Machine Learning Tools and Shear Velocity Prediction using Conventional Logs: An Alternative Approach

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Abstract
Machine learning is a branch of artificial intelligence that concerns with the construction and study of systems that can learn from data. The core of machine learning deals with representation and generalization of data. Representation of data means function evaluation on these data. Generalization is the property that the system will perform well on unseen data instances using evaluated functions in representation.
Reservoir characterization, like pore fluid type determination, lithology identification and its interpretation, require accurate geophysical studies. Geophysical studies of such kind need accurate data of elastic logs such as compressional sonic, shear sonic and density. Compressional sonic and density logs are generally available in most of the wells. But shear sonic logs are either not available in very old wells or available in a few wells in an area. Cost is also a factor for not recording Dipole/ Quadruple sonic in all the wells. In this scenario, shear sonic can be modelled through rock physics provided geological setting is same in zone of interest for the considered wells. Rock physics modelling (RPM) is time consuming process and it involves data those are mostly unknown. An alternative approach of rock physics modelling is artificial intelligence which do not involves geophysical principles rather applies training rules on the input data and target.
Study area was selected from Krishna-Godavari offshore basin, east coast of India. Three wells were used to construct intelligent models in a Pliestocene sandstone reservoir and fourth well was used to validate the models. Artificial neural network approach was used as intelligent tools to predict shear wave velocity (Vs) using other conventional logs (Gamma Ray, Neutron Porosity, Density and P-wave Velocity) which intern will be input for pre-stack inversion process.

Introduction

Development of any oil and gas field require characterization of its reservoir. One of the characterization technique is inversion of seismic reflection data for various lithological and petro physical attributes and shear wave velocity (Vs) is an important parameter for such studies. Compressional and shear waves are categorised as body waves. Shear waves do not propagate through fluids and when associated with P-waves can provide useful information for reservoir characterization. Though, there are several factors like, environment, fluid and rock which can influence seismic velocities (Wang, 2001), Vs has strong dependence on P-wave velocities, clay content and bulk density of the rock (Rezaee, 2001).
Compressional wave velocity is obtained from sonic transit time. But Vs is either measured at laboratory at core samples or by means of Dipole Sonic Imager (DSI) in wells. Shear sonic logs are either not available in very old wells or available in a very few wells in an area. High cost is one of the factor for not recording Dipole/ Quadruple sonic in all the wells. At times, shear wave velocity (Vs) may be available in limited interval of reservoirs due to high cost of measurement or technical complexities. This poses limitations on prospect evaluation through advanced studies. AVO modeling also requires accurate shear wave data.
It is worthwhile to predict shear wave velocity (Vs) from other well log data without direct measurement. For this purpose, several studies have been carried out by Castagna et al. (1985), Kreif et al. (1990), Greenberg and Castagna (1992), Castagna et al. (1993) etc. They introduced empirical relationship for Vs. But these empirical relations have following limitations and disadvantages:

1. Most of the empirical relations have been developed for sand stone reservoir and not efficient for all lithologies (Razaee et al., 2007)
2. Most of the empirical models are mathematical models that have used limited petrophysical inputs, missing the generalization capabilities (Eskandari et al., 2004).

Shear sonic can be modelled through rock physics provided geological setting is same in zone of interest for the considered wells. Rock physics modelling (RPM) is time consuming process and requires detail parameterization. Apart from this, simple mathematical models may become inaccurate because several assumptions are made to simplify the models in order to solve the problem. On the other hand, complex models may become inaccurate if additional equations, involving more or less approximate description of phenomena, are included. In most cases these models require a number of parameters that are not physically measurable.
Neural networks (Hecht-Nielsen, 1989) and fuzzy logic (Zadeh, 1965) offer a third alternative and have potential to establish a model from nonlinear, complex and multidimensional data.

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Neural Networks:

Artificial neural network is an alternative tool for solving complex problems in petroleum industry. The widespread usage of neural networks with back propagation for modeling complex multidimensional field data has been popular due to following features of neural networks (M. Nikravesh et al., 2001):

1. They do not require specification of structural relationships between input and output data.
2. They can extract and recognize underlying patterns, structures, and relationships between data.
3. They can be used with parallel processing.

