# Impedance prediction using seismic inversion based on a Hybrid Global and Local Optimization

Nitin Verma[1]*, S.P. Maurya[1], Ravi Kant[1]
*1Department of Geophysics, Institute of Sciences, Banaras Hindu University, Varanasi-221005, India*
Email ID: nvnitin@bhu.ac.in

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**Abstract**

The present work created a methodology to forecast impedance in the inter-well zones of the Blackfoot field, Canada, by combining Global optimization (genetic algorithm) and local optimization (pattern search) while utilizing exclusively seismic reflection data. The Blackfoot Field is an oil and gas field where a glauconitic compound incised-valley system describes a region where sediments rich in glauconite serve as reservoir rocks for fossil fuel. The algorithms are first tested on artificially generated data based on the wedge model. The actual post-stack seismic data is then converted into impedance utilizing a designed hybrid optimization approach in the Blackfoot field, Canada. Very high-resolution subsurface information may be seen in the inverted or anticipated sections, where impedance ranges from 6000 to 12000 m/s*g/cc. The results also showed a low impedance (6000-9000m/s*g/cc) sand channel anomaly in the 1040–1060ms time range. This work shows that by employing seismic inversion based on combined global and local optimization, subsurface parameters like acoustic impedance may be quickly and inexpensively calculated.

## Introduction

Seismic inversion, specifically, is the process of determining subsurface acoustic impedance from seismic reflection data. There are numerous ways to accomplish this inversion, which is still in the development stage (Sen and Soffa, 1991; Sayers and Chopra, 2009; Jeong et al., 2017). In local optimization, the algorithm iteratively modifies the model parameters depending on the gradient data provided by the cost function. To arrive at a local minimum (for minimization problems) or a local maximum (for maximization problems), one must aim to proceed in a manner that locally reduces the cost function (Zhang et al., 2022). In contrast to local optimization algorithms, global optimization algorithms aim to find the global minimum (or maximum) of a function, even in the presence of multimodality (Jeong et al.,2017). These algorithms are designed to explore the entire parameter space and search for the best possible solution across multiple regions. The steepest descent method, conjugate-gradient method, pattern search, etc. are examples of local optimization techniques. These contrast with the global optimization techniques, which also include the Monte-Carlo method, genetic algorithm, simulated annealing method, etc (Sen and Stoffa, 1991). In this study, to overcome the above-discussed problem, combined local and global optimization techniques as a part of hybrid optimization(Sen, 2006). Particularly, in local optimization, we have used pattern search and a genetic algorithm is used as a global optimization technique. In comparison to traditional approaches, genetic algorithms (GA) and pattern search techniques provide advantages, especially when derivative information is unavailable or challenging to compute for practical issues. These strategies are nonetheless capable of optimizing the objective function while not requiring explicit derivative knowledge. (Dadashpou et al., 2009). The primary objective of the paper is the performance evaluation of seismic inversion utilizing a Hybrid global and local optimization process, which solely employs post-stack seismic data, identifies potentially productive zones, and predicts their impedance in the Blackfoot field in Alberta, Canada.

## Hybrid global and local optimization optimization

A combined global and local optimization optimization approach in this case comprises using a genetic algorithm (GA) as the initial solver and a pattern search method to perform further optimization. The GA is used to survey the potential solutions, and it also generates a first, pretty basic solution. The hybrid function refines and enhances the solution it has generated after the genetic algorithm reaches a stopping point. The GA's rough solution is the starting point for the pattern search algorithm, which then conducts a more focused search in the area surrounding it.

**Framework for impedance prediction using hybrid optimization**

From the hybrid optimization, the acoustic impedance may be estimated as follows. Firstly, choosing the desired seismic and well-log data for input. Then converting the well-log's depth domain to the time domain to use it with seismic data, which is time-domain data. To obtain the starting population that contains the acoustic impedance vector, we then choose a desired genetic operator and apply it. Calculate reflectivity from the impedance using Eq.1 Calculate synthetic trace using Eq.2.

$$R_i = \frac{V_p\,\rho(i+1) - V_p\,\rho(i)}{\left(V_p\,\rho(i+1) + V_p\,\rho(i)\right)} \qquad (1)$$

$$Syn(t) = w * r = \int_0^{\infty} r(n)w(n-t)dn \qquad (2)$$

Further, we calculate the RMS error between synthetic data and the input seismic data using Equation 3.

$$\text{Error (E)} = \frac{1}{n}\sqrt{\sum_{j=1}^{n}\left(S^{i}_{obs} - S^{i}_{mod}\right)^2} + \frac{1}{n}\sqrt{\sum_{j=1}^{n}\left(AI^{i}_{obs} - AI^{i}_{mod}\right)^2} \qquad (3)$$

Modify the initial population to reduce RMS error as much as possible within a limited time interval. The output of this step will be acoustic impedance (say$AI_0$) that satisfies equation 2. Use a pattern search algorithm by choosing the initial model ($AI_0$) as input. Construct a pattern vector and create the mesh. Calculate the RMS error using equation 3. Identify the best solution based on the RMS error and modify the new solution based on the best solution. Check whether the new solution is better than the existing best solution or not. Based on these, expand or contract mesh. We can Repeat the last three steps to terminate the program and get the desired acoustic impedance.

