Introduction

The conventional method for calculating residual statics corrections (Taner et al., 1974; Wiggins et al. ,1976) has two steps: Firstly use crosscorrelation to estimate the total time delay for each trace and then use least squares to find the parameters in the total time delay equation. Stack energy maximization is a one-step alternative approach proposed by Ronen and Claerbout (1985). They defined an objective function that measures the correlation between all of the traces in each CMP gather. Changes in the parameters in the total time delay equation cause a time shift for each trace and change the correlation between traces. The parameter values are varied to maximize the stack energy. The stack energy function depends on thousands of traces and hundreds of parameters and can have a very large number of local maxima. Most optimization methods find a local maximum. A problem with many local maxima requires a global optimization method. Rothman (1985) recognized that the residual statics problem was a global optimization problem and proposed to solve the problem using the simulated annealing method. The computation of residual static correction is a non-linear optimum problem. Faced with the disadvantages of slower computational speed and lower precision that are characters using genetic algorithm or simulated annealing algorithm alone to compute residual statics, this paper presented an automatic residual static corrections characterized by hybrid global optimum automatic residual static correction by involving Energy maximization, simulated annealing and genetic algorithms. It is seen from application of method in some areas of the South America that the hybrid optimum technique is superior to other methods both in computational speed and in precision of solution.

Method and theory

In order to find the global solution, Monte Carlo optimization in terms of simulated annealing (SA) has been applied in the stack-power maximization technique. SA is based on the similarities between the process of solving optimization problems and the behavior of atoms in cooling metals or magma. SA utilizes the Metropolis algorithm and a number of strategies that enhance the optimization process by controlling the update function to appropriately control the process of accepting solutions in order to reach the objective of global optimization (Figure 1a). However, a major problem when using simulated annealing is to determine a critical parameter known as the temperature.

The genetic algorithm (GA) is a global optimization algorithm that simulates biological evolutionary selection. The algorithm uses the objective function of the solution to guide the search process to an optimal solution zone in the search space by means of the transitional rule of probability (Holland 1975; Goldberg, 1989). It has the characteristics of simplicity, easy implementation, and a powerful global searching capability. GA repeatedly propagates generations for a large population by applying three operators, which consist of selection, crossover and mutation as shown in Fig.1 (b). Therefore, GA requires the long computational time (Masaya, et al. 2008).

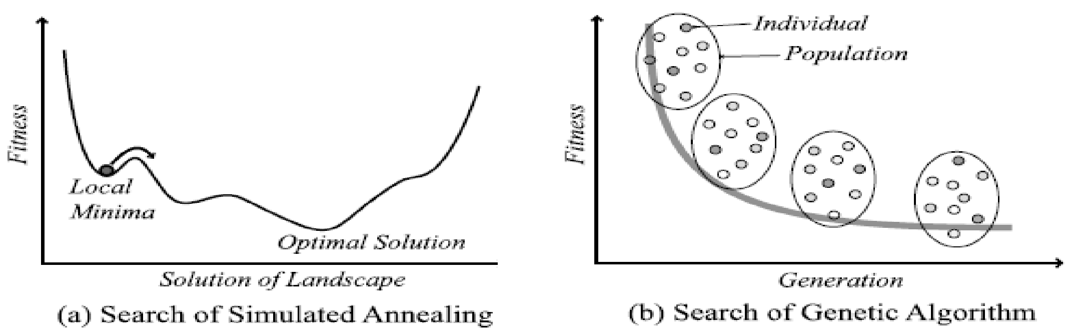


Figure 1 *One point search and population search (Masaya, et al. 2008)*

The maximum power method has the advantage of fast convergence and strong local convergence energy. Putting the three algorithms together, an alternate and new algorithm was developed (Yihua, 2003), the Hybrid Optimization Algorithm that combines the advantages of each as well as getting around their individual limitations. The basic idea of the hybrid optimization algorithm is to take the solutions obtained by the maximum power method and simulated annealing as the initial solution for the genetic algorithm. This provides strong individual relevance, effectively controls the solutions scale, and makes searching more efficient. As well, maximum power and simulated annealing can be iterated after the genetic algorithm to further strengthen the ability of using the genetic algorithms solution to perform local searching, and to compensate for the limitations of the genetic algorithms lack of centralized searching, finally quickly converging to an optimum solution, and obtaining optimum statics.

