Prediction of shear and Compressional Wave Velocities from petrophysical data utilizing genetic algorithms technique: A case study in Hendijan and Abuzar fields located in Persian Gulf

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Abstract

Shear and Compressional Wave Velocities along with other Petrophysical Logs, are considered as upmost important data for Hydrocarbon reservoirs characterization. Shear Wave Velocity (Vs) in Well Logging is commonly measured by some sort of Dipole Logging Tools, which are able to acquire Shear Waves as well as Compressional Waves such as Sonic Scanner, DSI (Dipole Shear Sonic imager) by Schlumberger and MDA (Monopole-Dipole Array) by Weatherford Company. Usually in Old Wells, there is lack of Shear Velocity data, or in other Wells, only some intervals may have Vs data. Shear Wave Velocity is of high importance in Geophysical studies such as AVO (Amplitude Variation with Offset) and VSP (Vertical Seismic Profiling) and along with Compressional Wave Velocity, it can be used for identification of Fluid Type, Lithology and Mechanical Rock Properties. Genetic Algorithms Technique as a subset of Evolutionary Computing is an important part of Intelligent Systems for solving Optimization Problems. In this study, Compressional and Shear Wave Velocities were modeled by Genetic Algorithms Technique in Ghar member of Asmari Formation, Hendijan Field. For measuring the accuracy of the method, predicted values were compared with the real data in Ghar member of Asmari Formation, Abuzar Field. Multiple Regression Analysis was used as alternative technique to evaluate the accuracy of the GA Model. The results of this study show that GA could be considered as an efficient, fast and cost-effective method for predicting Vs and Vp data from conventional well Log data. Predicted Compressional Wave Velocity along with Shear Wave Velocity, validates the reliability of Genetic Algorithms as an Optimization Technique for predicting parameters such as Vs.

Keywords: *Genetic Algorithms, Regression Analysis, Compressional Wave Velocity, Shear Wave Velocity, Asmari Formation, Ghar member, Hendijan Field, Abuzar Field.*

Introduction

Shear Wave Velocity (Vs) data are one of the most important Petrophysical data for evaluation of reservoir properties, so that combining these data with Compressional Wave Velocity (Vp) data could be used in Reservoir Characterization Studies including identification of Lithology, Fluid Type, Mechanical Rock Properties and Geophysical interpretations such as Vertical Seismic Profiling (-VSP) and AVO studies. In most of Old Wells there is lack of Shear Wave Velocity Data. In recent years, Intelligent Systems and Genetic Algorithms Technique have been used as powerful tools for prediction of parameters, Logs and other sort of data in petroleum industry. (Saemi *et al*., 2007), (Rezaee *et al*., 2007), (Kadkhodaie *et al*., 2007), (Eskandari *et al*., 2004), (Nikravesh *et al*., 2001), (Rogers 2001), (Wong & Nikravesh, 2001), (Johnson *et al.,*

2001), (Zadeh, 1994), (Zadeh & Aminzadeh, 1995), (Aminzadeh & Jamshidi,1994) and other researchers have used intelligent systems to predict reservoir parameters from well Log data.

The present study concentrates on following objectives.

1- Application of intelligent Modeling system based on Genetic Algorithms to predict Compressional and Shear Wave Velocities from Petrophysical Data.

2- Application of Multiple Regression Models for predicting Compressional and Shear Wave Velocities from Petrophysical data.

3- Comparing the results of the Genetic Algorithm and Multiple Regression Model for predicting Vs and Vp.

Geological Settings of the Studied Fields

Data for this study came from two wells of the Hendijan and Abuzar Fields, located in Persian

Gulf. The Ghar member of the Asmari Formation forms the main reservoir unit. The sequence represents a transgressive-regressive cycle deposited under shallow water marine and marine marginal-lagoonal conditions in an overall regressive setting. The Carbonate units indicate a lateral westward extension of the prolific Asmari Formation while the Ghar Sandstone is equivalent to the onshore Ahwaz member.

The main objective of this study is to estimate the accuracy of optimization techniques used in prediction of parameters in two fields about 100 Kms apart with slightly different facies and Lithologies. As it is obvious from Petrophysical Logs and Geological Studies of the Fields, Ghar member in Hendijan Field is a Clastic Reservoir mostly composed of Sandstone, Dolomite and some layers of Shale, whereas in Abuzar Field the Lithology of Clastic Ghar member is composed of Sandstone, Dolomite, Limestone and Shale.

