "gas lithology".

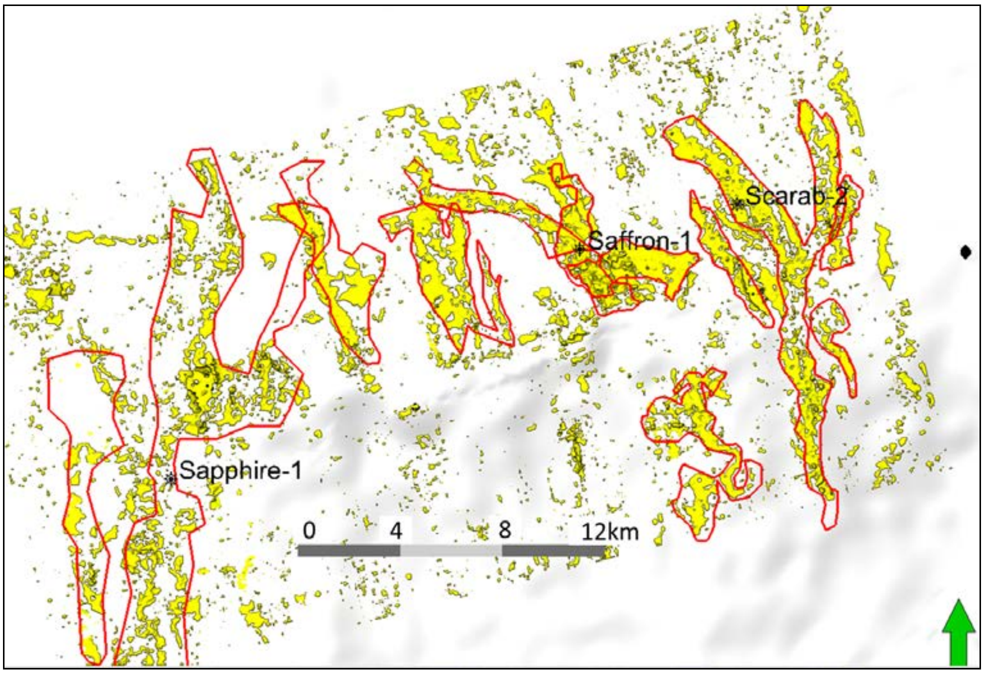

Figure (15): 2D map view for "gas lithology" and highlights the main WDDM fields.

The Multi-Layer Feed Forward Neural Network (MLFFN) and the Probabilistic Neural Network (PNN) were applied to the target logs with the best attribute set and operation parameter, after many trials with different parameters of the Neural Network. It's noticed that, the Probabilistic Neural Network (PNN) is better for both target logs; gas volume log and lithology log. This is because, the PNN contains a copy of all the target data within its operator, and hence the prediction results are always higher than the case with linear regression. Mathematically, this is analogous to kriging, in which the derived maps will always honor the input well information; in which the real measure of performance is the cross-validation. Table (3) shows the full results of the MLFN and PNN for each target log. The PNN approach gave a better result in classification lithology log and predicting gas volume.

Figure (6) shows the application of the probabilistic neural network. The classified lithology logs (in blue) and the predicted ones (in red) use all the wells in the training are noticed. The fractional classification error for all the wells is 0.24. Figure (7) shows the validation of the probabilistic neural network. The fractional classification error for all the wells is 0.47. These fractional error is reasonable in comparison to Russell's study (2004),Where he also applied an example to porosity classification over Blackfoot oilfield in Alberta, Canada. By using three wells, the maximum distance between the two wells is 3000 meters and the fractional classification error in training is 0.185 and the validation error is 0465. Our example applied to regional fields, where the maximum distance between two wells is 24900 meters and the results are near to what he had found.

The same work flow was applied to predict the gas volume log; the only difference is that, we are using the predicting algorithm instead of the classification. Figure (8) shows the application of the probabilistic neural network. Note that, the calculated gas volume log (in blue) and the predicted ones (in red), using all the wells in the training. The normalized correlation coefficient for all the wells is 0.951. Figure (9) shows the validation of the probabilistic neural network. Note that, the calculated gas volume log (in blue) and the predicted ones (in red), using all the wells in the training. The normalized correlation coefficient for all the wells is 0.42.

Now we have two trained neural networks; the first one is the probabilistic neural network classification, which used to classify the output lithology log; the second is the probabilistic neural network predicting-based, which used to predict the gas volume. The two trained neural networks are ready to be applied to the whole seismic volume to produce a lithology cube and gas volume cube. Figure (10) showsan inline post-stack seismic cube through Saffron-1 well. Figure (11) shows an inline of classes of lithology cube through Saffron-1 well. Figure (12) shows an inline of gas volume cube through Saffron-1 well.

As a direct application of the resulted volumes, we combine them together to get what we can call "Gas-Lithology" volume. The combination process includes filling the gas volume's values in the gas-sand class, which comes from the lithology classification volume. The best case for validation is testing the results, using a "blind" section. In our case, the shallow Sequoia field wasn't included in the study. Sapphier-1 well penetrated

Sequoia field from 1438.5 to 1586.5 MD (from 1692.96 to 1851ms in the TWT),as shown in Figure (13.Note the high values of resistivity log, which indicate gas sand. Figure 1 (a) shows the x line 2630 on the seismic volume, and (b) the same x line on the “Gas-Lithology” volume. Figure (15) shows a 2D map for the “Gas-Lithology” volume at El-Wastani level. It high lights the main WDDM fields.

CONCLUSION

The main aim of the paper is the lithology characterization and Gas Volume Prediction by characterizing the Pliocene gas sandstone reservoir. We’ve found that, the best way to do that is using the artificial neural network analysis with two different workflows. The two workflows aim to predicting the gas volume probability cube and the lithology identification. Significant results come out of this research article after its three main phases of the work: data gathering, multi-layer feed forward neural network and probabilistic neural network analysis.

The analysis of all the results helped us to study the chance of success for many prospects. Another goal of this research paper is achieved through exploring new prospects and maturing the previous prospects. The blind field validation give us a good confidence of the results of this study. Two different neural networks were tested, along with the results of the multi-attribute transform. The results suggest that, the PNN is the best one to use.

Further investigation about the validity of the neural-network method is needed. The most limiting factor of the PNN method is the need for, at least, three wells for the training stage. The more well data available, the more reliable and accurate the neural-network results. Results suggest that the application of the proposed neural network method leads to reliable inferences and has a positive impact on the exploration and development over the area of study.

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