However, developing a proper neural network model requires sufficient experience and insight into the physical behavior of the model. Unlike statistical methods, conventional neural network models does not deal with probability. Neural network method for predicting Vs does not involve any geophysical principles, rather it trains intelligent network using input and target data.

A typical neural network has an input layer in which input data is presented to the network, an output layer in which output data is presented to the network and at least one hidden layer. Several techniques have been proposed for training neural network models. The most common technique is back propagation approach (Hecht-Nielsen, 1989). The block diagram of implementation of the processes are shown in the figure.

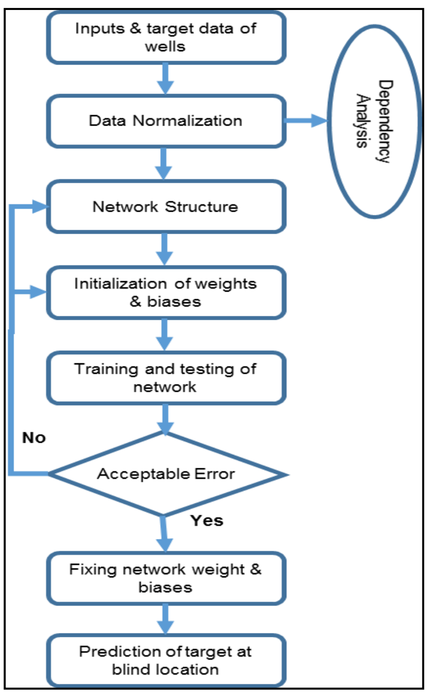

Figure 1: Work flow of the study

Back Propagation Neural Network (BP-ANN):

This is a supervised training technique that sends the input values forward through the network then computes the difference between calculated output and corresponding desired output from the training dataset. The error is then propagated backward through the net, and the weights are adjusted during a number of iterations. The training stops when the calculated output values best approximate the desired values (Bhatt and Helle, 2002).

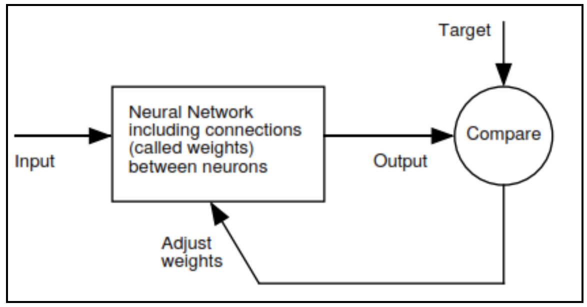

Figure 2: Schematic of neural network

In this study, a three layered BP-ANN was used to predict shear velocity from other conventional logs like Gamma Ray, Neutron Porosity, Density and P-wave Velocity.

Study area falls in Krishna-Godavari offshore basin, east coast of India. Pliestocene sand stone reservoirs are the major producer of oil and gas in this area. Out of several wells available in the study area, seven wells (A, B, C, D, E, F, and G) were selected for the study. Shear wave velocity are available in wells (A, B, C, D). Three wells (B, C, D) were used to construct intelligent models in a Pliestocene sandstone reservoir and fourth well (A) was used to evaluate the reliability of the models. Three more wells (E, F, G), with no shear velocity, were selected for checking the reliability of the trained network. Well F & G are hydrocarbon bearing while well E has indicated the presence of hydrocarbon. Matlab neural network tool was used for making neural network model, training and prediction of shear velocity. Display of input logs, predicted log and cross-plot analysis were done in Jason Geoscience Workbench. The methodology adopted are as follows:

1. Input Data:

Seven wells (A, B, C, D, E, F, and G) were considered for this study (Fig. 3). Out of seven, four wells (A, B, C, D) were having shear velocity and were used for training and validation of network. All wells were having Gamma Ray (GR), Neutron Porosity (NPHI), Density (RHOB) and P-Wave Velocity logs. Logs of well A is shown in Fig. 4.

