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Growing Application of Artificial Intelligence in Optimising Productivity and Efficiency in Oil and Gas

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Abstract. Machine learning through artificial intelligence have been successfully applied in solving variety of problems in several disciplines. In the energy sector, oil and gas industry there is potential and opportunities attract maximum investment. The benefits are (1) Reduction of operational costs, (2) Improvement in Efficiency, (3) Reduction of cycle time span, (4) Replacing knowledge and know-how of experienced staff, (5) Filling in information gap in company

A.I. Technology has tremendous potential in streamlining many processes in oil and gas both upstream and downstream.

The key benefit would be optimization and efficiency in scheduling, maintenance and product delivery. A.I. is also making inroads in Refinery Operations in corrosion detection and mitigation.

1. Introduction

Machine learning through artificial intelligence have been successfully applied in solving variety of problems in several disciplines. Its application in oil and gas has been until recently lukewarm. In the energy sector, oil and gas industry is fortunate to attract maximum investment. This has been justified by high return on investment.

However, with oil price dropping from a staggering USD 100/bbl or more to a record low at USD 40/bbl, and the industry is still recovering from this collapse.

In a way this is a kind of wakeup call where now there is a realization that if things are expected to turn around, the following has to happen :

- Reduction of operational costs
- Improvement in Efficiency
- Reduction of cycle time span
- Replacing knowledge and know how of experienced staff .
- Filling in Information Gap in Company.

In an interesting article by Kumba Sennaar (2017) quote that several oil major companies are investing heavily on artificial intelligence technology. As these technologies are not the forte of these companies, they are likely to team up with IT specialist or outsource to Universities or Research Institution to provide them with solutions.

1.1. Field of application in Oil and Gas

In reality, the Petroleum industry is ideal playground for A.I. technology.

The reasons are:

- Financially, the petroleum industry can afford to invest heavily on 'system' that can be self-learning as a return of benefits which can be substantial
- The industry is blessed with a lots of '*big data*' that is good for machine learning
- The data appears to be incomplete or sometimes unreliable and Fuzzy also good for self-learning.
- As a self-learning system or machine or Deep learning can possible detect a 'pattern' that has been overlooked when evaluating manually.

The two main components in the Oil and Gas Industry are:

1.1.1. Downstream.

This part deals with Oil and Gas downstream large number of operations and processes are massively routine and repeatable. As such there is a case to be made for automation and optimization. This situation is ideal for Robotic technology to perform in an organized manner and faster leading to processes being streamlined leading to better productivity. With human intervention as and when needed

In the Oil refinery system, hydrochloric acid attack is one of the possible causes of erosion and wear to equipment used in refining the gas. Besides that, unmanaged or unmitigated problem of presence of salt water in the crude oils could lead to serious formation damage. Proper detection system is needed to alleviate the problem and subsequently avoids short-term and sudden failure of equipment and cumulative formation damage. Corrosion monitoring and prediction is one of the important elements of any effective corrosion management and mitigation strategy. The monitoring is essential in verifying the effectiveness of predefined mitigation processes.

Even though there are existing methods in monitoring corrosion occurrence, it presents two major weaknesses. First, most of the commercially available solution are intrusive in nature. This could lead to risk of loss of production and complete well due to the mechanical damage from the equipment used. Second, existing solutions are also localized and not equipped with real time monitoring capability. The operator still needs to be near the monitoring device in person and download the data manually.

One of the consequences from this activity is the cost needed for hiring personnel to manually collect the data from the devices. The absence of ability to predict the corrosion occurrence also inhibit any proactive actions to prevent accidents due to unmitigated corrosion. Hence, the development of an AI online corrosion monitoring system is vital to address the above issues. The proposed online corrosion monitoring system will consist of non-intrusive technology which will not affect any production process. It will also be able to intelligently identify the signal signature of corrosion presence using customized Artificial Neural Network (ANN).

This intelligent system will be able to provide predictive analytics which is essential in preventing sudden changes to the integrity of the refinery equipment go unnoticed. This system is also able to predict the corrosion occurrence using the existing parameters that are being measured in the refinery.

The customized ANN is trained using real time data feed from the sensors attached to overhead condenser. Due to the customization done, the weights in the training phase can adapt to the nature of equipment, thus, providing a much more accurate prediction and forecast in comparison to existing implementation of ANN.

1.1.2. ***Upstream****.*

In the upstream channel of business, there has been several fields where AI specifically 'Neural Net' technology has already played a role, such as:

1.1.2.1. Petroleum engineering.

- Infill drilling location in field development
- Optimizing reservoir production
- Reservoir surveillance (Time-lapse)
- Production History Matching. Both from production data and prediction from Seismic Time lapse Reservoir Survelance

1.1.2.2. Petroleum Geoscience.

- Characterizing the unknown complex geological subsurface requires integration of various disciplines such as Seismic, Geology and Petro-physics.
- Usage of AI in characterizing Geological Facies.
- Key parameter desired in P.E are Porosity(Phi) and Permeability (Kv Kh)
- They define the productivity and flow rate of the producing reservoir
- Using neural network to predict Hydrocarbon Saturation from Seismic and Petro and Rock -physics.

Given the vast amount of data available from geological analysis, well log information, seismic analysis, it is next to impossible to manually manage the data, let alone to meaningfully interpret it to find the connectivity for future prediction.

AI is the best method to 'unlock' the complete relationship and find the best solution which usually difficult to find by using a single algorithm. Due to many variables and not enough equation, neural network are 'brain neuron' and act as the key is to find interconnection of the neurons or nodes.

