Building more robust low-frequency models for seismic impedance inversion

Amit Kumar Ray[1] and Satinder Chopra[1*]

Abstract

Seismic impedance inversion is an important tool for estimating rock and reservoir properties from the seismic data. Seismic data is band-limited in nature and lacks the low-frequency component. As the low-frequency component holds the basic information on geological structure, the lack of low-frequency information degrades the quantitative prediction based on seismic inversion. It is therefore essential to build an accurate low-frequency model to have confidence in seismic inversion and in turn on the quantitative predictions made therefrom.

In this paper, we develop a novel workflow of predicting the low-frequency impedance model that uses a single-well low-frequency model apart from other relevant seismic attributes in the multi-attribute regression analysis. The workflow was successfully applied to a number of impedance inversion exercises out of which two cases are discussed here. Our inversion exercises were carried out on datasets from northeastern British Columbia and Alberta, in Canada. The inversion results using this approach have been validated at blind well locations and an excellent match between well logs and inversion results has been observed.

Introduction

Impedance inversion of seismic data is a standard tool for estimating elastic properties for reservoir characterization projects. Knowledge of relative impedance may work well for qualitative interpretation, but absolute impedance is necessary for quantitative predictions of the reservoir properties. As the seismic data is band-limited and does not contain the low-frequency band of the spectrum, it is essential to build an accurate low-frequency model for confident estimates of the reservoir properties. Sams and Saussus (2013) have shown some practical implications of low-frequency model selection on quantitative interpretation results.

Typically, a low-frequency model is built by using well log data, interpreted horizons and sometimes the seismic velocities provided the velocity data is of good quality. The low-frequency model is constructed such that the different subsurface interval impedance values are constrained by the horizons interpreted on the seismic data. This leads to more meaningful inverted impedance data. In cases where there are lateral variations in the elastic properties across the 3D volume, if the low-frequency trend extracted from a single well is used for inverting the 3D data, the impedance profiles may or may not match the impedance logs at the other well locations.

Another way to generate a low-frequency model is to make use of a few wells for generating the low-frequency model for inclusion in the impedance inversion. Such a technique linearly interpolates the impedance data between the wells using weights calculated on the basis of inverse distance, and similarly extrapolates away from the well control. When quality checks are performed on the generated low-frequency models using the technique, often they are found to exhibit artifacts in the form of artificial tongues with anomalous impedance values, appearing more like bulls' eyes. Such patterns are not geological and do not generate meaningful impedance sections or volumes.

A novel approach has been devised that uses the multi-attribute regression technique for building the low-frequency impedance model. Multi-attribute regression is a good interpolation technique that uses both well log and seismic data to establish a relationship between various seismic attributes and the available log curves (Hampson et al., 2001). The application of multi-attribute regression analysis for building low-frequency models has been discussed by Zou et al. (2013), wherein the authors discuss a workflow utilizing seismic velocity data, seismic data and its derived attributes (usually derived within the software package used) and relative impedance attribute. On many occasions the seismic velocities determined during processing of seismic data are not reliable, which can lead to erroneous results when they are utilized in seismic impedance inversion. In our approach, the low-frequency model generated using a single well has been included in the multi-attribute analysis, whereas the approach of Zou et al. (2013) does not follow this. It is important that suitable attributes are included in the analysis, so that a proper regression relationship gets

[1] *Arcis Seismic Solutions, TGS, Calgary, Canada.*
[*] *schopra@arcis.com*

established. In this paper, we discuss a different workflow using multi-attribute regression analysis for predicting the low-frequency component that is used in seismic impedance inversion.

Method and analysis of results

We begin with generating a low-frequency impedance model for the seismic volume using a single well that seems to represent the overall compaction trend within the 3D volume. Using this low-frequency model, inversion is run on the seismic data. Though the inversion result shows a reasonably good match for some of the wells, we notice mismatches for other wells in the 3D area. This suggests that an improved low-frequency model is required for a better estimate of impedance volume from seismic inversion. For this purpose, we attempted multi-attribute regression analysis (Hampson et al., 2001) to generate the low-frequency impedance model.