Methods
Genetic Algorithms (GA)

Evolutionary computing was firstly introduced by Richenberg in his research: "Cybernetic solution path of an experimental problem" in 1960s. Genetic Algorithm was invented by John Holland in 1975 and then developed by his coworkers and students that resulted in publish of his book: "Adaptation in natural and artificial systems".

Optimization methods are mainly of three kinds:
1- Calculus-based method.
2- Enumerative method.
3- Random-based method.

Genetic Algorithm is a Random-based method of optimization techniques.

Principle terms in Genetic Algorithms can be stated as below (GA Toolbox, MATLAB):

- Chromosome: a string of information that includes all the needed information to search the optimum point in the search space, in other words it is a coded string, which includes all the characteristics and properties of a problem. In this study each variable (predictors or response), is considered as a chromosome or coded string.

- Gene: a part of the chromosome, which is the smallest antiseptic unit of that chromosome. In this study, each coded string of data is made of binary codes, which are called genes in biology terms.

- Generation: is a loop of the populations.
- Population: the responses make the population, in other words population includes set of points in the search space, which by using them we look for the optimum point. Chromosomes make the population; each population contains certain amount of chromosomes.
- Search space: when solving a problem, the aim is to find the best response among all different responses. The space of all possible responses in solving a problem is defined as the search space. Each response can be defined by a value, which is an indication of its Fitness (Gen & Cheng 1994). Searching for a response is equal to finding the domain (maximum or minimum) in that search space.

The objective function: is the function we want to optimize:

$$y = f(x_1, x_2) \qquad (1)$$

Where:

$$x_1, x_2 \in [a_i, b_i]$$

a_i, b_i are the lower and upper limits, respectively. In this study the objective functions are as below, which will be explained in detail in section 4.

$$\text{MSE} = \sum_{i=1}^{n} [Vs\ (real) - Vs\ (predicted)]2/\ [n\text{-}p]$$

$$\text{MSE} = \sum_{i=1}^{n} [Vp(real) - Vp\ (predicted)]2/\ [n\text{-}p]$$

MSE=*f (Vs (real), Vs (predicted))*

The procedure of Genetic Algorithms is performed in several steps (figure 1):

1- At Initialization step, a population of potential responses is created in the search space.

2- At Evaluation step, the potential responses (individuals) are evaluated.

3- At Selection step, a number of individuals based on their fitness, are selected to enter to mating process.

4- At Recombination process, mating processes (Genetic Algorithms operations such as crossover and mutation) are performed on individuals to produce new generations.

5- The evaluation of the new generation's individuals is performed and all the processes are

redone.

These procedures are repeated until the stopping criteria are met, when the population gets closer to the optimum point.

```
begin
   t ←— 0
initialize p (t)
evaluate p (t)
while (not termination condition) do
select  p (t+1)
recombine  p (t+1) to yield c (t)
   p (t+1)←—  c (t)
   t ←— t+1
evaluate p (t)
end;
end;
end;
```

Figure 1:The outline of simple Genetic Algorithms (Goldberg, 1989).

Stopping criteria (GA Toolbox, MATLAB) can be met at one of these criteria:

1- The Algorithm stops when the optimum point is reached (the response is found), in other words when the chromosome includes the best value, the response is reached, here MSE should be almost equal to zero.

2- The Algorithm stops when no improvement is reached after X times the Algorithm is repeated by the old chromosomes reinserting into the new generations, whether Algorithm reaches the global optimum or is stopped in a local minimum.

3- As a statistical condition, the Algorithm stops when the fitness function reaches a specific value.

4- Genetic Algorithm stops when the weighted average change in the fitness function value over Stall generations is less than Function tolerance.

5- The Algorithm stops if there is no improvement in the objective function during an interval of time in seconds equal to stall time limit.

6- Genetic Algorithm runs until the weighted average change in the fitness function value over Stall generations is less than Function tolerance.

Regression Analysis (RA)

Regression Analysis is used to estimate and Model the Relationship between a response variable and one or more predictors. Regression Analysis is a good method to be compared with Models obtained by Genetic Algorithms technique. To make it clear, we would explain some principles of RA.