**Synthetic and Real data examples**

***The wedge model***

Wedge modeling helps us create a synthetic wedge model based on elastic characteristics, and then we look into how wavelengths, lithology, and bed thicknesses affect tuning. Figure 1 shows the wedge model and related results. Figure 1a represents a geological wedge model created based on three layers. With the top and bottom layers of sandstone, a wedge-shaped coal seam pinch-out model is built between the (middle) layers. The model has a 50m by 100m footprint and an impedance of 2600 m/s*g/cc for coal pitchout and 5700 m/s*g/cc for the sandstone

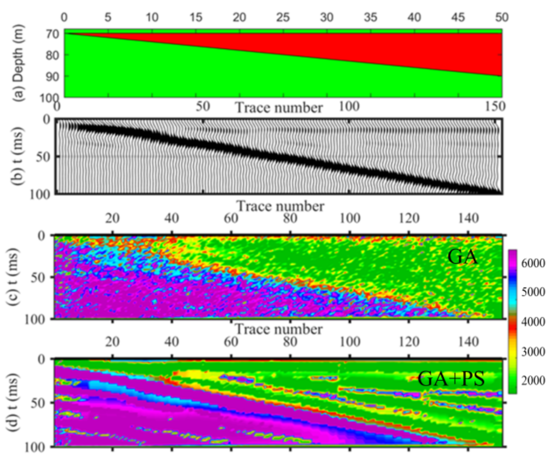


Figure 1: Presentation of the wedge model

The synthetic traces in Figure 1(b) are generated from a "wedge model" where the thinner part is not clear due to wave interference. This likely means that the seismic synthetic traces show a geological structure that resembles a wedge shape, but the details of the thinner part are obscured by the interference of seismic waves. This phenomenon, referred to as the tuning effect shown in Figure 1(b), is partially mitigated during the inversion process, which relies exclusively on the genetic algorithm, as depicted in Figure 1(c). But after, the combined hybrid optimization one can notice the layers are well separated in Figure 1(d) since the tuning effect has been minimized to a minimum, producing improved layer estimates as illustrated in Figure 1(d).

***Real field data application***

The application to the real data is done in three steps, the first process involves selecting an anomalous target zone with the help of well logs, the second process involves selecting a specific seismic trace (composite trace) that corresponds to the location of the well or is in close proximity, and the hybrid optimization is performed on it. In the third step, the entire seismic volume is inverted into an acoustic impedance.

***Case 1:Well log analysis***

Figure 2 represents an acoustic impedance plot in the time range of 900-1100ms for all 4 wells. From the figure, it can be seen that there is low acoustic impedance in the time range of 1050-1065ms in almost all wells plotted here. This low impedance zone is due to the presence of a sand channel. Having a low impedance for this sand channel generally means higher porosity. However, we are unable to obtain comprehensive and precise information on Impedance just from well logs as they are very sparse. In this situation, seismic inversion plays a crucial role in providing a means of estimating impedance in inter-well zones

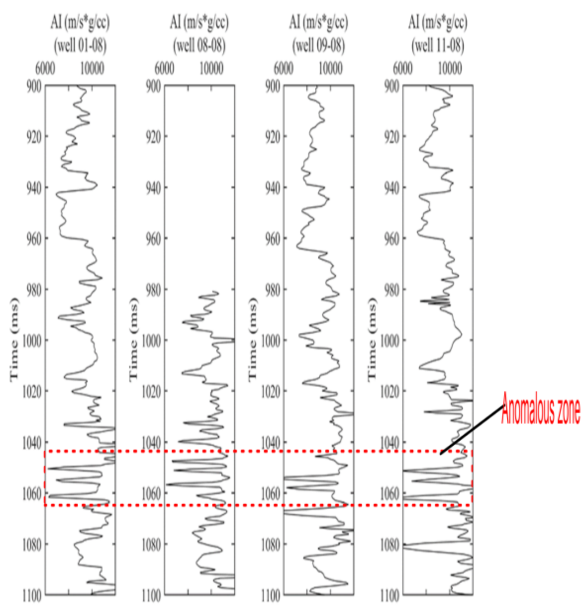


Figure 2: Presentation of the anomalous zone

***Case 2: Composite trace analysis***

This study targeted to predict acoustic impedance in the inter-well region using seismic inversion based on a hybrid optimization technique. For impedance prediction, one needs to apply hybrid optimization to the composite trace directly.