The objective of multi-attribute analysis in our exercise is to find a relationship between the well log data and seismic data at the well locations. Once this relationship is obtained it will be used to predict a volume of the log property, i.e. the low-frequency trend at each trace location of the 3D seismic grid. A simple way of doing this is to crossplot the two in the broad zone of interest, where a cluster of points is usually seen. A best-fit or regression line is then drawn through the cluster of points, which represents the relationship between the two variables crossplotted. But in such cases in general, a large scatter of points is noticed on the crossplots, which prevents us from using a single seismic attribute for predicting the target log property.

In order to improve upon the scatter of points on the crossplot, we try bringing in more attributes in our analysis and executing multi-attribute regression analysis. In this method, the target log is modelled as a linear combination of several input attributes at each sample point. This modelling yields a series of linear equations, which are solved for obtaining a linear weighted-sum of the input seismic attributes in such a way that the error between the predicted and the target log is minimized in a least-square sense.

We determine the correct number of attributes to use by what is referred to as a cross-validation method (Hampson et al., 2001). While the additional attributes always improve the fit to the training data, they may be useless or worse when applied to new data not in the training set. This is called overtraining and is described by Kalkomey (1997). In the process of cross-validation, one well at a time is excluded from the training data set and prediction error is calculated at the blind well location. The analysis is repeated as many times as there are wells, each time leaving out a different well. The total validation error is the RMS average of the individual errors. Though training error decreases as we increase the number of attributes, validation error decreases up to a given number of attributes and then increases as further attributes are added. We pick the number of attributes at the point of minimum validation error so as to avoid over-training in the analysis.

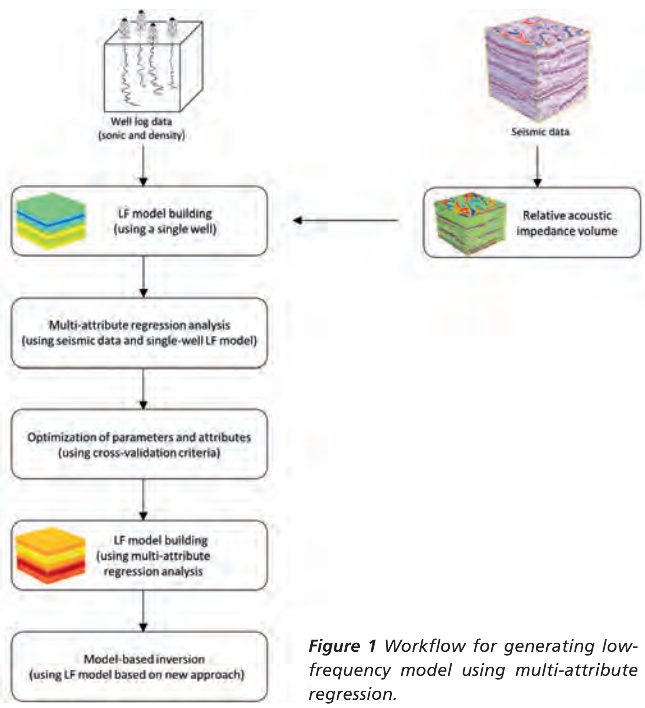

Figure 1 *Workflow for generating low-frequency model using multi-attribute regression.*

Thus the different steps followed in our proposed workflow for building a low-frequency model are listed below, and also pictorially represented in Figure 1.

1. We generate a low-frequency impedance model using a single well. This model represents the overall compaction trend within the 3D area.
2. Multi-attribute regression analysis is performed to predict the low frequency component of the impedance log at each trace location of the 3D seismic grid. Different seismic attributes such as relative acoustic impedance derived from coloured inversion, instantaneous attributes and different filtered versions of seismic data are used for this purpose.
3. Observing a poor match between the predicted low-frequency impedance curves and actual low-frequency curves for different wells, a new strategy is envisaged.
4. We include the low-frequency model derived using a single-well in step 1 as another attribute along with the other set of attributes, earlier used in the multi-attribute regression analysis and repeat step 2.
5. We then generate the low-frequency model by applying the multi-attribute transform determined in step 4.