Relations between Variables

It is crucial to distinguish between a functional Relationship and a statistical Relationship (Draper & smith, 1981).

Functional Relation between two Variables:

A functional Relationship between two variables is expressed by a mathematical formula:

$$y = f(x) \qquad (2)$$

Where:

x is the independent variable

y is the dependent variable

Statistical Relation between two Variables:

A statistical Relationship is not a perfect Relationship. In general, the observations for a statistical Relationship do not fall directly on the curve of Relationship (Figure 2).
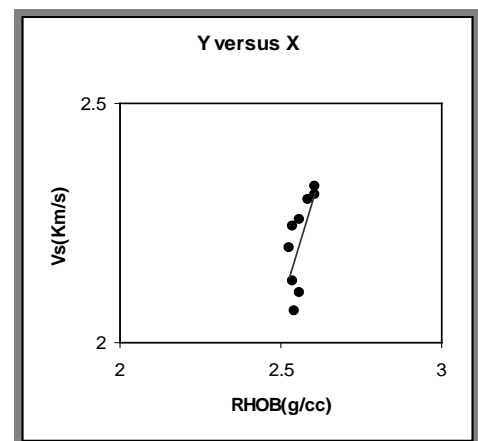

Figure2: an example of statistical Relationship between two variables

Regression Models
Simple Linear Regression Models

In this Model, there is only one predictor variable and the Regression is Linear. The Model can be stated as follows:

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i \qquad (3)$$

Where:

Y_i is the value of the response variable in the ith trial

β_0 and β_1 are parameters

X_i is a known constant, namely the value of the predictor variable in the ith trial

ε_i is a random Error term.

Multiple Regression Models

In this Model there are more than one predictor variables and the Model may be Linear (first-order Model) or Non-Linear (second, third or higher order Models).

In general, the Multiple Regression Model can be stated as below:

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + ... + \beta_{p-1} X_{i,p-1} + \varepsilon_i \quad (4)$$

Where:

Y_i Is the value of the response variable in the *i*th trial

$\beta_0, \beta_1, \beta_2 \dots \beta_{p-1}$ are parameters

$X_{i1}, ... X_{i,p-1}$ are known as predictor variables.

ε_i is a random Error term.

Other form of Multiple Regression Model is the polynomial Regression Model that is not Linear. It can be stated as follows:

$$Y_i = \beta_0 + \beta_1 X_{i1}^{\beta_2} + \beta_3 X_{i2}^{\beta_4} + ... \\ + \beta_{p-1} X_{i,p-1}^{\beta_P} + \varepsilon_i \quad (5)$$

Where:

Y_i Is the value of the response variable in the *i*th trial

$\beta_0, \beta_1, \beta_2 \dots \beta_{p-1}$ are parameters, where the odd subscripts refer to the multiplier parameters and the even subscripts refer to the exponential parameters.

$X_{i1}, ... X_{i,p-1}$ are known as predictor variables.

ε_i is a random Error term.

Relations between Petrophysical data, Compressional, and Shear Wave Velocities

Neutron Log: Neutron Porosity indicates the formation hydrogen index, which is detected by Neutron tool (Rezaee & Chehrazi, 2006). Neutron Log indicates the formation Porosity. The more the Porosity of the formation, the less the Velocity passing through the formation (figure 3), (Eq. 6)

$$\frac{1}{v} = \frac{\phi}{v_f} + \frac{1-\phi}{v_m} \quad (6)$$

Where ϕ is formation Porosity (directly measured by Neutron tool). v_f is the fluid Velocity, and v_m, is the matrix Velocity.

So in intervals with higher Porosity (higher Neutron Porosity), Shear and Compressional Wave Velocities decrease.

It should be considered that Neutron Log is proportional to hydrogen content of the formation, so in formations containing Hydrocarbon (Oil or Gas), not only Neutron Log is reading lower values, but also Velocity of Compressional Wave is also decreased and although Shear Wave Velocity is not affected by Fluids but the denser (lower Porosity) the formation, the higher the Shear and Compressional Wave Velocities.
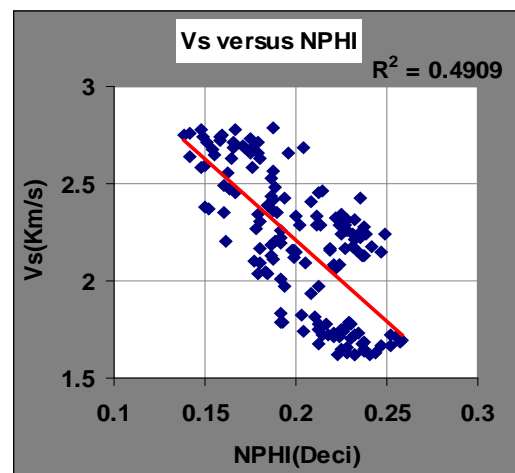