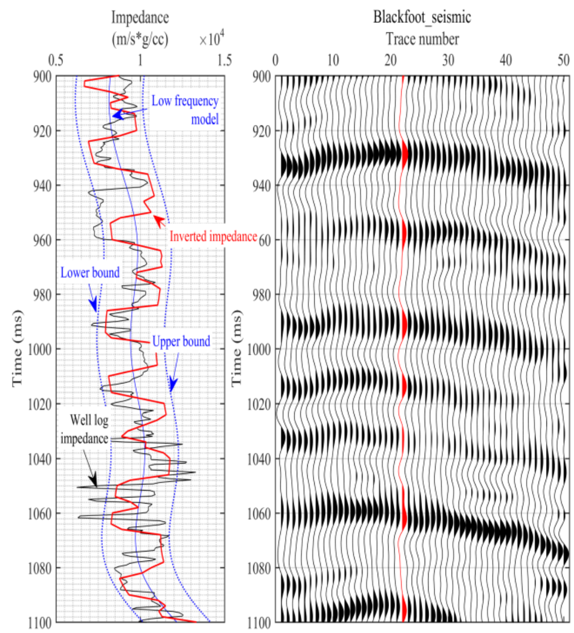


Figure 3: This figure represents composite trace analysis for a single trace chosen very close to a well-log location.

The idea is that the composite trace is very close to the well location (shown in the right track of the figure with red color) and hence the same stratigraphy can be expected. The low-frequency acoustic impedance from the well-log is used to constrain the solution and also as an initial model to start the hybrid algorithm. Also, this is the biggest advantage of using an initial model from the well-log information to reduce the significant time of convergence. Apart from that, we have also used lower bound and upper bound to further restrict search space within the desired range shown with a dotted blue line in both panels of Figure 3. This range can be chosen from any possible value but in this study, we have used upper and lower bounds based on the initial model generated from the well-log data. The well-log impedance (black solid line) is compared with the inverted impedance (red solid line) and presented in panel 1 of Figure 3. We do not observe a peak-to-peak match between the two acoustic impedances and the reason behind this is, seismic

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frequency typically ranges from 10 to 80 hertz, whereas well log data has a greater frequency range of 20 to 40 k-Hertz.

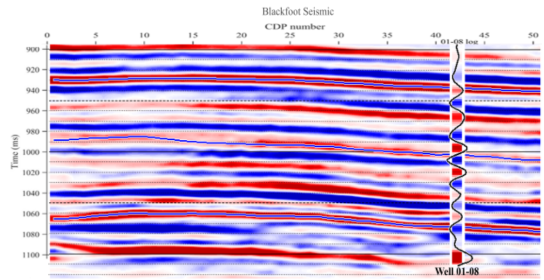
| Parameters | Well log impedance | Inverted impedance |
|---|---|---|
| AI correlation | - | 0.71 |
| Minimum | 6230 | 7080 |
| Maximum | 13300 | 11960 |
| Mean | 9536 | 9682 |
| Median | 9600 | 9788 |
| Mode | 6230 | 7080 |
| Standard deviation | 1299 | 1207 |
| Range | 7071 | 4881 |

Table 1: Variation of basic data statics for well log impedance and inverted impedance

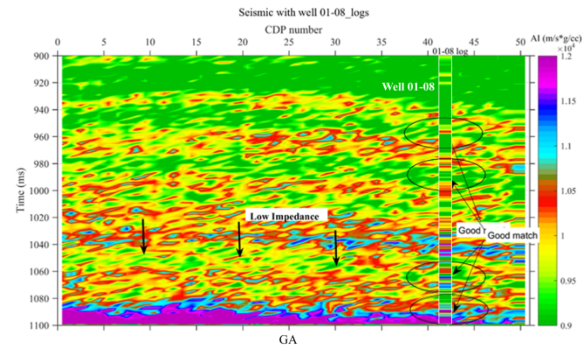
The statistical parameters estimated for the composite trace case are given in Table 1. From the analysis, it is found that the inverted results are very close to the original one and hence the algorithm performance is satisfactory.