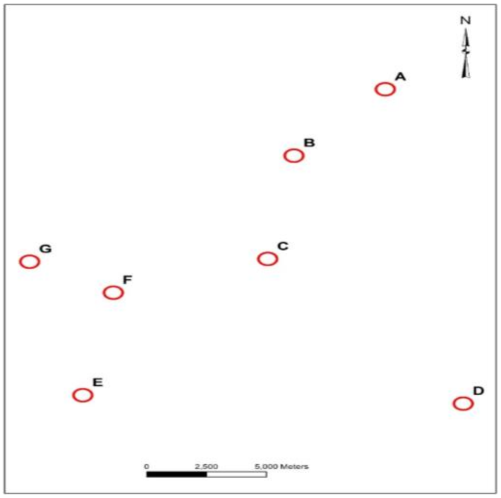

Figure 3: Base map showing the relative position of wells. Wells B, C and D were used for training network. Well A was used for blind testing.

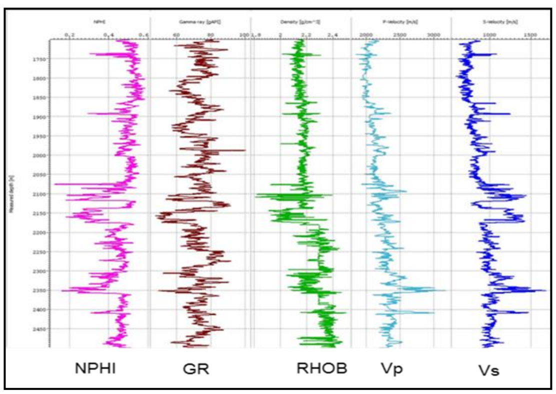

Figure 4: Logs of well A.

2. Mutual Information Analysis:

Before training the network using input data, mutual information analysis was done to check the dependency of target on input variables. Several input variables may be used to train the network for mapping from input to target but some input variable may not contribute much in training the network. There are two ways, namely cross plot analysis and probabilistic mutual information, to analyze the dependency of target on inputs. The input data which is having very less mutual information or correlation with target may be dropped from training the network. Mutual information is calculated on the basis of Bayesian probability.

In the present study, Gamma Ray, Neutron Porosity, Density, and Compressional Velocity logs were selected as input and Shear Velocity as target for training the network. Cross plots of GR, NPHI, RHOB and P- wave velocity with Shear velocity for the wells (B, C, and D) combined together are shown in Fig. 5 respectively. Only P-wave velocity is having good linear trend with shear velocity with correlation of 88%. GR, NPHI and RHOB show only partial correlation with target. The mutual information of all the four input logs with target log for wells combined together are shown in the Fig.6. P-wave velocity and NPHI are having maximum mutual information for target whereas dependency of S wave on GR, RHOB appears to be very little.

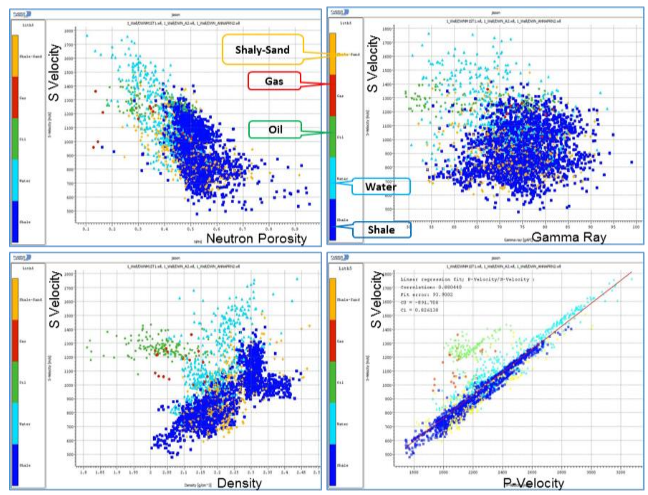

Figure 5: Three wells (B, C, D, used for training network) combined data cross plot of S Velocity (Vs) with Neutron Porosity (NPHI), Gamma Ray (GR), Density (RHOB) and P Velocity (Vp) coloured with lithology log.