Neural network is an artificial intelligence method which attempt to mimic the way human recognize and remember the pattern. Neural network consists of three major layer of nodes; *input, hidden and output*. Input and output are only one layer meanwhile hidden layer can be made up by more than one layer (Wang, 2003) (Fig. 2). Neural network is basically made up of various architecture and algorithm such as feedforward (An et al., 2001), fuzzy (Kovalevsky & Denisov, 1997), back propagation (Guo et al., 1992), probabilistic (Thadani, 1994), Kohonen self-organizing (Addy, 1998) and hierarchical clustering (Conticini, 1984).

In Exploration and Development phase, human intelligence is of paramount importance. The upstream activities in exploration and production follow a workflow called life of field, described as follows:

Fig. 1. Workflow used in Petroleum often called as 'Life of Field'. There a potential, that AI can play a significant role in each step particularly in Exploration and Production.

The acquisition of seismic data in both land & sea and difficult to access. AI can play a significant role by streamlining it and significantly reduce time and cost. The land acquisition over vast inaccessible area is a time consuming difficult process could be streamlined.

Significant discovery of petroleum is in offshore area, sometimes in deeper water to the tune of 1- 3km water depth and vast stretches of oceans. Satellite data in the past has been used to detect oil slicks for possible hidden petroleum reservoirs leaking due to poor reservoir seals. Automated systems can be used for this reconnaissance survey to narrow down sweet spots making significant reduction in work activities . Some major Petroleum companies are report to be interested in this technology.

1.2. Neural Network

A neural network consist basically of three part as shown in fig. 2. The unit are commonly termed as 'Nodes' comparable to 'neuron' in brain. All the hidden nodes receive information from all input nodes that guarantee' connectivity' that aids processing the information.

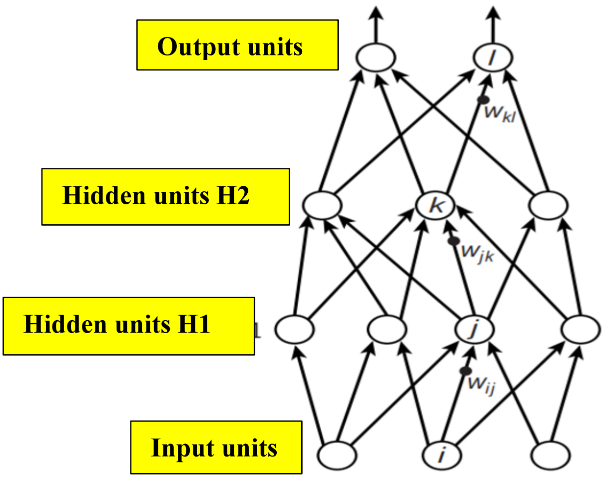


Fig. 2. Neural network architecture consists of input, hidden layer and output (Lecun et. al, 2015)

2. Determination of geological facies using neural network in classifying the Seismic waveform signature

The oil and gas exploration in the Malay Basin has focused on structural traps for decades with the structures such as faults and anticline act as main traps for the hydrocarbon accumulation and exploration. With depleting reserves the focus now on other traps such as stratigraphic. Recent attribute analysis has been able to identify abundance of channels that previously could not be imaged due to poorer data quality. (Ghosh et al, 2010.). The Malay Basin is a mature Tertiary extensional basin with a later inversion regime in the Late Miocene. The rocks are unconsolidated and geophysical techniques such as amplitudes and other attributes should work well (Ghosh et al., 2014).

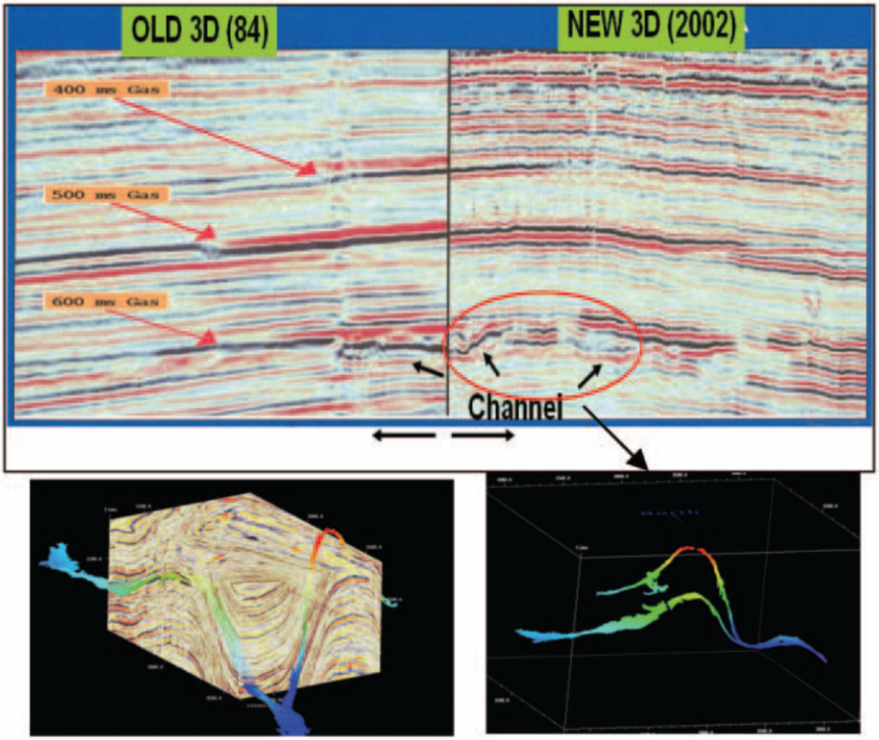


Fig. 3. Comparison of old seismic data in Malaysia Basin with new seismic. New 2002 data shows increased resolution and images channels missed on the older data. (bottom) Channels missed in the old data have prompted us to improve acquisition and processing efforts to chase potential stratigraphic plays. Bottom right shows an image of the channel missed. These advances lead to more realistic Reservoir model and better Production history matching (Ghosh et.al 2010)

