JOINT INVERSION OF RAYLEIGH WAVE DISPERSION and H/V CURVE INVERSION BY USING PARTICLE SWARM OPTMIZATION & GENETIC ALGORITHM

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INTRODUCTION

Joint inversion of surface wave dispersion and ellipticity curves with its highly nonlinear nature has some difficulties using traditional inverse methods due to need and strong dependence to the initial model, possibility of trapping in local minima and evaluation of partial derivatives (G. Dal Moro & Pipan, 2007; Song, Tang, Lv, Fang, & Gu, 2012). There are some modern global optimization methods to overcome of these difficulties in surface wave inversion such as Genetic Algorithm (GA) and Particle Swarm Optimizaton (PSO). GA is based on biologic evolution consisting reproduction, crossover and mutation operations have used a few surface wave analysis studies such as Giancarlo Dal Moro, Pipan, & Gabrielli, 2007; Pezeshk & Zarrabi, 2005; Yamanaka & Ishida, 1996. Even though PSO and GA processes are similar in appearence, the cross-over operation in GA is not used in PSO and the mutation operation is a stochastic process for changing the genes within chromosomes in GA, but in PSO, this similar process is performed intellectively by sharing information between particles. Unlike GA, the particles in PSO algorithm change their position with logical velocities according to particle's own experience and swarm's experience (Gill et al., 2006; Shi & Eberhart, 1998). PSO algorithm developed after GA is inspired from the social behaviour of birds or fish of swarms have just been used one Rayleigh wave dispersion inversion study as Song et al., (2012). In this study, we used PSO and GA optimization technique to determine shear wave velocity structure by using multiobjective surface wave dispersion curve and ellipticity curve for which observed H/V spectral ratios. *Utility of these multiobjective inversion provide reliable results, plausible convergence rate, acceptable relative error and optimum computation cost with global optimization techniques that are important for modelling studies.*

OBJECTIVES

In this study, we applied PSO and GA technique to estimate S wave velocities and thicknesses of the layered earth model by using multiobjective optimization of the misfit between calculated dispersion & ellipticity curve and observed dispersion & H/V spectral ratios.

We emphasize on the advantage of global optimization methods to avoid

- trapping of local minima/maxima
- dependence to initial model and partial derivatives
- difficulties on taking derivatives

We emphasize on the advantage of PSO modern global optimization algorithm compare with GA which is other global optimization method for geophysical modelling studies considering its

- rapid convergence
- low misfit error
- computation cost

We also emphasize on the advantage of using multiobjective optimization methods

- Reliable results are obtained with different and non-comparable solutions

METHODS

Particle Swarm Optimization

The PSO based on social behaviour of swarms of insects or flocks of birds discovering to the food or reaching to the nests by shortest path way was originally proposed by Kennedy and Eberhart in 1995. Particles distributed by randomly in search space denoting the individual parameters changes their own velocity with equation (1) and position with equation (2) using their own intelligence and swarm intelligence for reaching minimum error value/values by using objective function (Figure 1).

$$V_i^{k+1} = w\,V_i^k + c_1\,rand_1 \times (pbest_i - s_i^k) + c_2\,rand_2 \times (gbest - s_i^k) \quad (1)$$

$$s_i^{k+1} = s_i^k + V_i^{k+1} \quad (2)$$

s_i^k : i_{th} particle position at iteration k, V_i^k : i_{th} particle velocity at iteration k,

w : inertia weight, c_1 and c_2 : cognitive and social learning factor, $rand_1$ and $rand_2$: uniformly distributed random numbers