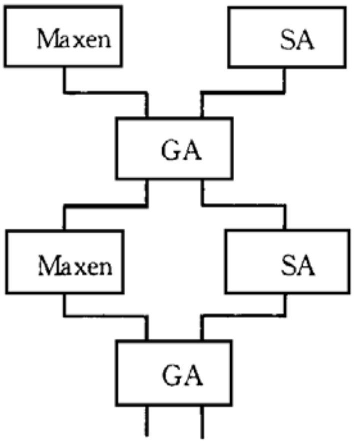


Figure 2 *Flowchart of the hybrid method*

The optimization procedure of this hybrid method is,

1. Obtain the partial local optimal solution by maximum energy method
2. Obtain the partial local optimal solution by simulated annealing algorithm
3. Perform the Repeat alternate genetic algorithm to the local optimal solution from step 1 and step 2
4. Repeat the step 1to 3 until the specific probability achieved

The objective function for the method is,

$$E(t)=\sum_{W_1}^{W_2}\left[F\left(t-\tau\right)+H(t)\right]^2$$
$$=\sum_{W_1}^{W_2}\left[F^2\left(t-\tau\right)+H^2(t)\right]+2\sum_{W_1}^{W_2}\left[F\left(t-\tau\right)H(t)\right]$$

Here, W_1 is the start time of the window, W_2 is the end time of the window, $H(t)$ is the model trace, $F(t)$ is the record trace, τ is the static correction value.

The probable value is given as below,

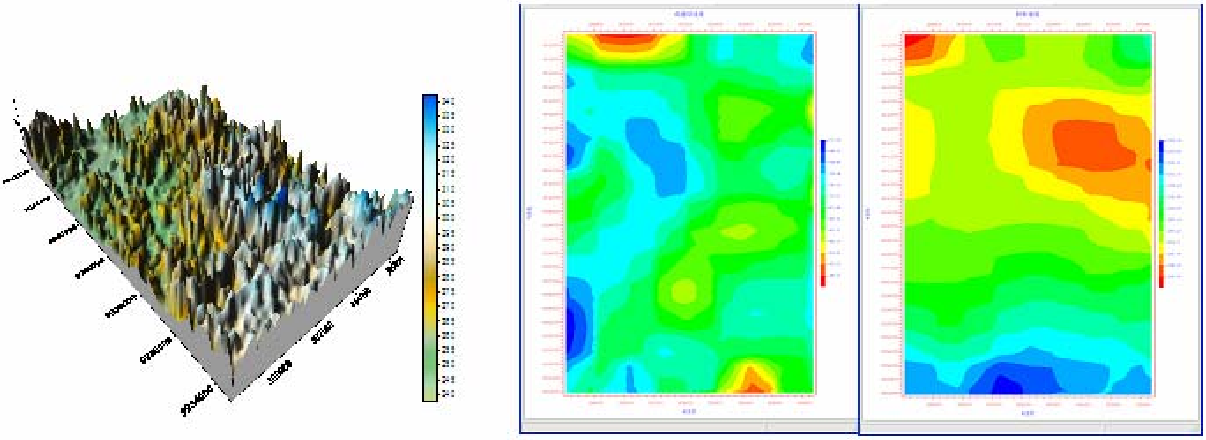
$$P_i=\exp(E_i/T)\Big/\sum_{j=1}^{N}\exp(E_j/T)$$

Here, N is the number of unknown static value, E_i is the energy when time shift is τ , T is the temperature.

Case History

The hybrid fast global optimization method has been successfully applied in areas of South America and has proven to be effective, robust, fast, and simple to use. We use one of the cases here as an example. The near surface condition of the area is complicated, both velocity and thickness of the weathering layer change rapidly. Most of the seismic data in this area has a serious static correction problem.

The figures 3a is the surface elevation map of the survey, which shows the subsurface geology of the survey is very complicated. The thickness of weathering layer has great lateral variation (Figure 3b). There is a stable refractor layer exists. Thickness of weathering layer varies from13-43m. Velocity of refractor layer varies from 2300-2400m/s.



(a) (b) (c)

Figure 3 *(a)Surface elevation map (b)Thickness of weathering layer (c)Velocity of weathering layer*

First arrival travel time was picked and refraction tomography statics was applied，then hybrid global optimization residual statics method was used for short wavelength static corrections. Figure 6 shows stack sections before and after hybrid global optimization residual static correction. As shown in figures, the high frequency component of statics problem had been solved perfectly even the statics value larger than 60ms. Stack section after residual statics shows better image quality with reflections stand out distinctively after the residual travel time distortion corrected.

