examine that how strong and how independent the neural network can be trained to predict impedance from seismic data. Several types of seismic attributes were created and the best input training attributes are chosen as: Second derivative, Quadrature amplitude, Trace gradient, Gradient magnitude, Instantaneous frequency (for more explanation refer to Appendix).

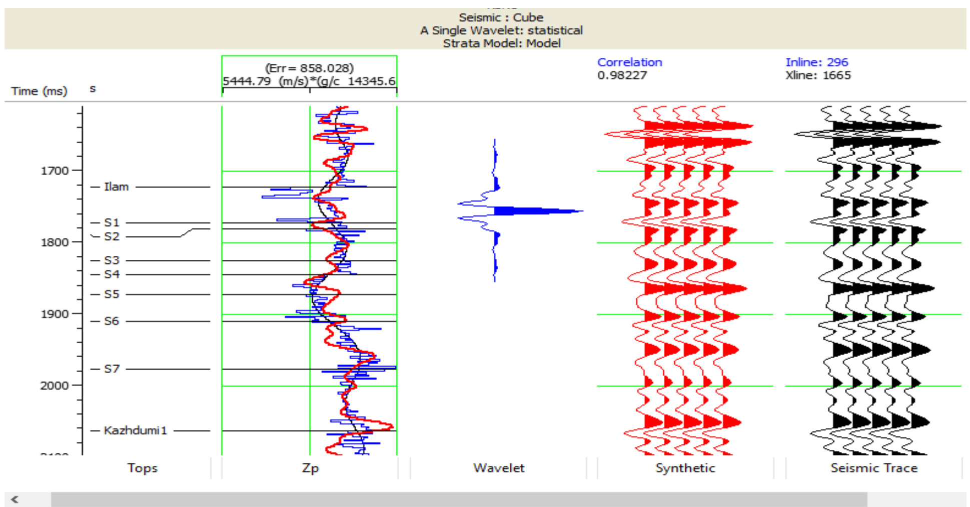

Figure 1: seismic inversion result in left track (red) is overlaid with log-calculated impedance (blue). Zero-phase wavelet extracted from entire seismic cube is shown in next track. Using impedance from inversion result, reflectivity extracted then convolved with wavelet to generate synthetic track (red). High correlation with real seismic amplitude profile can be interpreted as inversion accuracy.

The plot of these training set and target can be seen in figure 2. Operationally, there are several factors that control cost of calculation including: number of attributes as input training, number of hidden layers and nodes in each layer and number of data points (in other word sample rate). It is recommended to start with simple network structures and then approach to optimal design. Using TensorFlow library in python programing, it is gained the following optimum network: 2 hidden layers where each contains 100 and 50 neurons, respectively. The data matrix size is (30,000×6) which is divided into 70% for training and the rest for validation and test.

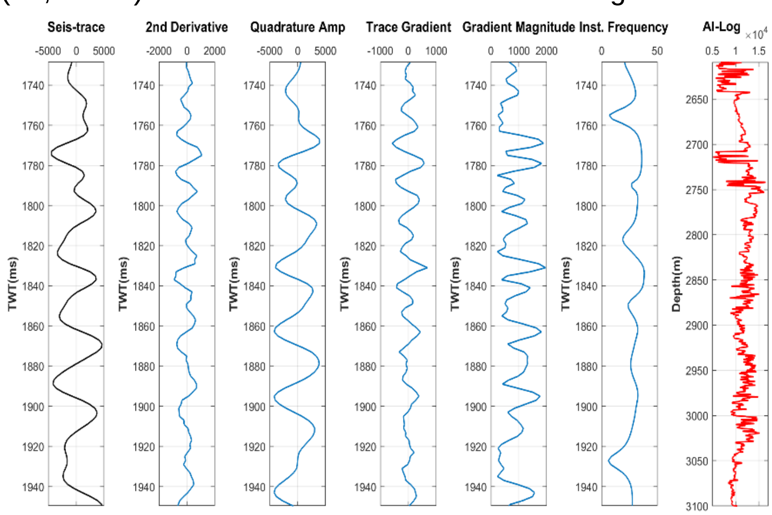

Figure2: this figure illustrates zero-offset seismic trace in one well location in first track, left. Training input attributes is extracted from seismic traces for all wells as Second derivative, Quadrature amplitude, Trace gradient, Gradient magnitude and Instantaneous frequency. The target of network is AI.

Although iteration was programed into 1500 cycle of calculation for error minimization, model starts to overfitting after epoch 200. To avoid such problem, early stopping is enforced when validation error starts to build up in certain amounts (figure 3, left). Epoch 70 seems appropriate selection for training. Having built model, we may examine model accuracy on test data. True AI is in agreement with prediction output from model by 88% correlation coefficient (figure 3, middle). Error has zero mean Gaussian distribution (figure 3, right).