Figure 3: The Relationship between Shear Wave Velocity and Neutron Porosity

Density Log: Density Log has a direct proportion with Shear and Compressional Wave Velocities (figure 4 and 5).

According to the Eq. 6 and Eq. 7, Vp and Vs increase as the formation Density (ρ_b) increases and vice versa (Schlumberger Log Interpretation, 1989):

$$\phi = \frac{\rho_{ma} - \rho_b}{\rho_{ma} - \rho_f} \quad (7$$

Where ρ_{ma} is the matrix Density, ρ_b shows the formation bulk Density, and ρ_f is the fluid Density.

$$Vs \alpha \rho_b \quad (8)$$
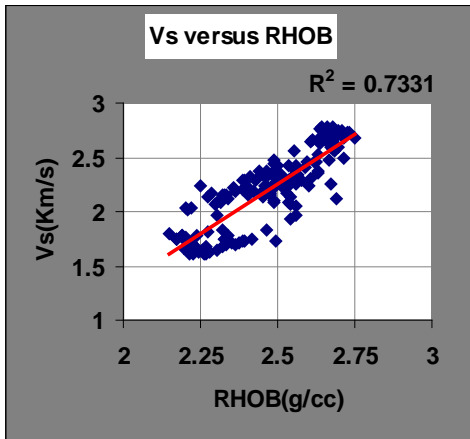$$V_P \alpha \rho_b \quad (9)$$

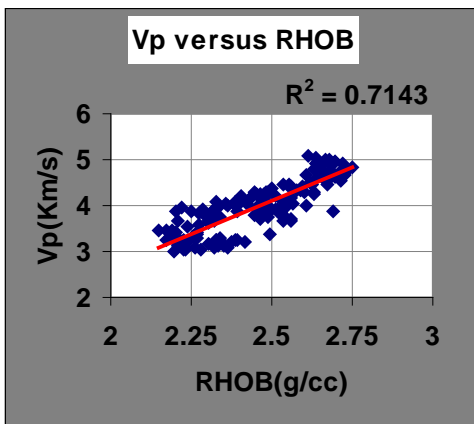**Figure 4: The Relationship between Shear Wave Velocity and Formation Density**

Figure 5: The Relationship between Compressional Wave Velocity and Formation Density

Sonic Log: There is a Linear and direct proportion between Shear and Compressional Wave Velocities (figure 6).

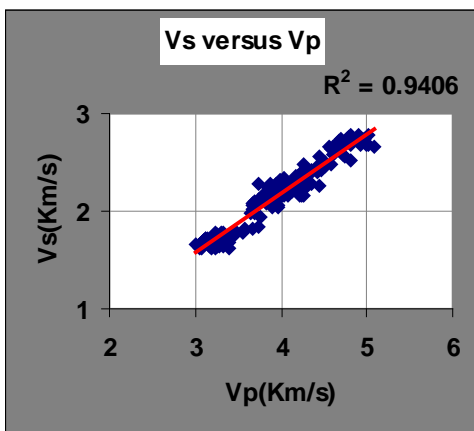The simplest proportion between them is expressed as below:

$$V_s = V_p + c \qquad (10)$$

Figure 6: The Relationship between Shear Wave and Compressional Wave Velocity

Resistivity Log: Resistivity Log (Deep Resistivity *LLD* and Shallow Resistivity *LLS*), has a non-linear Relationship with Shear Wave Velocity (figures 7-a & 7-b). The equation below demonstrates the Archie (Schlumberger Log Interpretation, 1989) formula:

$$R_t = \frac{R_w}{\phi^2 S_w^{\;2}} \qquad (11)$$

Where R_t is the formation true Resistivity, R_w is the formation water Resistivity (where formation is mostly filled with water), S_w is the formation water salinity, and ϕ is the formation Porosity, we can conclude that as Porosity increases the formation true Resistivity decreases. But considering the fluid effect, Resistivity is increased when Hydrocarbons are present and when pores are filled with water, Resistivity will decrease depending on the salinity of water filling pore-spaces. As Shear Wave Velocity is not influenced by fluids, there is no change in Vs when fluids would change, so Vs and Resistivity are related mostly by Porosity effect and Lithology type.