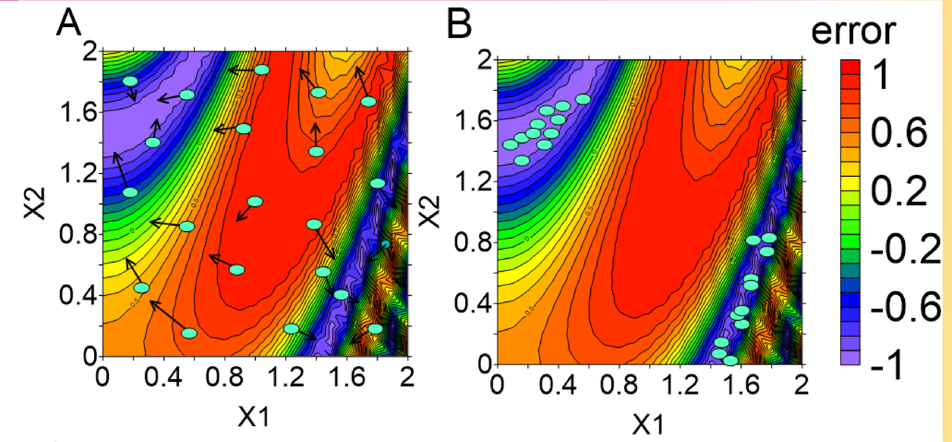

Figure 1. Estimation of two parameters (x1 and change position with velocity (A), particles reach minimum error (B).

Genetic Algorithm

GA, invented by Holland (1975), is based on the principles of natural genetics and selections having elements are reproduction, crossover and mutation. Reproduction operator selects the good strings (minimum error values) of the population to form mating pool by using Roulette-wheel selection scheme representing the fitness values which are inverse related with error values (Figure 2). This scheme increases the probability of selection of minimum error values. Crossover operator creates new substrings and new solutions by changing information of strings with other strings. Error values of the new strings are most important to survive in the next reproduction stage. Mutation operator changes the new strings using small mutation percentage number. The use of these 3 operators yield new generation containing new strings with decreased error values.

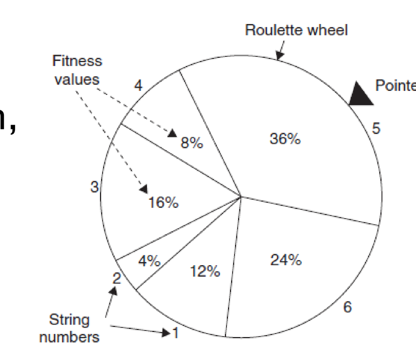

Figure 2. Roulette – wheel selection scheme (Rao, 2009).

RESULTS

Synthetic Data

We first used noise free synthetic data to estimate S wave velocity and thickness parameters of each layer by using PSO and GA multiobjective optimization of Rayleigh wave dispersion curve and H/V spectral ratios. '*gpdc' and 'gpell'* tool developed by *Geopsy* team is used for computing Rayleigh wave dispersion and ellipticity curve respectively (Bard et al. 2000). Table 1 shows synthetic data model parameters and estimated model parameters, which are S wave velocities and thicknesses within search space. P wave velocities change at each layer by exponentially from Vp/Vs = 4 to Vp/Vs = 2. Table 2 shows the PSO and GA parameters used in the application and their results in terms of error and elapsed time. The objective function that we used in both optimization algorithm is *goodness of fit* function expressed as normalized root mean square (NRMS) error function given as equation (3). According to this equation error costs vary bewtween –Inf (bad fit) to 1 (perfect fit). Figure 3 and Figure 4 shows the results of PSO and GA techniques, respectively. These results show that PSO method rapidly converges to 1 indicating the minimum normalized root mean square (RMS) error compared to GA.

Table 1. Synthetic data model parameters, optimized parameters –search space and estimated parameters by using PSO and GA

	Synthetic model				Search Space		Estimated Parameters (PSO)		Estimated Parameters (GA)	
Layer No	S Wave Velocity (m/sec)	Thickness (m)	Density (g/cm³)	P Wave Velocity (m/s)	S Wave Velocity (m/sec)	Thicknes s (m)	S Wave Velocity (m/s)	Thickness (m)	S Wave Velocity (m/s)	Thickness (m)
1	100	10	1.6106	400	80 – 120	6 - 14	99.8	9.89	98.2	9.82
2	200	10	1.6662	672	160 – 240	6 - 14	203.6	10.7	205.7	9.62
3	300	10	1.7020	848	240 – 360	6 - 14	308.3	9.8	282.9	10.1
4	400	10	1.7230	951	320 – 480	6 - 14	396.4	10.6	408.3	11.3
5	500	10	1.7329	1000	400 – 600	6 - 14	504.4	10.9	492.5	10.1