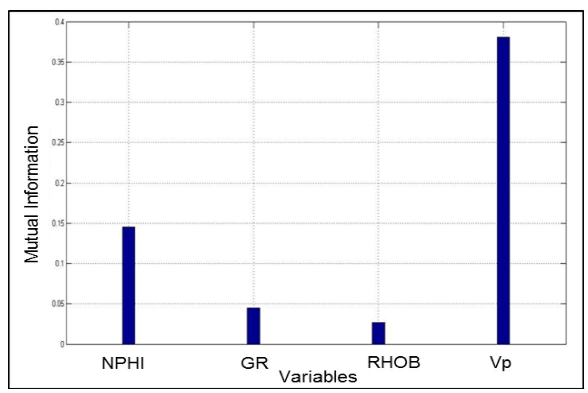

Figure 6: Showing mutual information of Vs with NPHI, GR, RHOB and Vp from left to right respectively.

3. Network Training:

Three layered back propagation artificial neural network (BP-ANN) was generated in MATLAB environment and consisting of an input layer, a hidden layer and an output layer. The dataset (GR, NPHI, RHOB, Vp and Vs) of three wells (B, C, D) were selected for training the network. Well A was used for blind testing of trained network. Number of neurons in the hidden layer is 20. Lavenberg-Marquardt training function associated with MSE (Mean Squired Error) performance function was used to optimize weights and default bias values. TANSIG transfer function was used from layer one to layer two and LOGSIG from layer two to layer three Fig. 7.

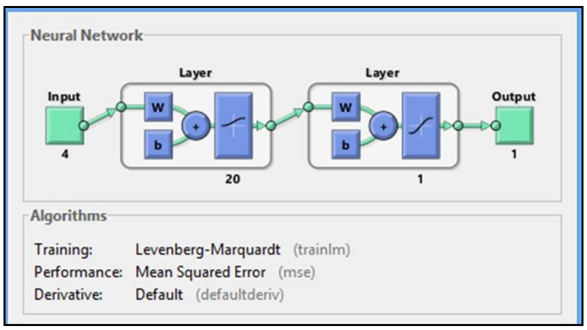

Figure 7: Flow diagram of neural network implementation

Several iterations were made changing the training algorithm, number of neuron, transfer function and number of epochs. Final network structure was arrived with the parameters shown in figure and number of epoch as 500.

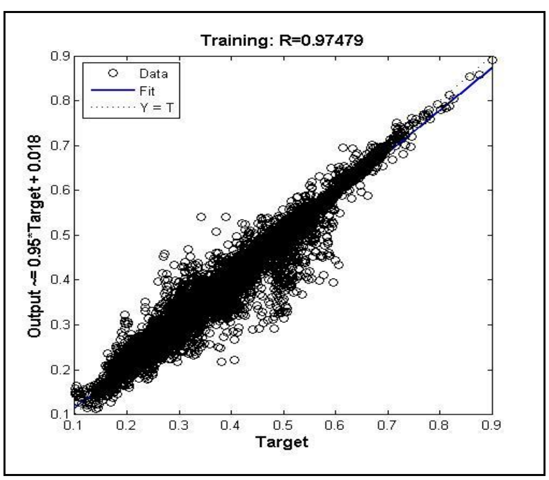

Figure 8: Trained network showing correlation of 97.5% between output and target samples.

Final trained network showing correlation of 97.5% between output and target samples (Fig. 8) which is quite good.
Vs was predicted using trained network for all the wells used for training and testing the network. Correlation coefficients were calculated between predicted and original Vs logs (Fig. 9). Correlation for blind well (A) was nearly 90%. Training and testing samples plot is shown in Fig. 10. Training samples plot is for wells B, C and D. Testing sample plot is for blind well A. Blind well prediction is very good and is matching well with the recorded Vs.