$$Rt\alpha \frac{1}{\phi^2} \qquad (12)$$

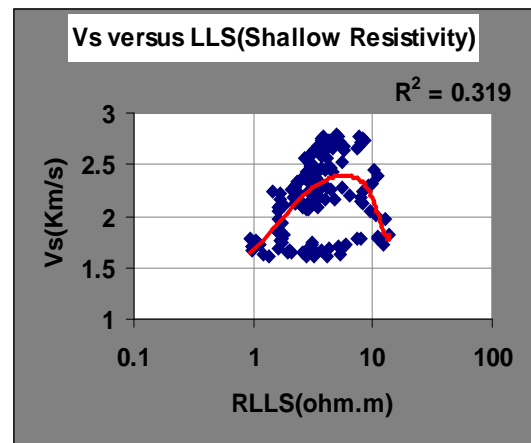$$Vs\alpha \frac{1}{\phi} \qquad (13)$$

Figure 7-a: The Relationship between Shear Wave Velocity and shallow Resistivity

Gamma Ray Log: The Relationship between Compressional Wave Velocity and Gamma ray is reverse (figure 8).
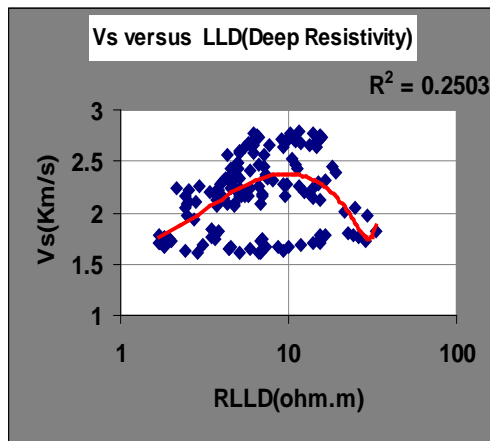
Figure 7-b: The Relationship between Shear Wave Velocity and Deep Resistivity

Gamma Ray Log reading is a measurement of formation radioactivity, which is achieved by:

$$GR = \sum \rho_i V_i A_i \Big/ \rho_b \qquad (14)$$

In this equation ρ_i is the Density of radioactive minerals, V_i is the minerals volume, A_i is the ratio factor based on the mineral radioactivity intensity, and ρ_b is the formation bulk Density. Therefore, formation bulk Density increases as the GR decreases and viceversa. As the Velocity is dependent on the formation bulk Density (Eq. 6&7), by increasing formation bulk Density (decrease in GR), the Velocity increases and viceversa. So the GR increases, as the Velocity decreases.

It should be noted that GR reading is the summation of three main elements: Uranium, Thorium, Potassium, where in this case is called SGR.
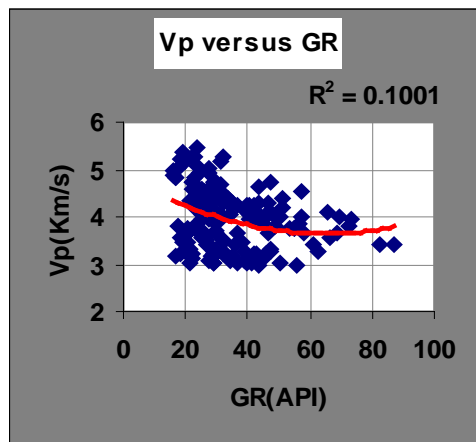

Figure 8: The Relationship between Compressional Wave Velocity and Gamma Ray Log.