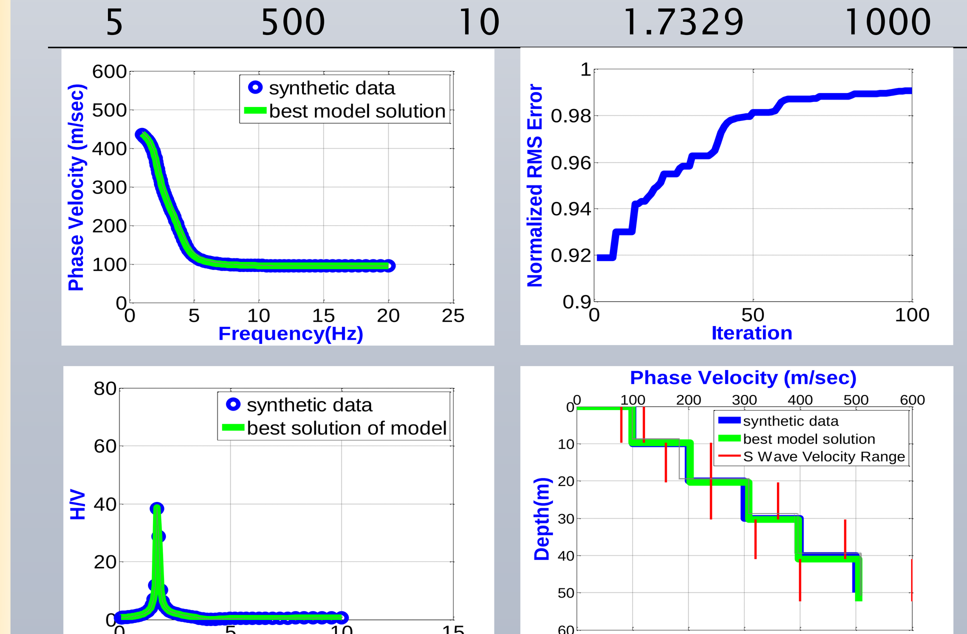

Figure 3. PSO results

Table 2. PSO and GA parameters

PSO		GA
50	Particle / Population Size	50
100	Iteration	100
0.9907	NRMS Error	0.986
501.42 sec	Elapsed time	720.25 sec