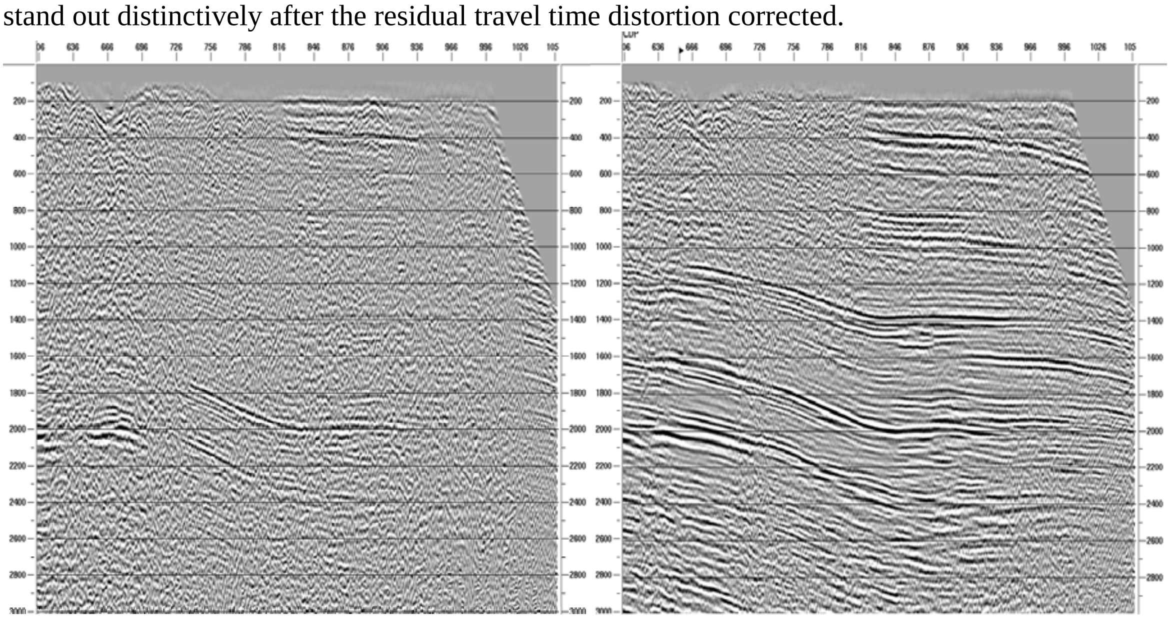


Figure 6 *Left: Stack section before residual statics(part)):*
Right: Stack section after residual statics (part);

The quality of solution is measured by the objective function, stack power. Comparing to Max power or SA&GA only, the final stack power for the hybrid solution is 4137, with higher energy ratio of 88.80 %. The computation time and iteration numbers of different method are also showed in table 1, from that we can see that the hybrid method can converge to the global optimum solution very fast without null space effect.

Method	*Time cost (Minutes)*	*Iterations*	*Convergence Power*	**Power Ratio (%)*	*Description*
Max. Power	*5*	*12*	*1722*	*41.53*	*Converged at a local solution*
SA & GA	*1270*	*3338*	*3633*	*87,62*	*Converged at a null space*
Hybrid	*10*	*30*	*4137*	*88.80*	*Converged at global solution*
**Power ratio = (Convergence Power/ desired Power)*100, Desired Power=4146*					

Table 1 *Comparison between Max energy, Simulated Annealing & Genetic algorithm, and Hybrid method*

Conclusions

Linearized residual statics estimation will often fail when large static corrections are needed. Cycle skipping may occur and the solution will be trapped in a local maximum of the stack-power function. In order to find the global solution, Monte Carlo optimization in terms of simulated annealing has applied in the stack-power maximization technique. But Monte Carlo method has severe limitations, namely time-consuming iterations (above 1000 times) and good temperature parameter for converging to optimum solution. Therefore a hybrid optimization algorithm was proposed. Energy maximization simulated annealing and genetic algorithms are involved. The application of the method shows high stability, time saving, fewer iteration times and fast convergence to the global optimum solution.

Acknowledgements

The authors acknowledge the LandOcean processing center for their cooperation in providing the data and support, and the management of both LandOcean and Petroamazonas for permission to publish this work.

References

Taner, M. T., Koehler, F., and Alhilali, K. A., 1974, Estimation and correction of near-surface time anomalies: Geophysics, 39, 441-4 6 3

Wiggins, R. A., and Lamer, K. L., Wisecup, R. D., 1976, Geophysics, 41, 922-938.

Ronen, S., and Claerbout, J., 1985, Surface-consistent residual statics estimation by stack-power maximization: Geophysics, 50,2755-2767.

Rothman, D. H., 1985, Nonlinear inversion, statistical mechanics, and residual statics corrections: Geophysics, 50, 2784–2796.

Holland, J. H., 1975, Adaptation in natural and artificial systems, Univ. of Michigan Press

Goldberg, D. E., 1989, Genetic algorithms in search, optimization and machine learning: Addison-Wesley Publ. Co.

Masaya Yoshikawa, Hironori Yamauchi, Hidekazu Terai. 2008, Hybrid Architecture of Genetic Algorithm and Simulated Annealing. Engineering Letters, 339~345

Y. H. Lin, Z. J. Zhang, C. Yin, X. X. Zhou, 2001, Hybrid Optimization of Optimization of Static Estimation in Complex Topography, Chinese Journal Of Geophysics, 46(1), 101-106