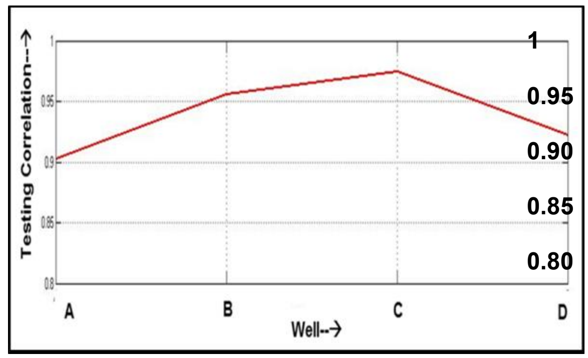

Figure 9: Plot of correlation between predicted and original Vs for wells (A, B, C, and D).

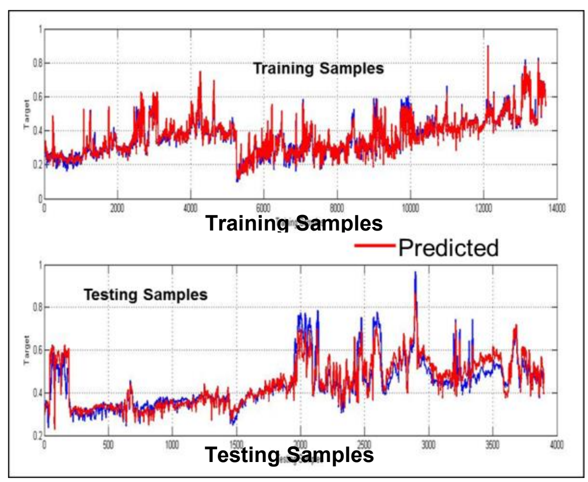

Figure 10: Plot of training (well B, C, and D) and testing samples. Testing samples plot is for blind well A.

Results & Discussion:

Out of seven wells, one well (A) was used for blind testing and other 3 wells (E, F, G) were not having shear velocity (Vs) log and were selected for shear velocity prediction. Rock physics analysis was carried out to understand the pay behaviour for well A. Since wells (E, F, and G) are in the same area, their rock physics analysis would be carried out and compared with the observed pay details in the wells.

Well-A:

Shear velocity (Vs) was predicted using trained network for wells A, E, F and G. Shear velocity (Vs) is available in well A and is used for blind testing also. Predicted log along with inputs is shown in Fig. 11 for well A. There is a good correlation (97.8%) between original and predicted for well A as shown in Fig.12.

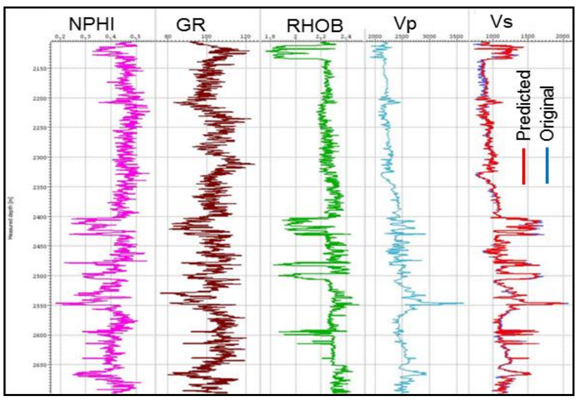

Figure 11: Plot showing the input and predicted logs of blind well A.

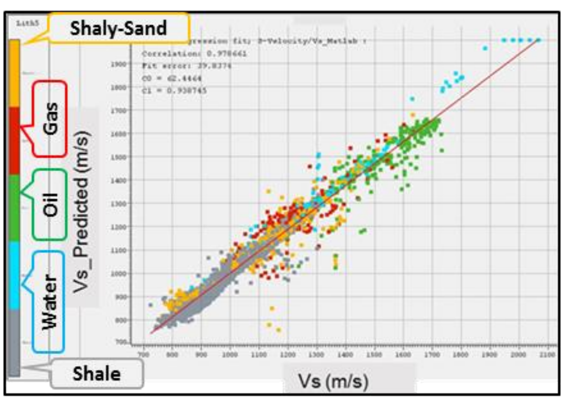

Figure 12: Cross plot of recorded vs. predicted shear velocity coloured with lithology showing the good correlation of 97.8% for blind well A.