We have applied this novel approach for generating low-frequency impedance models for two datasets, one from northeast British Columbia, and another from south central Alberta in Canada.

Example 1: Northeast British Columbia dataset

As mentioned above, we first carried out model-based impedance inversion using the low-frequency model derived from a single well. Observing a poor match between actual impedance curve and inverted impedance curve at other wells, we went ahead to perform multi-attribute regression analysis for predicting a low-frequency impedance model. First, relative acoustic impedance derived from coloured inversion, instantaneous attributes and different filtered versions of seismic data were used in the multi-attribute regression analysis. Figure 2 shows the outcome of this analysis, which is a match between the predicted low-frequency impedance curve in red and the actual low-frequency curve in black for different wells. For each of the wells, a poor correlation is seen between the two types of curves over the target window that includes the broad zone of interest indicated with the yellow bars.

Disappointed with the poor correlation, we repeated the multi-attribute regression analysis by bringing in the low-frequency model derived using a single well as another attribute, along with the other seismic attributes. Figure 3 shows the match between the predicted impedance log using this workflow and the low-frequency component of the actual impedance log curves. There is now a very good correlation between the two sets of curves at each well location.

To gain more confidence in the analysis, we go through another process called cross-validation, wherein we exclude one well from the multi-attribute regression analysis and use the process to predict it. The analysis is repeated as many times as there are wells on the 3D volume. Once this is done, the cross-validation prediction error/correlation is calculated at each of the well locations. The validation match is shown in Figure 4. The correlation in this case was found to be very high, lending confidence in the regression process, which is then run for the full volume and the low-frequency model is computed.

The output volume was examined for its quality and a horizon slice from this volume is shown in Figure 5. We observe that there is a gradual transition of low frequency impedance from one well to another as is expected. In contrast to this we show an equivalent horizon slice from the low-frequency impedance volume generated using the inverse-distance interpolation method in Figure 6. Notice the pronounced low-frequency impedance anomalies seen as a bull's eye at

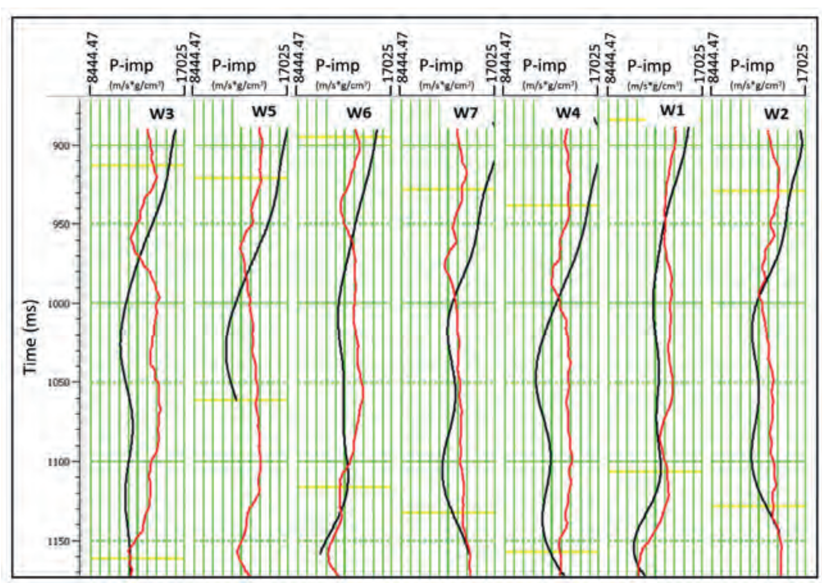

Figure 2 *Match between the modelled impedance log and actual filtered impedance log using multi-attribute regression. Black curve represents the filtered impedance log and red curve represents the modelled impedance curve. Analysis window is marked by yellow bar. Poor correlation coefficient of 0.4 is observed.*