***Case 3: Seismic volume analysis***

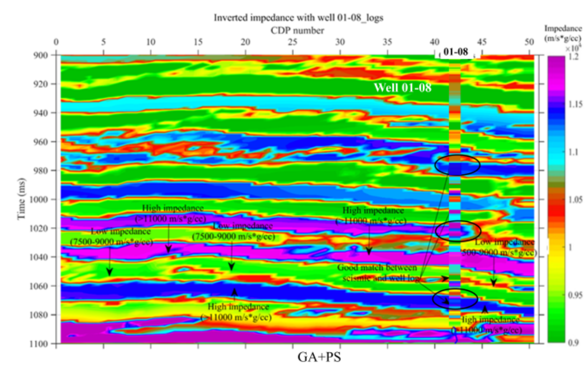
A cross-section at inline 1 and cross lines 1 to 50 within the two-way-travel time from 900ms to 1100ms is shown in Figure 4. Figure 4a is a straightforward illustration of post-stack seismic traces with well 01-08 in color density plot mode from the Blackfoot field, Canada shown. The sand channel is not clearly visible, and its thickness can not be viewed properly. Figure 4b shows an inverted section showing impedance based on the Genetic algorithm. Still, the resolution is not very high and the boundaries of the sand channel are not very clear. In Figure 4c hybrid optimization is performed. These inverted sections provide a comparatively better level of resolution along with within-layer information, whereas seismic data just provides interface information.




(a)




(b)




(c)

Figure 4(a) Post-stack seismic traces with well 01-08 from the Blackfoot field, Canada. 4(b) shows an inverted impedance cross-section along with Well impedance based on the Genetic algorithm only. 4(c) depicts an inverted impedance along with a Well impedance section estimated using a hybrid optimization technique.

The impedance varies from 8000-12000m/s*g/cc with the high impedance layer (>11000 m/s*g/cc) surrounding the low impedance (7500-9000 m/s*g/cc) reservoir zone from both sides, defining the boundary at 1040ms as a high reflecting layer. The impedance from well-log 01-08 is also plotted in color density plot mode on the same location in Figures 4(b) and 4(c) which matches extremely well with seismic impedance. The inverted acoustic impedance volume analysis shows a low AI anomaly zone between 1040 and 1060 TWT (two-way travel time). The special features of the data are highlighted by the arrow.

Further, the variation of error with iterations is shown in Figure 5. Figure 5 shows error variation with iteration for the impedance prediction process. One can notice that the GA alone is taking too much time to reduce error whereas the pattern search quickly reduces error hence the combination of GA and PS together can be used for quick convergence for the nonlinear geophysical problems. The error is estimated from a hybrid optimization algorithm.

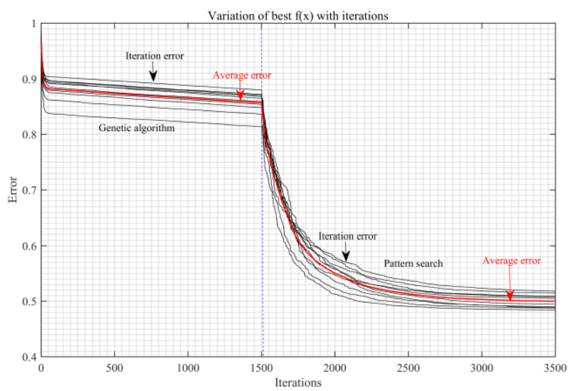



Figure 5: Showing the variation of error with increasing iterations in this GA and GA_PS hybrid optimization

## Conclusions

In the current study, a methodology is created to integrate local and global optimization to address the problem raised above. The idea is that first, a genetic algorithm as a part of global optimization runs to minimize the error between modeled and observed data within certain time/iterations, and thereafter, straightforwardly we run pattern search methods as a part of local optimization to the same data to reduce further error. The result estimated by GA is used as a starting model for PS so that it does not get stuck at local minima/maxima. The algorithm is tested by 'the wedge model', which found that the hybrid optimization performs extremely well and gives better results in comparison to the GA optimization alone. The well-log analysis is performed for all four wells which helps in selecting a target zone. Thereafter, the hybrid optimization is applied to the real data from the Blackfoot field, Canada to test their efficacy to estimate subsurface lithology. The study demonstrates that, among algorithms that impose limits on the solution and greatly improve outcomes, hybrid optimization is the most appropriate. The investigation also shows that all methods perform best for synthetic data initially, followed by hybrid optimization for actual data. For real data, the error analysis for algorithms is also displayed. The interpretation of the inverted section from the real data indicates an anomaly zone with low acoustic impedance (7500-9000m/s*g/cc) in between 1040 to 1060ms time interval, most probably due to Glauconitic minerals filling the reservoir rock which is the sand channel. This low impedance is noticed in the inverted section (GA_PS) Hybrid optimization and interpreted as the sand channel. The interpretation of the inverted section indicates an anomaly zone with low acoustic impedance (6000- 9000m/s*g/cc) in between 1040 to 1060ms time intervals, most probably due to a sand channel. It is clear from this work that hybrid optimization can be utilized to characterize the reservoir by finding the best solution to any inverse problem without the need for any prior knowledge. Finally, it can be said that the GA and PS-based hybrid optimization developed is extremely beneficial and appropriate for looking for fresh prospects in offshore or onshore exploration projects.

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