$$NRMS = 1 - \frac{\|Model - Data\|}{\|Model - mean(Model)\|} \quad (3)$$

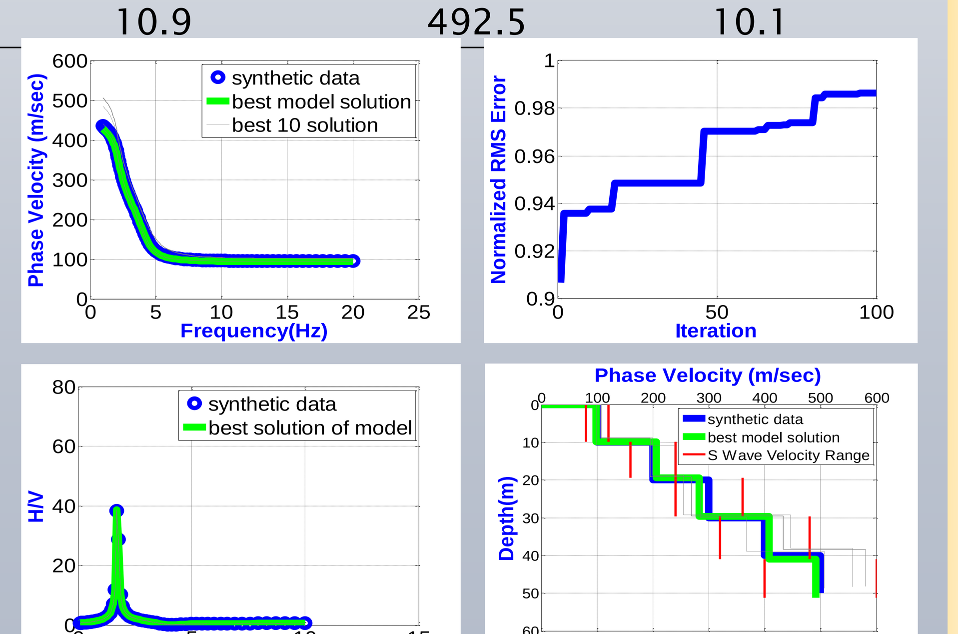

Figure 4. GA results

RESULTS

Real Data

We modelled real dispersion data obtained from a site in Bursa region (Bursa Project, TÜBİTAK MAM YDBE) to estimate S wave velocity and thickness of each layer fitting the dispersion and H/V elipticity curve inversion by using multi-objective PSO optimization technique. The objective function that we used is the NRMS error function same as eq (3). Particle number and iteration number is 100 and 200 respectively. Vp/Vs range changes at each layer by exponentially from 4 to 1.7. Figure 5 shows the results of multiobjective PSO technique as the dispersion and H/V curve fitness and their total NRMS error. This figure also shows the estimated velocity model and the search space. According to results, remarkable fit is provided with the multiobjective PSO technique.

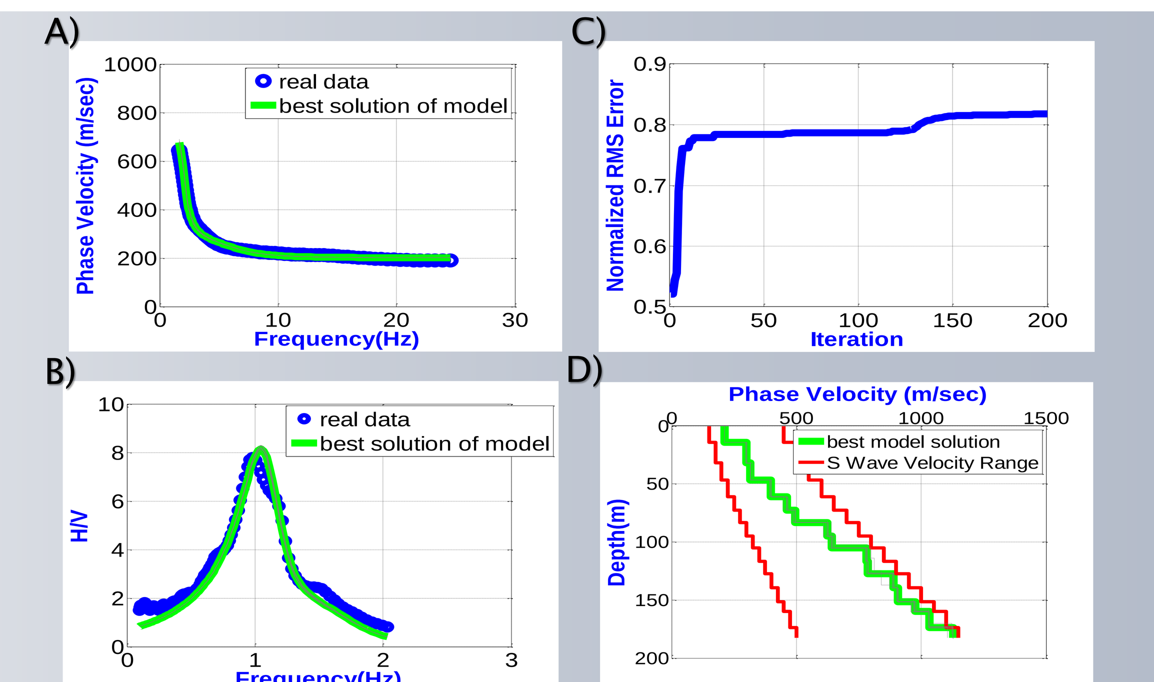

Figure 5. A) Dispersion curve B) Ellipticity curve C) Changing of NRMS error with iteration D) Estimated phase velocity-depth model.

CONCLUSIONS

Global optimization methods such as PSO and GA provide many advantages that they don't trap any local minima and they don't depend on initial models and partial derivatives. Compared with GA, PSO has also many advantages which has rapid convergence to minima and less computation time. Solving the PSO method with multi-objective function, in which dispersion and ellipticity objective functions are different and non-comparable with each other, provides reliable results. In this study, we normalized the errors getting from dispersion and ellipticity curve objective functions to avoid of contributions of non-comparable errors. *Pareto optimality as another method used in the literature for multi-objective solutions is also planned to be used for future works.*

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