Stratigraphic trap is also known for its complexity and difficulty to be identified using conventional seismic or well log data and deals mainly with the changes of seismic waveform. The changes in amplitude, frequency and phase of seismic waveform are usually small and unable to be detected using the interpreter's eyes (Fig 3). Hence, an automated clustering method or artificial neural networks are utilized in order to identify the small and subtle changes of the seismic character by classifying seismic waveform to multiple classes. The produced seismic facies map help to develop the understanding on depositional environment and facies of the study area which closely related to reservoir efficiency (Fig. 4). The productivity of a given well is depend on the geological environment of deposition that determines porosity and permeability to the reservoir (Pore-Permeability) in seismic terms each environment gives rise to a specific geological facies whish is identified by its "own" seismic signature or waveform. Later in the paper we will demonstrate how the neural net can detect this signature and hence determines the reservoir efficiency.

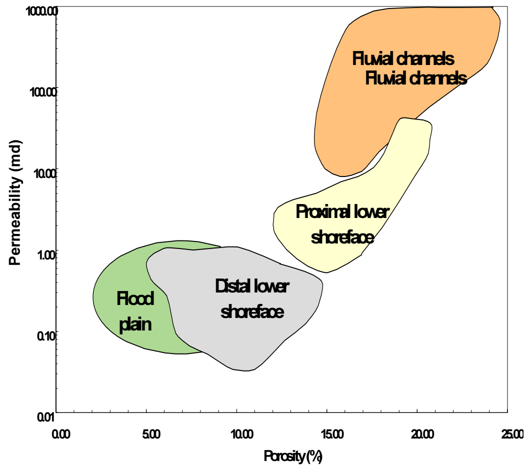


Fig. 4. A crossplot of Porosity vs Permeability, (key parameters) in defining reservoir productivity and efficiency of K reservoir at Malaysia Basin (Salih & Kadir, 1995).

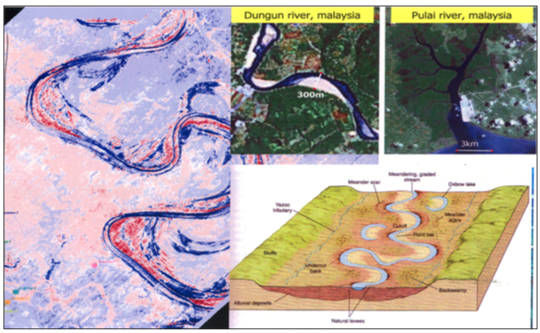


Fig. 5. Example of Stratigraphic channel in Malay Basin and its analogue in modern environment. The integration of modern and ancient example helps to develop the reservoir deposition model . This meandering channel can possibly be detected by Neural net as it has an unique pattern

3. Unsupervised Neural Net using Automated clustering .

Widely used in oil and gas industry especially for facies prediction, petrophysical prediction, seismic processing, imaging and interpretation. In this study, automated clustering method using Kohonen Self-organizing Map (KSOM), a type of neural network is utilized for classification of seismic waveform. A seismic waveform is a small portion of seismic trace that consists of one or several lobes that represent a single seismic reflection or a pattern of interfering reflections (Barnes, 2012) (Fig. 6). KSOM is one of the best automatic methods due to its ability to apply competitive learning to its neurons and input data. It is not bias to number of classes and be able to reduce the noise in seismic data with the help of other statistical approach such as Principal Component Analysis (PCA). KSOM helps to detect the small changes in seismic waveform morphology laterally and vertically. This meaningful change implies the important geological features such as channel, floodplain and point bars. It is also able to indicate the direct hydrocarbon indicator such as fluid contact and bright spots (Fig 7).

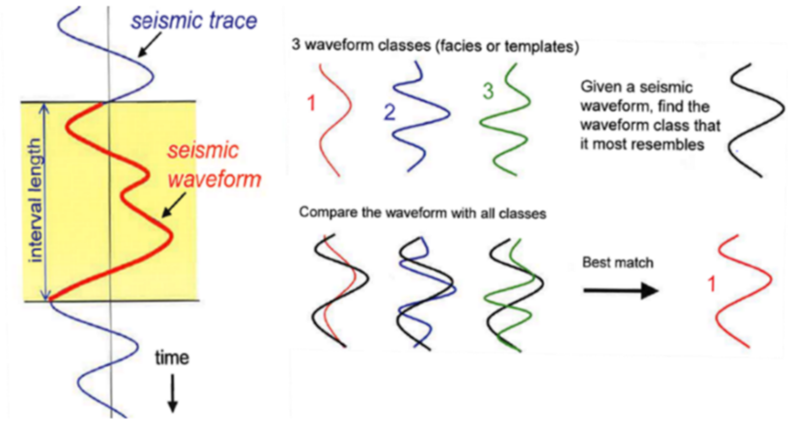
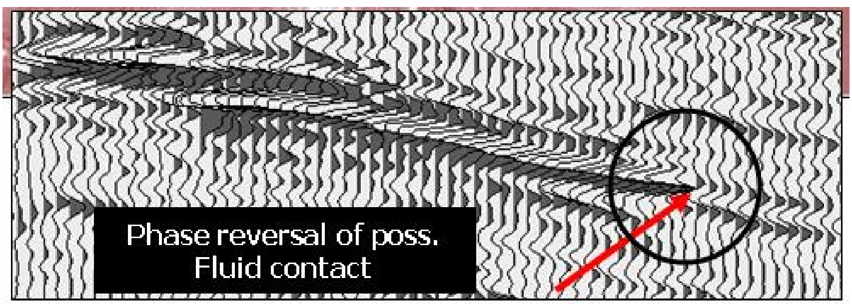
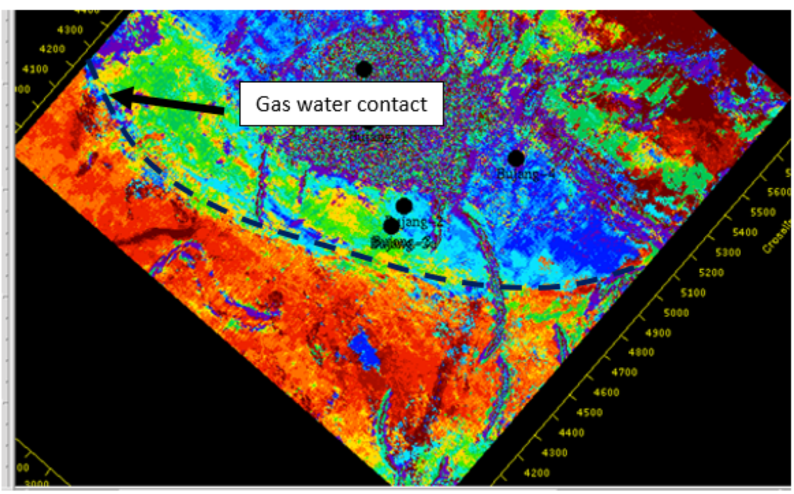