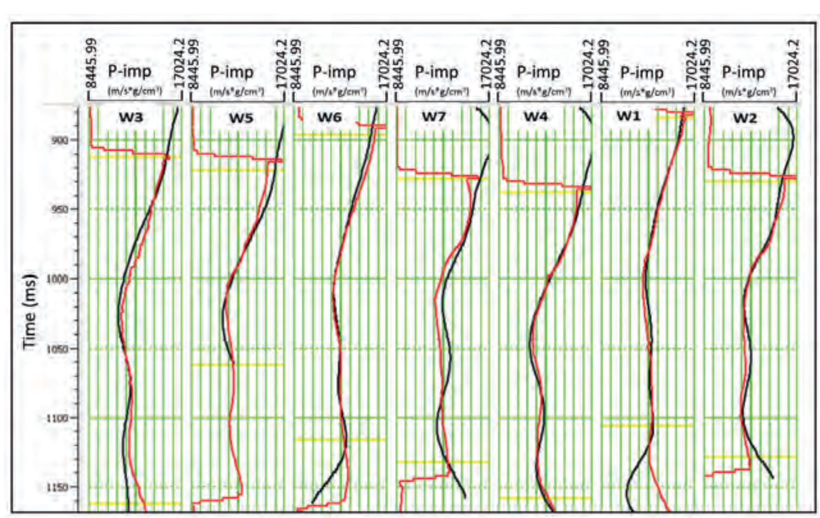

Figure 3 *Match between the modelled impedance log and actual filtered impedance log using multi-attribute training network after including single well low-frequency model as one of the input. Black curve represents the filtered impedance log and red curve represents the modelled impedance curve. Analysis window is marked by yellow bar. Correlation coefficient improves significantly to 0.96.*

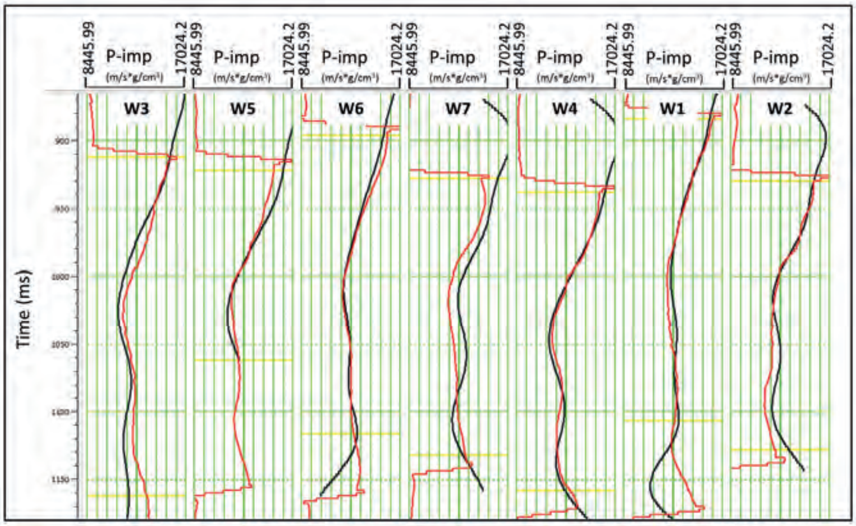

Figure 4 *Validation match between the modelled impedance log and actual filtered impedance log using multi-attribute network after including a single well low-frequency model as one of the input. Black curve represents the filtered impedance log and red curve represents the modelled impedance curve. Analysis window is marked by yellow bar. A high correlation coefficient of 0.92 is observed.*