PEF Log*:* photoelectric index is determined by:

$$Pe = \frac{1}{k} \frac{\sigma_{Pe}}{Z} \qquad (15)$$

K is a constant coefficient and is a property of gamma energy, where the photoelectric absorption is occurred:

$$K \approx \frac{48 \times 10^3}{E_\gamma^{3.15}} \qquad (16)$$

and

$$\sigma_{pe} = \sum (\sigma_{Pe})_i \qquad (17)$$

$(\sigma_{Pe})_i$ is the absorption area in E_i

As Pe is proportional to σ_{Pe} and is related to formation atomic number (Z), increase in Pe is proportional to increase in formation bulk Density (ρ_b) and by increasing formation bulk Density (ρ_b) the Velocity increases. Therefore, Compressional Wave Velocity has a direct relation with PEF Log (Figure 9).
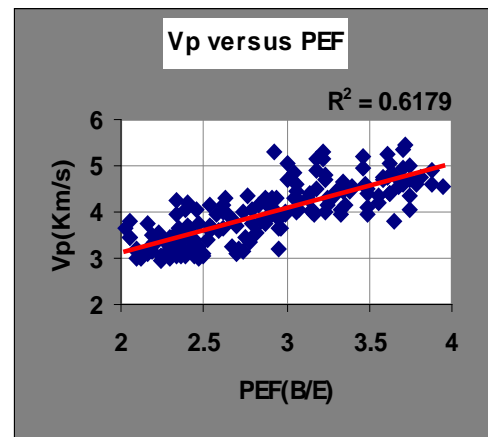

Figure 9: The Relationship between Compressional Wave Velocity and photoelectric factor (PEF).

Modeling and Prediction of Shear and Compressional Wave Velocities

Genetic Algorithms Technique
To predict Shear Wave Velocity from Petrophysical data, we used MATLAB Software (Genetic Algorithms Toolbox). The parameters of the toolbox were adjusted so that the best global minimum (best fitness), was achieved:

Population:
Population Type: Double Vector
Population Size: 20
Initial Range: [0; 1]
Fitness scaling:

Scaling Function: Rank
Selection:
Selection Function: Roulette
Reproduction:
Elite Count: 2
Crossover Fraction: 0.8
Mutation:
Mutation Function: Gaussian
Crossover:
Crossover Function: Single Point
Migration:
Direction: Forward
Fraction: 0.2
Interval: 20
Stopping Criteria:
Generations: 10000
Time Limit: infinite
Fitness Limit: infinite
Stall Generations: 10000
Stall Time Limit: infinite
Shrink value: 1
Scale: 0.1
To achieve the best fitness, the fitness function is defined in two Models: Linear and Polynomial (Non-Linear).
a- Non- Linear Model:
For Vs, we have:
Fitness Function= Mean Squared Error =

$$\sum_{i=1}^{n} [Vs\ (real)\text{-}\ Vs\ (predicted)]^2 {}_{/\ [n\text{-}p]}$$

$$=\sum_{i=1}^{n}[Vs(real)-$$

$$(\beta_0 + \beta_1 Vp^{\beta_2} + \beta_3 Nphi^{\beta_4} + \beta_5 Rhob^{\beta_6} + \beta_7 Rlld^{\beta_8} + \beta_9 Rlls^{\beta_{10}})]^2 /[n-p] \quad (18)$$

Where:
[n-p] is the present degrees of freedom and p is the number of freedom related to associated predictors: (Vp, Nphi, Rhob, Rlld & Rlls)
$\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7, \beta_8, \beta_9 \& \beta_{10}$ are parameters predicted by Genetic Algorithms.
For Vp, we have:

Fitness Function= Mean Squared Error =

$$\sum_{i=1}^{n} [Vp\ (real)\text{-}\ Vp\ (predicted)]^2 {}_{/\ [n\text{-}p]}$$

$$=\sum_{i=1}^{n}[Vp(real)-$$

$$(\beta_0 + \beta_1 Vs^{\beta_2} + \beta_3 Rhob^{\beta_4} + \beta_5 GR^{\beta_6} + \beta_7 PEF^{\beta_8})]^2 /[n-p] \quad (19)$$

Where:
[n-p] is the present degrees of freedom and p is the number of freedom related to associated predictors: (Vs, Rhob, GR & PEF).
$\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7 \& \beta_8$ are parameters predicted by Genetic Algorithms.
b- Linear Model:
For Vs, we have:
Fitness Function= Mean Squared Error =

$$\sum_{i=1}^{n} [Vs\ (real)\text{-}Vs\ (predicted)]^2 {}_{/\ [n\text{-}p]}$$

$$=\sum_{i=1}^{n}[(Vs(real)-$$

$$(\beta_0 + \beta_1 Vp + \beta_2 Nphi + \beta_3 Rhob + \beta_4 Rlld + \beta_5 Rlls)]^2 /[n-p] \quad (20)$$