Fig. 6. The waveform classes/templates are identified during the training stage. Other waveform is being compared to the initial waveform classes and is clustered to the class it most resembles. (Barnes, 2012)

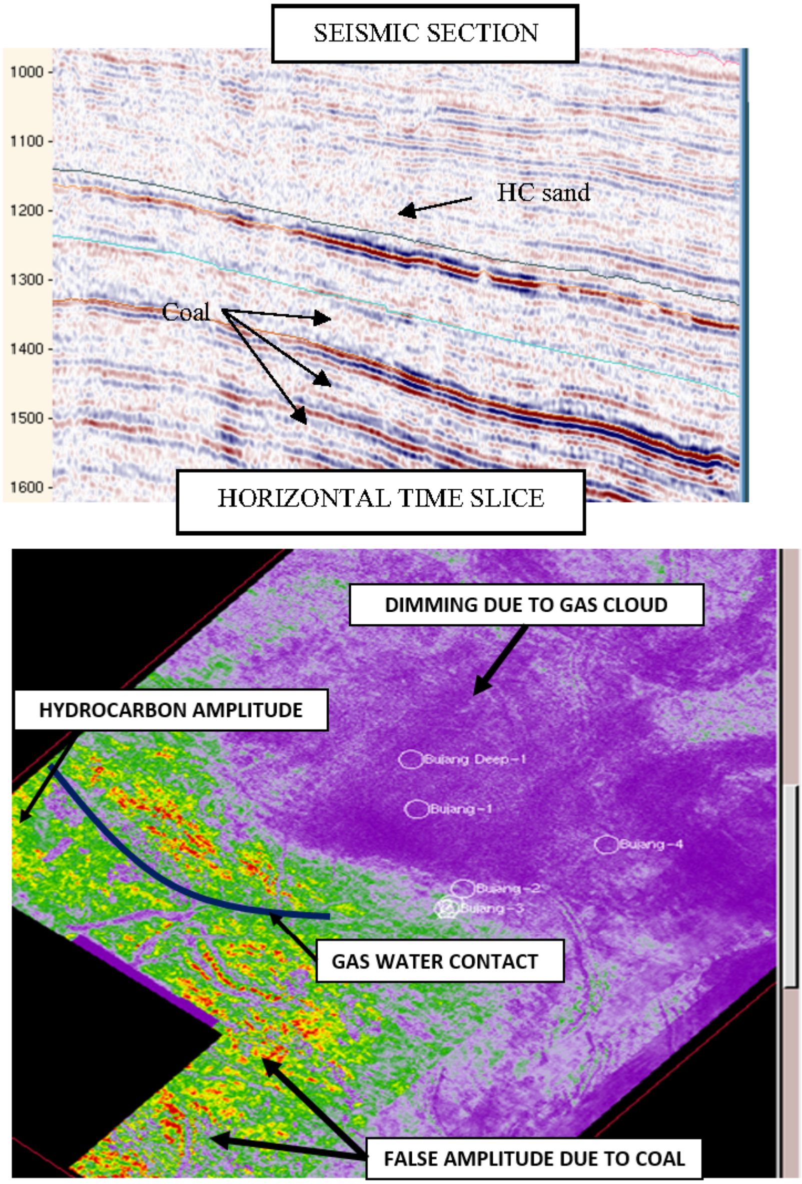


(a)



(b)

Fig. 7. a) Seismic signature is a direct hydrocarbon indicator as shown in above figure. Change in phase results in different signature (black circle) b) This possibly indicates a change in reservoir fluid (gas/oil to water or Gas/oil Contact) . This signature waveform can be use in an to track oil-water contact for future exploration.



(a)

(b)

Fig. 8. (a) Ambiguity due to coal bed is show in Figure 8a. Of the four bright spot are only the top one is due the presence of hydrocarbon. Rest is all coal as proven by D.H.I, AVO analysis. (b) Amplitude time slices of the hydrocarbon reservoir do not give a clear gas/water contact compared to Neural net using seismic waveform seismic waveform (Fig. 7.). Hence, seismic waveform A.I does a better job than traditional Amplitude/AVO

Seismic facies map offers a better visualization compare to conventional amplitude map due to its discreet color characters (Fig. 8). Neural network classification is the best method to be used especially to predict the geology without the presence of nearby wells. Each of the seismic facies classes can also be defined in term of geological facies by replacing one of the seismic classes with the known trace model at the well log location. This method is called as supervised classification and mostly used for well validation in this study. Unsupervised study consists of classification of seismic waveform without the introduction of trace model as the cluster center. The neural network will determine by itself the best trace model to be selected to represent the seismic facies class. Seismic waveform is also considered as one of seismic attributes. Ghosh et al (2014) classified seismic waveform as a structural attributes with ability to delineate fractures and faults. However, in this study, seismic waveform is not only used to define fractures but also geological features and hydrocarbon indicator, which play important role in exploration and development stage.