Well A is a good producer of oil and gas. It would be relevant to compare the recorded and predicted shear velocity (Vs) pay wise. P-Impedance and Vp/Vs cross plot clearly separates the pay and non-pay zones. Oil and gas pay zones fall in low P-impedance and Vp/Vs (Fig. 13) encircled by polygon and is called pay polygon. Points falling in pay polygon has been highlighted in log view of P-Impedance and Vp/Vs.

Corresponding plot using predicted Vs also show the same pay behavior as that of recorded Vs as shown in Fig. 14.

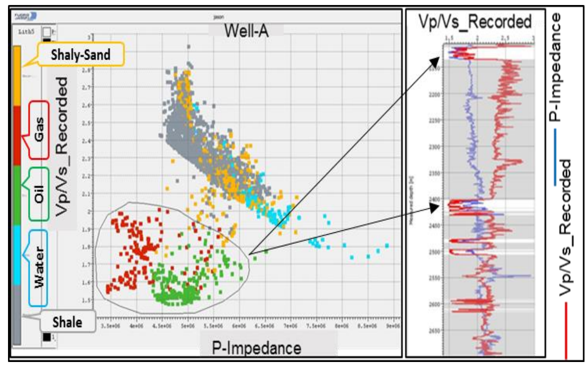

Figure 13: Cross plot of P-Impedance and Vp/Vs_Recorded coloured with lithology showing the low P-impedance and Vp/Vs_Recorded corresponding to pay zones for well A.

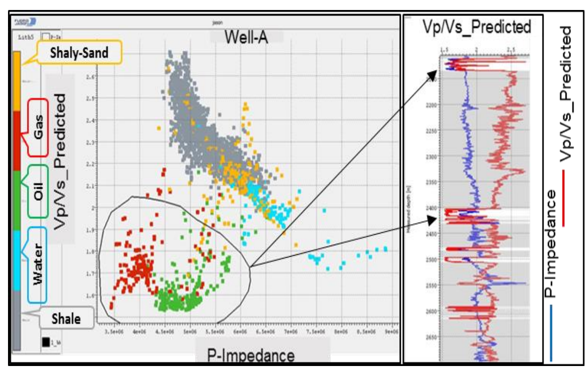

Figure 14: Cross plot of P-Impedance and Vp/Vs_Predicted coloured with lithology showing the low P-impedance and Vp/Vs_Predicted corresponding to pay zones for well A.

Both the cross plots are very much similar highlighting the pay zones except a few points outside the pay polygon in predicted case.

Lithology logs are not available in wells E, F and G. Gamma Ray logs were used as lithology indicator for these wells.

Well-E:

Shear velocity predicted in well E is shown along with input logs in Fig. 15.

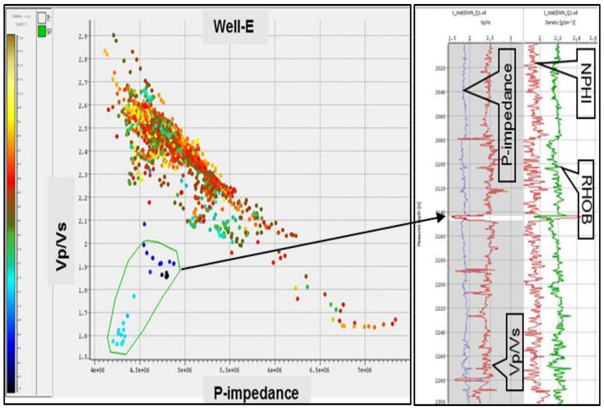

Figure 15: Cross plot of P-Impedance and Vp/Vs_Predicted coloured with Gamma Ray, showing some points having low P-impedance and Vp/Vs_Predicted, encircled by polygon, corresponds to a gas indication bearing zones in well E.

Well E has some points with low Vp/Vs and P-Impedance, encircled by a polygon, in cross plot which corresponds to hydrocarbon bearing zone as reported in the well completion report. These points have been highlighted in log view and is supported by NPHI and RHOB cross over.