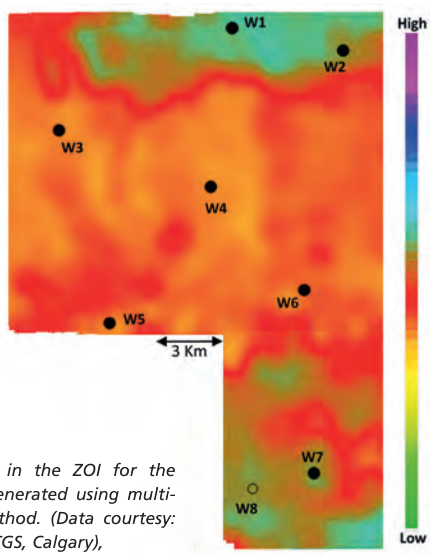

Figure 5 *Horizon slice in the ZOI for the low-frequency model generated using multi-attribute regression method. (Data courtesy: Arcis Seismic Solutions, TGS, Calgary),*

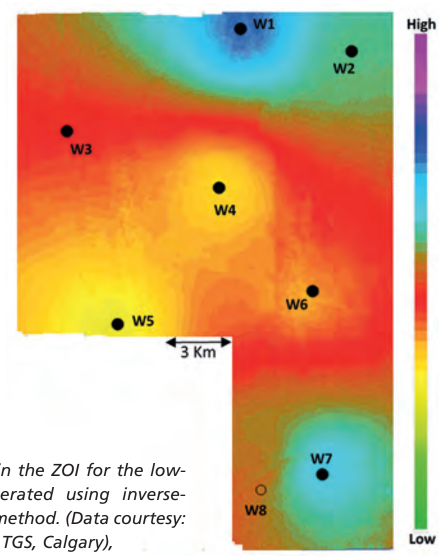

Figure 6 *Horizon slice in the ZOI for the low-frequency model generated using inverse-distance interpolation method. (Data courtesy: Arcis Seismic Solutions, TGS, Calgary),*

wells W1, W4, W5, W6 and W7, which will surely result in artifacts if used in impedance inversion.

Now, we run the model-based impedance inversion using a low-frequency model generated with the proposed approach. We get an excellent match between the actual impedance log and the inverted impedance log for all the wells on the 3D volume. Figure 7 shows the match in a blind well between the actual impedance log (blue curve), inverted impedance using single well low-frequency (black curve) and the inverted impedance using the low-frequency based on the proposed approach (red curve). It may be noticed that this low-frequency model gives an excellent and improved match with the actual impedance log at the blind well, and thus lends more confidence in our approach for generating a low-frequency model.

Example 2: South central Alberta dataset

For this dataset also, we first carry out model-based impedance inversion using the low-frequency model derived from a single well. Again, observing a poor match between actual impedance curve and inverted impedance curve at other wells, we follow the proposed workflow for computing the low-frequency impedance model. Figure 8 shows the match between the predicted low-frequency impedance curve in red and the actual low-frequency curve in black, for different wells, when the low-frequency model derived from a single well was not included in the multi-attribute regression analysis. Again, a poor correlation is seen between the two types of curves over the target window, for each of the wells.

Figure 9 shows a similar match between the predicted and the actual low-frequency impedance log curves, when the low-frequency model derived using a single-well is included as another attribute along with the other set of attributes in the multi-attribute regression analysis. Notice now there is a very good correlation between the two sets of curves at each well location. The cross-validation match between the predicted low-frequency impedance curve (red) and the actual low-frequency curve (black) for different wells is shown in Figure 10.