4. Self-Organizing Map

Self-organizing Map (SOM) or KSOM, a type of neural network is being used as main architecture for seismic waveform classification and identification. SOM is known as the best method for seismic waveform classification as it is

- The most robust method with the ability to naturally order the classes by similarity, and the easiest to be implemented (Barnes & Laughlin, 2002)
- Less sensitive to the number of classes and noise contributing to well definition of classes in sequence by preserving its topological nature (Coleou et al., 2003)
- Able to identify the isolated data cloud and intracluster organization of continuous cross plot which usually concealed by noise (Coleou et al, 2003).

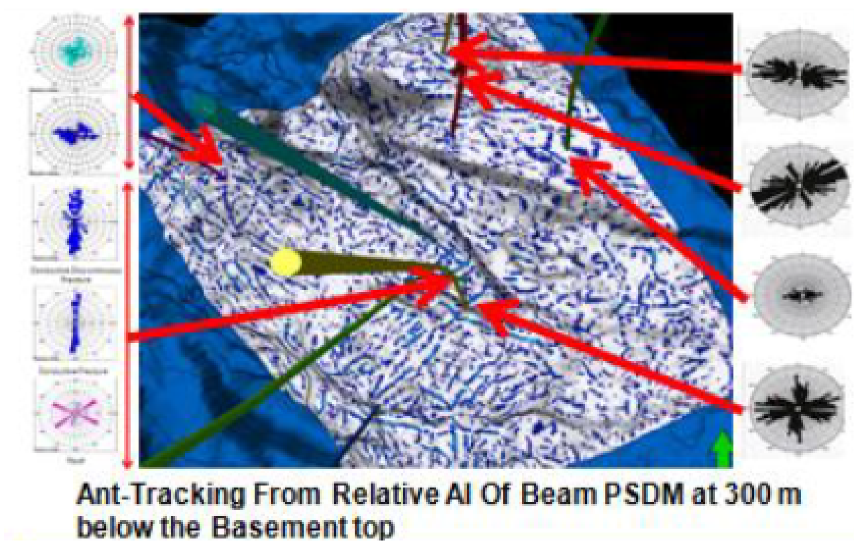


Fig. 9. Seismic could be used to predict fracture characters inside the Basement (Ngoc, 2012). Better delineation of fracture pattern is possible with the use of AI.

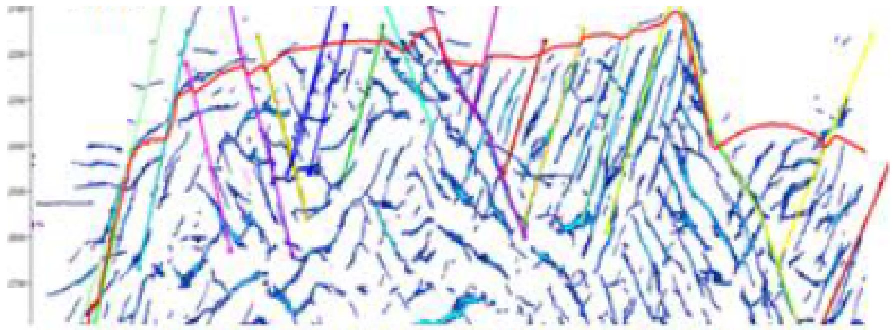


Fig. 10. In this project, artificial neural network is applied for waveform classification by using Strati magic software by Paradigm. The software use Kohonen Self-organizing Map (KSOM), a type of unsupervised neural network that convert multidimensional data to lower dimensional latent space (Kohonen, 2001).

4.1. Waveform Classifier Workflow

There are two stages in using neural network for seismic waveform classification; data training and propagation. The training stage is the class determination stage in which it "educates itself" using the data to identify discriminant patterns, and the class construction, where the discriminant properties are materialized in the form of a set of typical values, called classes. In this stage, a competitive process, also called as vector quantization or VQ is applied and closely related to SOM method. VQ is essentially used for data compression by dividing the large set of data into multiple data clouds with center point and same number of points closest to them. Before the training, neurons may contain some random weight or many input connections of related physical and geometric attributes combination such as coherency and amplitudes. The input are assumed to be represented by J vectors in a N dimensional vector space $R^n, x_j = [\, x_{j1}, x_{j2}, x_{j3} \dots x_{jN}]$ where N is the number of input attributes such as amplitude of seismic waveform and j=1,2,…,J is the numbers of vector analyzed. The algorithm organize the dataset of seismic attributes input into SOM structure in which neurons are transferred into lower dimensional grid such as 2D. This grid represents the dimension of input data within the same dimension of seismic attributes input and it usually preserves the neighborhood relationships between neurons. With 2D SOM represented by P neurons, $m_{i\,,} m_i = [m_{i1}, m_{i2} \dots, m_{iN}]$ where i= 1,2, …P and N is the dimension of neurons, equal to the input vectors. During training, the data points, x is randomly choose from input data set and is introduced to the neurons. After some number of iterations of data point presentation, neurons start to learn and cluster the data point to different classes. The training process change their individual weight values depending to the input data introduced. The distance between x and neurons is calculated to obtain the best matching unit (BMU). BMU is the map unit with the smallest distance m_bto data point x and is computed by Kohonen (2001).