Well-F:

Well F is a good producer of oil and gas. Cross plot of P-impedance and Vp/Vs, using predicted shear velocity, clearly demarcate these pay zones in this domain and also supported by crossover of NPHI and RHOB as shown in Fig. 16.

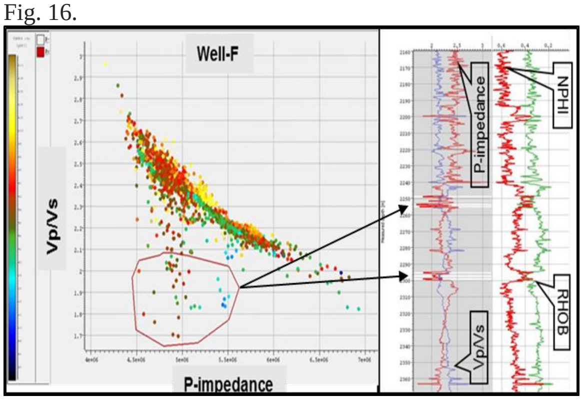

Figure 16: Cross plot of P-Impedance and Vp/Vs_Predicted coloured with Gamma ray, showing points having low P-impedance and Vp/Vs_Predicted, encircled by polygon, corresponds to a pay zones of gas and oil in well F.

Well-G:

Well G is also a producer of oil & gas. Cross plot indicates the points which are falling in low P-impedance and Vp/Vs. These points correspond to the pay zones.

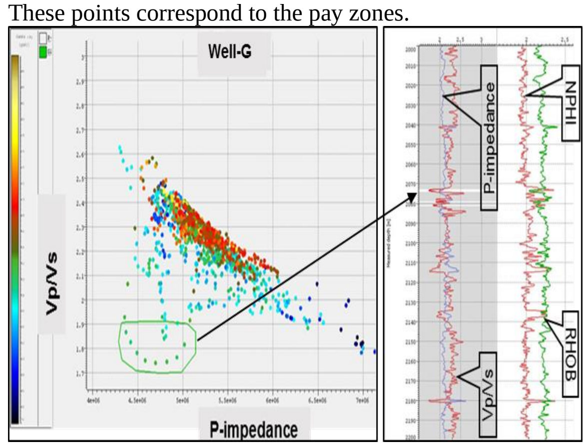

Figure 17: Cross plot of P-Impedance and Vp/Vs_Predicted coloured with Gamma Ray, showing points having low P-impedance and Vp/Vs_Predicted, encircled by polygon, corresponds to pay zones in well G.

Rock physics analysis of wells E, F, and G, using the predicted shear wave velocity, reveals that low P-impedance and Vp/Vs zones matching with the observed pay zones encountered in the wells and are having the same rock physical property as that of well A. This validates the predictability of shear wave velocity by this machine learning technique.

Conclusions:

Back propagation artificial neural network were successfully used to predict shear wave velocity (Vs) for other wells in the study area which has no recorded shear wave velocity data based on well data of wells having shear sonic and used for training the network. A comparison between measured and predicted shear wave velocity shows very good match. Most of the wells selected in the study are producing from Pleistocene formation. Depositional setting for all the wells is same for Pleistocene formation. So the rock physical behaviour is expectedly similar in this zone for all the wells. Rock physical analysis of wells E, F, and G corroborate with that of well A, which is also a good producer of hydrocarbon and taken as blind well in this study. Cross plot of P-impedance and Vp/Vs show that all the points having low values are exactly falling at observed pay zones in the respective wells. This provide confidence on the accuracy and validity of the technique used for prediction of Vs log.

If the object zone is very thick having several litho units with varying depositional environments, it would be better to make several zones for training and testing the network.

Prediction should be made zone wise and combined together to form a complete predicted log subsequently.
It is necessary to have input and target logs conditioned properly. Any erroneous values in either input or target will generate faulty network which in turn will predict wrong values other locations.
As there are some limitations of using this techniques, developing a proper neural network model requires sufficient experience and insight.

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