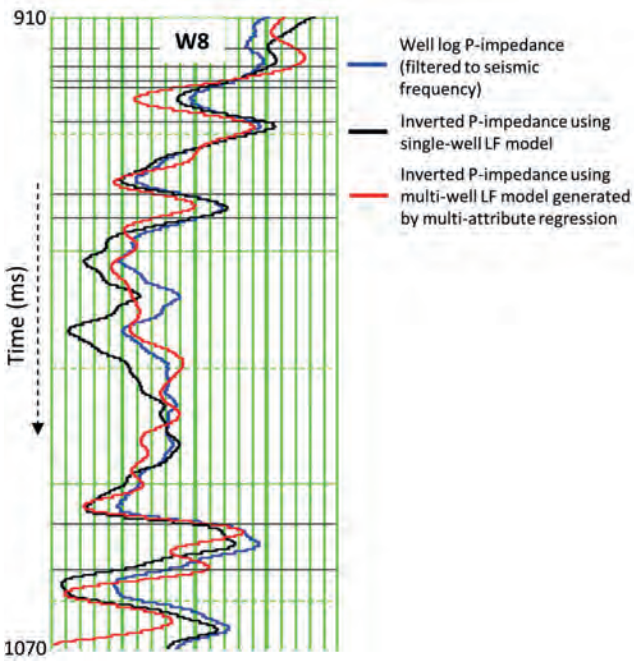

Figure 7 *Match at the blind well between the actual impedance logs (blue curve), inverted impedance using single well low-frequency model (black curve) and the inverted impedance using the low-frequency model based on the proposed approach (red curve).*

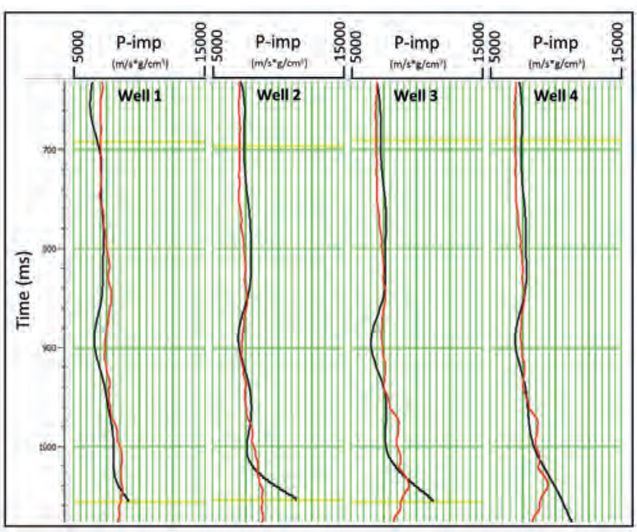

Figure 8 *Match between the modelled impedance log and actual filtered impedance log using multi-attribute regression. Black curve represents the filtered impedance log and red curve represents the modelled impedance curve. Analysis window is marked by yellow bar. Poor correlation coefficient of 0.7 is observed.*

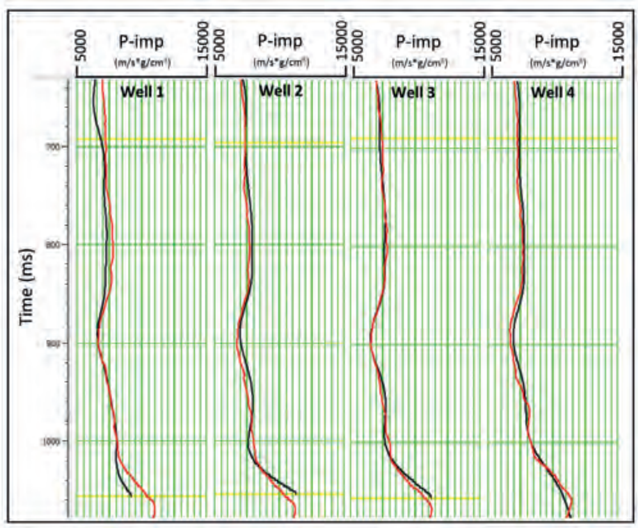

Figure 9 *Match between the modelled impedance log and actual filtered impedance log using multi-attribute training network after including a single well low-frequency model as one of the inputs. Black curve represents the filtered impedance log and red curve represents the modelled impedance curve. Analysis window is marked by yellow bar. Correlation coefficient improves significantly to 0.95.*