$$\|x - m_b\| = min\{\|x - m_i\|\} \tag{1}$$

The learning process depends on the learning parameter and learning iteration also called as epoch. Usually the number of iteration during the training is higher compare to propagation stage. 50 iterations are commonly used during the propagation and 100 iterations during the training. The reason of high number of training iterations is to ensure the neurons are properly introduced to data point and possess the ability to be unique and contain discriminant parameter that are different from other neurons. Competitive learning in SOM is a training process in which the neighbor neurons is adjusted together with the neurons itself. Hence, for every iteration, the neighborhood radius decrease. The neurons that are closest to the data points are known as winning neurons and are classified as a class (Taner, 2001). The updating rule for the ith unit us given by:

$$m_i(t+1) = m_i(t) + \lambda(t)h_{bi}(t)[x - m_i(t)] \tag{2}$$

where t is iteration, λ(t) is the learning rate and $h_{bi}(t)$ is the neighborhood size centered at the winner neurons. The value of $h_{bi}(t)$decrease for every iteration and is represented by

$$h_{bi}(t) = e^{-(\|r_b - r_i\|^2/2\sigma^2(t))} \tag{3}$$

where r_b and r_b are the positions of neurons b and i in the SOM grid and $\sigma^2(t)$ is neighborhood width.

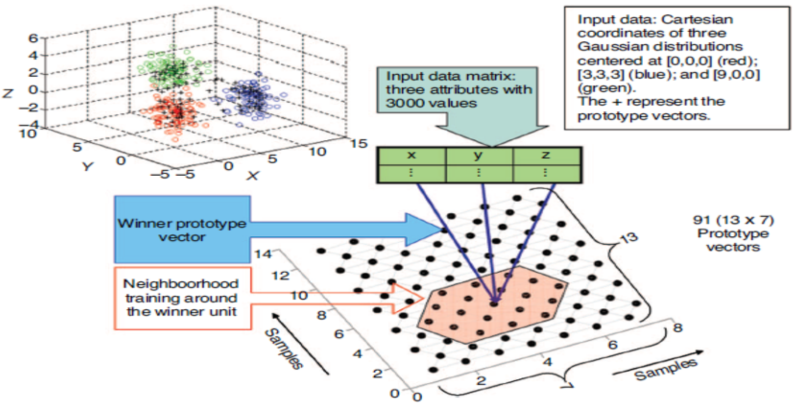


Fig. 11. The example of SOM application with the map of 91 (13x7) prototype vectors/neutrons using the coordinates of three Gaussian distributions in 3D space as input attributes (Matos et al., 2013).

4.2. Application of Neural Network

The seismic waveform classification using neural network is also known as trace-based method. Trace-based method uses the seismic waveform as the trace model for seismic class. Different trace shapes belong to different seismic class and these differences are commonly contributed by meaningful geological features or different depositional environment. The method is tested in a field, Malay Basin. Multiple seismic attributes are used in seismic waveform classification as the input. The trace models are being compared to the log motif of gamma ray such as coarsening upward or cylindrical in order to relate the seismic facies classes to geological features such as depositional environment and lithology value. The discriminant pattern or the winning neuron is best determined by the neural network itself without any introduction to the bias data such as in this case, the well trace. It is letting the system to decide which one is the best discriminant pattern for the overall traces. Within the time interval of -6ms+12ms , the multiple seismic attributes volumes are analyzed using the PCA in order to determine the best cluster data to be used as input for trace-based classification. After the PCA analysis, the redundant data are removed especially noise, commonly identified based on absence of similarity or correlation to other attributes value. The best data clouds are input for the training process. Trace models are represented in nine number of seismic facies class. The number of iteration is 100 for training and 50 for propagation with the total estimated training set size of 160368 traces and sampling rate of every four inline and crossline.

4.3. Results

Direct comparison between trace model and wells need to be made in order to determine the geological or lithological meaning of seismic facies classes. This method is possible due to abundance of well data in the field. The comparison is made by linking the log motif of the well to the class of seismic facies that the trace at the wells location is classified to (Fig 12). The log motif is determined from the gamma ray log which commonly used to determine depositional environment. Some wells are interpreted as ;

1) Sandy *fluvial* channel.
2) *Braided fluvial* environment have lesser porosity and quality of sand compared to other wells
3) Some wells however, show irregular shape, commonly for *floodplain*.