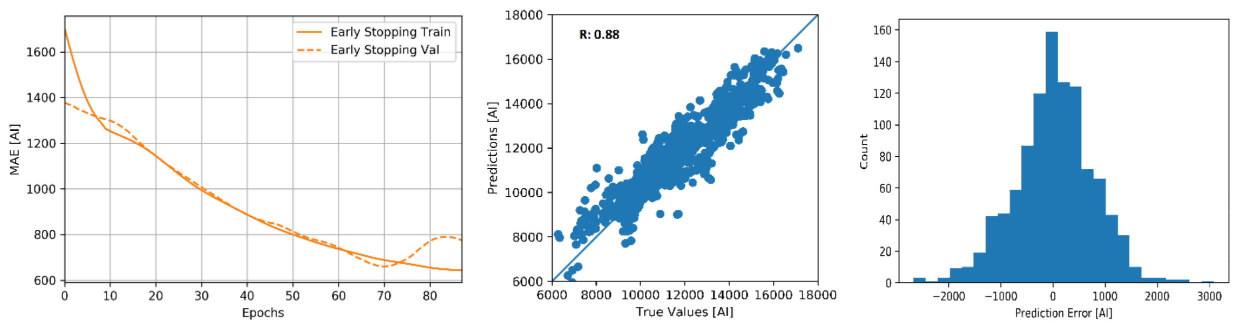

Figure 3: Mean absolute error (MAE) decay through training period (left). After epoch 70, training would not add accuracy in validation dataset. In the middle plot, correlation coefficient between real data and model prediction is 88% and the error has zero mean normal distribution (right).

Finally, plotting real acoustic impedance in well place with seismic-derived ANN impedance shows strong agreement between these two data sets (figure 4). For comparison, band-limited inversion results is also overlaid. After all, neural network like other mathematical approaches is sensitive to the noise in input data. In fact, the high level of noise can cause network to be trained for noisy predictions. It is not recommended but possible to remove some outliers from input data. Like human brain, learning level can be proportional to how wide range of learning data is offered. It is better to have plenty of data range with redundant data samples.

Computation cost is directly related to amount of input data, network layers and neurons. As these parameters increases, the estimation accuracy will increase but training process will be time consuming process.

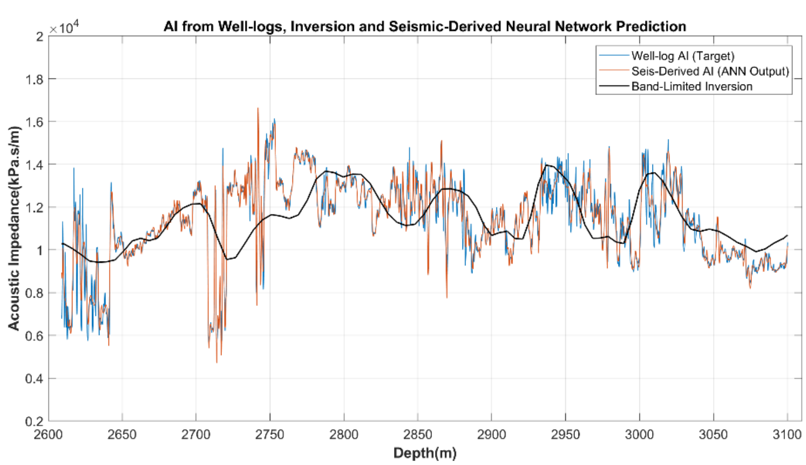

Figure4: Predicted and real AI are plotted in reservoir intervals in well place. The trend and values show strong agreement. Band limited inversion impedance is also plotted to see how it follows the property variation through the depth. Overall, it shows appropriate trend adaptation but for local variation it does not have enough ability to extract the same resolution.

Conclusion

The main purpose of this study was to investigate the possibility of other approaches rather inversion to estimate impedance using seismic and well data. It is tried to estimate AI using seismic data attributes as input to target AI. A network with two hidden layers (100 and 50 neurons in each layer, respectively) is trained employing TensorFlow library deep learning in python platform. These selected five attributes are: second derivative, quadrature amplitude, trace gradient, gradient magnitude and instantaneous frequency. The network could recognized appropriate relationship (correlation of 88%) between these seismic attributes and target data as impedance. Band-limited seismic inversion was also implemented and inversion result was compared with network estimation. The comparison illustrates that neural network can work effectively to estimate impedance even with more detail than band-limited seismic inversion because the network inherits target data frequency while recursive inversion is limited to seismic band frequency, although it is expensive approach.

References

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APPENDIX:

Second derivative: it is the second time derivative of the input seismic volume. This can work as helpful tools for interpreters in the places where continuity is poorly resolved on raw amplitude profiles (Barnes, 2016).

Quadrature amplitude: this attribute is the imaginary part of the analytic signal, which is calculated by phase shifting the original trace by 90 degrees. An analytic signal can be generated from the real seismic amplitude and the imaginary quadrature amplitude (Barnes, 2016).

Trace gradient: the gradient along the trace is calculated. It will have the highest values where the greatest changes are happening (Barnes, 2016).

Gradient magnitude: the magnitude of instantaneous gradient is computed in 3-dimention employing neighbor traces (Barnes, 2016).

Instantaneous frequency: it is the time derivative of phase angle and different from wavelet frequency. Commonly is used to estimate seismic attenuation. It can show cyclicity of geological features to assist interpretation. Reservoir oil and gas fluids may cause drop-off of high frequency components (Barnes, 2016).