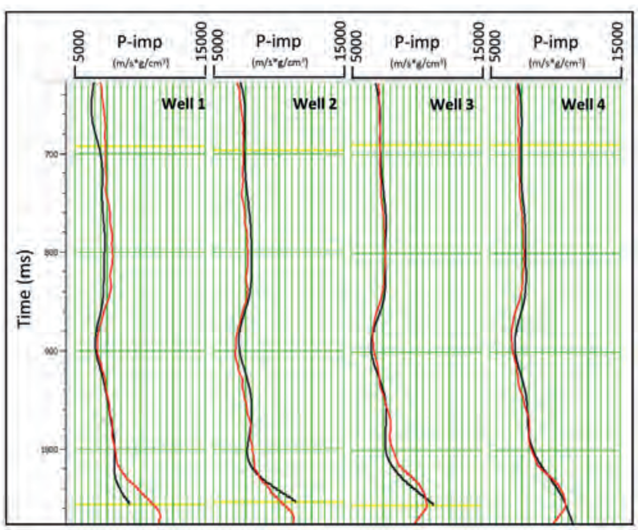

Figure 10 *Validation match between the modelled impedance log and actual filtered impedance log using multi-attribute network after including single well low-frequency model as one of the inputs. Black curve represents the filtered impedance log and red curve represents the modelled impedance curve. Analysis window is marked by yellow bar. A high correlation coefficient of 0.89 is observed.*

Again in this case, the correlation was found to be very high, confirming the applicability of the present approach.

After running the multi-attribute workflow on the full volume, the output volume was examined for its quality and horizon slice from this volume is shown in Figure 11. We make similar observation as we did in the previous example. An equivalent horizon slice from the low-frequency impedance volume generated using the inverse-distance interpolation method in Figure 12, show the pronounced low-frequency impedance anomalies as a bull's eye at well 2 and well 3.

Finally, Figure 13 shows the match at a blind well between the actual impedance log (blue curve), inverted impedance using single well low-frequency (black curve) and the inverted impedance using the low-frequency based on the proposed approach (red curve). It is again noticed that the low-frequency curve based on the proposed approach gives an excellent match with the actual impedance log at the blind well.

Using our proposed workflow, we have computed the low-frequency P-impedance model and used it in the model-based

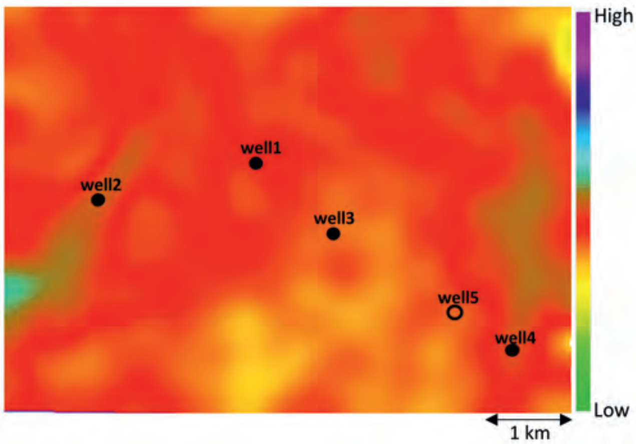

Figure 11 *Horizon slice in the zone of interest for the low-frequency model generated using multi-attribute regression method. (Data courtesy: Arcis Seismic Solutions, TGS, Calgary),*

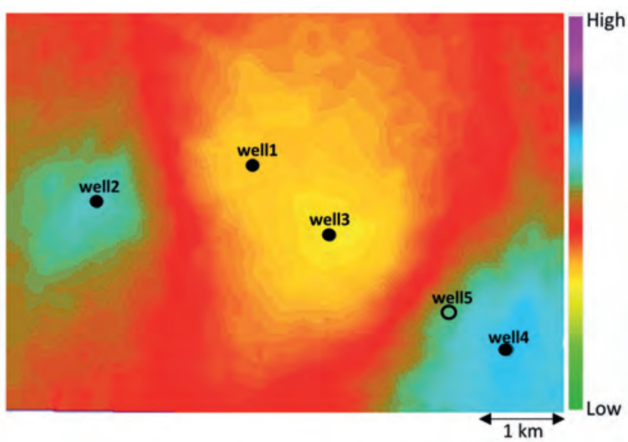

Figure 12 *Horizon slice in the zone of interest for the low-frequency model generated using inverse-distance interpolation method. (Data courtesy: Arcis Seismic Solutions, TGS, Calgary).*