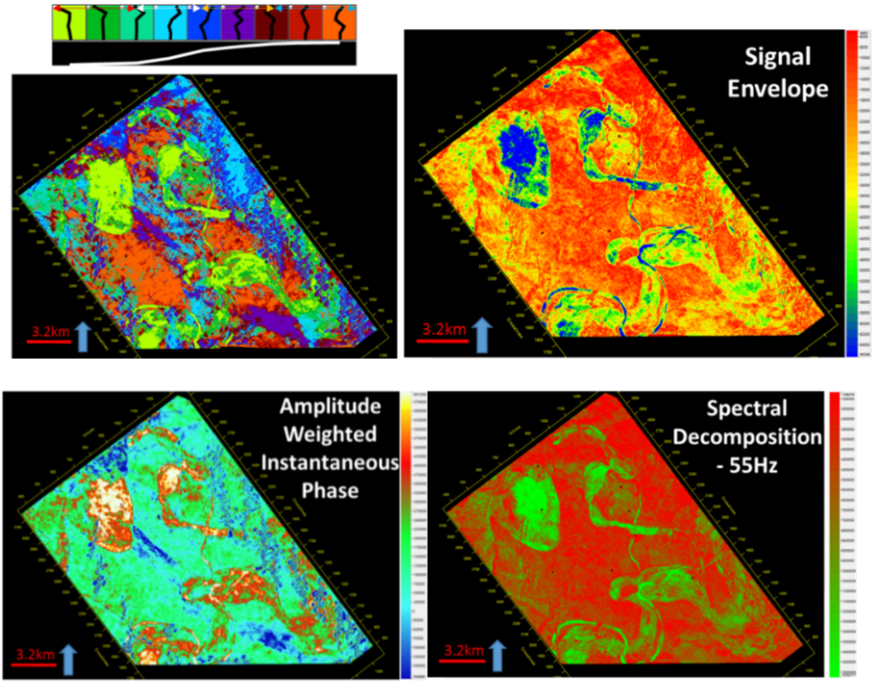


Fig. 12. Seismic attributes supporting the seismic waveform classification

SOM is the best method in finding the clusters and naturally order them in terms of similarity. We would not be able to see the classes with no relationship arrange besides each other in SOM classification. Hence, a trend can be drawn from SOM clustering order from class one to class nine seismic facies in terms of quality of the sand based on the log motif response. The quality of sands is interpreted to be decreasing along the classes with class one as the best quality and class nine with the worst sand quality. The interpretation of seismic facies map is further supported by other attributes (Fig. 14). The porosity maps show good correlation to interpreted seismic facies class (Fig. 13).

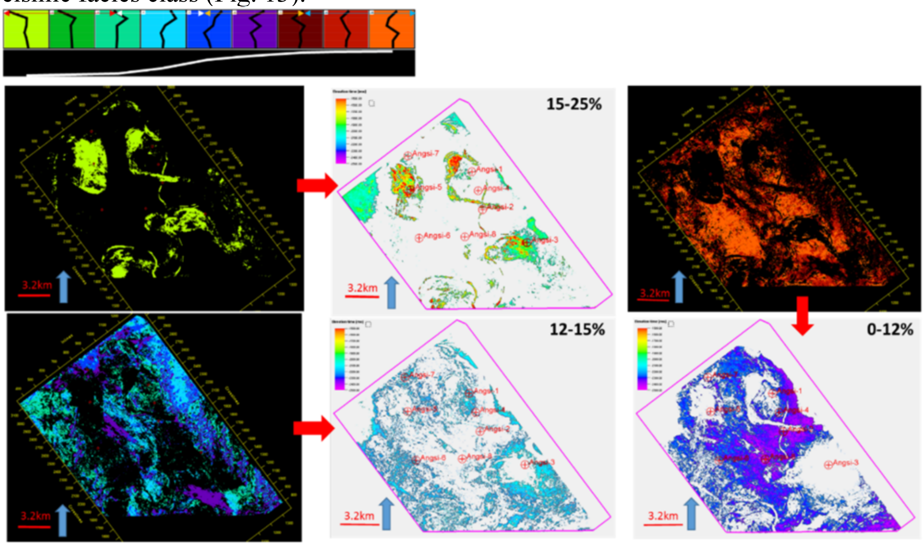


Fig. 13. The comparison between porosity map and seismic facies map. Class one until class three has good porosity (15%-25%), class four to class six has moderate value of porosity (12%-15%) and the worst porosity value (0%-12%) in class seven, eight and nine.

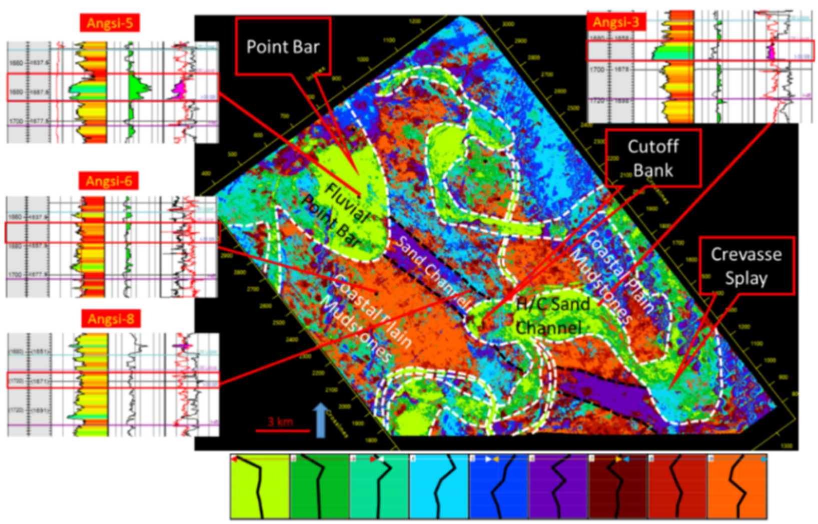


Fig. 14. The interpreted seismic facies map of a field in Malay Basin showing point bar and fluvial environment. The log motifs related to the environments are also shown

5. Determination of Reservoir Properties through Neural Net

5.1. Introduction

Generally, petro-physical properties are calculated using core plugs and well logs data. The derivation of porosity and water saturation from seismic volumes are always desirable for reservoir characterization as they are more reliable to reservoir engineers rather than elastic properties. In this section, linear and non-linear relationships from seismic data and well logging data are integrated to estimate the porosity and water saturation volumes.

The objective of this analysis is to use the correlation between SQp (P-wave absorption factor) and SQs (S-wave absorption factor) attributes with the porosity and water saturation as both logs are useful for determining the lithology and fluid respectively (Maman et. al, 2016). The program will select the best seismic attribute calculated from the input data which are pre-stack seismic, SQp and SQs volumes. In linear relationships, step-wise regression method is adopted, whereby the single best attribute, A is chosen with the best correlation with target log and minimum error. We select the best pair of attributes that include A as one of the members and the correlation coefficients and the error is calculated. The process is carried on as long as we reac the minimum error threshhold(Hampson et. al, 2001). However, one concern is different resolution of well logging and seismic data. Therefore, a suitable convolutional operator is used to solve this issue. The operator length will determine how many pairs of attributes are the best matcof the target log.