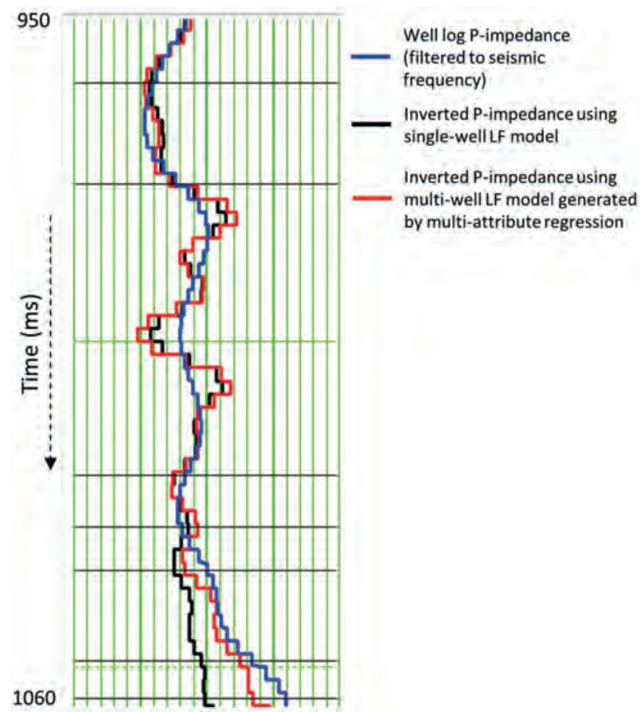

Figure 13 *Match at the blind well between the actual impedance logs (blue curve), inverted impedance using single well low-frequency model (black curve) and the inverted impedance using the low-frequency model based on the proposed approach (red curve).*

inversion. We have shown here the example of post-stack inversion only. This workflow can well be extended to the pre-stack inversion. Once the low-frequency P-impedance model is computed using our proposed workflow, S-impedance and density low-frequency models can be using suitable relationships from well log derived P-impedance versus S-impedance and P-impedance versus density crossplots for use in pre-stack simultaneous inversion.

Conclusions

The proposed workflow for generating a low-frequency impedance model is superior to the existing methods of low-frequency impedance generation. Determination of reservoir properties requires accurate absolute impedance data. This cannot be determined from relative acoustic impedance data which is ambiguous in most cases. Low-frequency trends estimated using single- or multi-well data may contain artifacts or may be biased in some way, and the absolute acoustic impedance determined therefrom could have a whole range of values that differ by as much as 1000 or 1500 m/s*g/cm$^{3.}$ Such differences will lead to misleading elastic parameter calculations. Thus, the quality of the low-frequency impedance model used in the inversion has a pronounced effect on the final impedance result, and a superior low-frequency impedance model when used in the inversion process yields a more accurate impedance inversion output. Our work on other such exercises corroborates this conclusion. We recommend this workflow for carrying out estimation of elastic parameters for quantitative interpretation of seismic data, especially when there is lateral variation of the impedance from well-to-well through the 3D volume.

Acknowledgements

We would like to thank Giles Watts for looking through the manuscript and suggesting changes that improved its quality. We would also like to thank Arcis Seismic Solutions, TGS, for allowing us to present this work.

References

Hampson, D., Schuelke, J. and Quirein, J.A. [2001] Use of multi-attribute transforms to predict log properties from seismic data. *Geophysics*, 66, 220-236.

Kalkomey, C.T. [1997] Potential risks when using seismic attributes as predictors of reservoir properties. *The Leading Edge*, **16** (3), 247-251.

Sams, M. and Saussus, D. [2003] Practical implications of low frequency model selection on quantitative interpretation results. *73rd SEG Annual Meeting*, Expanded Abstract, 3118-3122.

Zou, Z., Ling, Y. Wang, Y.J., Gao, J. and Xi, X.Y. [2013] Low frequency Impedance Modeling Based on Well Logs and Seismic Attributes. *75th EAGE Conference & Exhibition*, Expanded Abstract. We-P02-14.