5.2. Probabilistic Neural Network

The non-linear relationships uses the probabilistic neural network (PNN) approach that interpolates training data and suitable for predicting numerical values. It assumes that each new output log value can b written as a linear combination of the log values in the training data. The objective of PNN is to look for the set of sigma (σ) which minimize the error. Each of the input attribute contains one sigma, and the number of attributes will be multiplied with the operator length to look for how many sigma should be determined. In order to solve the problem, the best single sigma is determined based on assumption that all the different sigma are equal. Then, the individual sigma is determined using a conjugate-gradient analysis with the first “global” sigma as the starting point.

5.3. Application and Results

As an example, a dataset from Malay Basin is used to predict the reservoir properties from seismic data. The predicted logs match with the actual logs at the interval zone for all four wells. The correlation is reflected on the crossplot of actual porosity and predicted porosity as shown in Figure 15. The correlation coefficient is high i.e.0.85. The relationship derived from multi-attribute regression is applied to the seismic volume to yield porosity distribution .

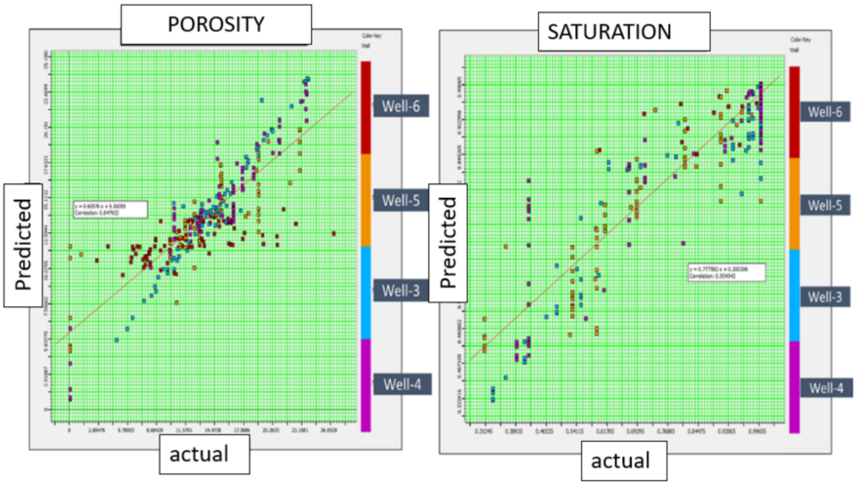


Fig. 15. The crossplots between predicted logs derived from multi-attributes and actual logs.

On the other hand, neural network (a non-linear mode) shows the highest correlation when predicting the water saturation. In this case, additional data input is chosen such as SQp, SQs and the ratio of both attributes. The training of data input is on an interval zone for each well. Figure 15 shows that predicted water saturation log is directly proportional to the actual water saturation log with correlation of 0.93.

The relationship derived from neural network is applied to the seismic volume in order to obtain water saturation volume. Since the correlation coefficient is high, the water saturation volume highlights the hydrocarbon reservoir and dims out the non-reservoir zones. The water saturation values are projected on the map to observe the coverage of reservoir.

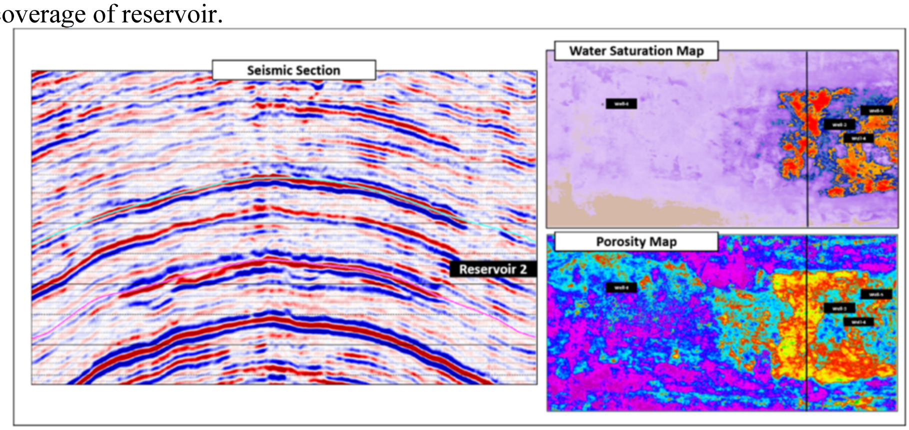


Fig. 16. High porosity and low water saturation zones highlight at the anticlinal structure.

Bright amplitude is seen on the stacked seismic section at reservoir 2 as displayed in Figure 16. Based on the porosity and water saturation maps, the targeted zones show high porosity value and low water saturation values that conform to the anticlinal structure. Hence, the results increase the confidence of hydrocarbon presence at the target area.

6. Conclusion

A.I. Technology has tremendous potential in streamlining many processes in oil and gas both upstream and downstream.

In downstream the key benefit would be optimization and efficiency in scheduling, maintenance and product delivery. A.I. is also making inroads in Refinery Operations in corrosion detection and mitigation.

In upstream particularly in seismic and geological analysis like facies and reservoir modelling, it can be particularly successful because of the abundance of data, complexity of the sub-surface and of the fuzzy and sometime unreliable data.

Neural net has been quite successful in Quantitative Interpretation (Q.I.) in predicting lithology and hydrocarbon Saturation for discovery of commercial hydrocarbons.

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