Where:
[n-p] is the present degrees of freedom and p is the number of freedom related to associated predictors (Vp, Nphi, Rhob, Rlld & Rlls)
$\beta_0, \beta_1, \beta_2, \beta_3, \beta_4 \& \beta_5$ are parameters predicted by Genetic Algorithms.
In equations (18) and (20), the predicted Shear Wave Velocity is a function of 5 predictors: Vp, Nphi, Rhob, Rlld & Rlls.
For Vp, we have:
Fitness Function= Mean Squared Error =

$$\sum_{i=1}^{n} [Vp\ (real)\text{-}Vp(predicted)]^2 {}_{/\ [n\text{-}p]}$$

$$=\sum_{i=1}^{n}[(Vp(real)-$$

$$(\beta_0 + \beta_1 Vs + \beta_2 Rhob + \beta_3 GR + \beta_4 PEF)]^2 /[n-p] \quad (21)$$

Where:
[n-p] is the present degrees of freedom and p is the number of freedom related to associated predictors: (Vs, Rhob, GR, PEF).

$\beta_0, \beta_1, \beta_2, \beta_3 \,\& \,\beta_4$ are parameters predicted by Genetic Algorithms.

In equations (19) and (21), the predicted Shear Wave Velocity is a function of 4 predictors: Vs, Rhob, GR, PEF.

Regression Analysis

To predict Shear Wave Velocity from Petrophysical data by Regression Analysis, we used the SPSS software the Models are given to the software and the Linear and Non-Linear Analysis is performed on data so that the best predicted Velocity is achieved.

To get to this goal, we used Multiple Regression Models in two cases: Linear and Polynomial (Non-Linear) Regression Models.

a- Non- Linear (Polynomial) Model:

For Vs, we have:

$$\hat{y}_i = Vs(predicted) =$$
$$\beta_0 + \beta_1 Vp^{\beta_2} + \beta_3 Nphi^{\beta_4} + \beta_5 Rhob^{\beta_6}$$
$$+ \beta_7 Rlld^{\beta_8} + \beta_9 Rlls^{\beta_{10}} \qquad (22)$$

Where:

$\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7, \beta_8, \beta_9 \,\& \,\beta_{10}$ are coefficients, which would be predicted by Regression Model.

For Vp, we have:

$$\hat{y}_i = Vp(predicted) =$$
$$\beta_0 + \beta_1 Vs^{\beta_2} + \beta_3 Rhob^{\beta_4} + \beta_5 GR^{\beta_6}$$
$$+ \beta_7 PEF^{\beta_8} \qquad (23)$$

Where:

$\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7 \,\& \,\beta_8$ are coefficients, which would be predicted by Regression Model.

b- Linear Model:

For Vs, we have:

$$\hat{y}_i = Vs(predicted) = \beta_0 + \beta_1 Vp + \beta_2 Nphi$$
$$+ \beta_3 Rhob + \beta_4 Rlld + \beta_5 Rlls \qquad (24)$$

Where:

$\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5$ are coefficients, which would be predicted by Regression Model.

The Mean Squared Error (MSE) in both polynomial and Linear Models would be estimated as

$$MSE = \frac{SSE}{[n-p]} = \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{[n-p]} =$$

$$= \frac{\sum_{i=1}^{n}(Vs(real) - Vs(predicted))^2}{[n-p]} \qquad (25)$$

Where Vs (predicted) is estimated by equation (25)

For Vp, we have:

$$\hat{y}_i = Vp(predicted) = \beta_0 + \beta_1 Vs + \beta_2 Rhob$$
$$+ \beta_3 GR + \beta_4 PEF \qquad (26)$$

Where:

$\beta_0, \beta_1, \beta_2, \beta_3 \,\& \,\beta_4$ are coefficients, which would be predicted by Regression Model.

The Mean Squared Error (MSE) in both polynomial and Linear Models would be estimated as:

$$MSE = \frac{SSE}{[n-p]} = \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{[n-p]} =$$

$$= \frac{\sum_{i=1}^{n}(Vp(real) - Vp(predicted))^2}{[n-p]} \qquad (27)$$

Where Vp (predicted) is estimated by equation (30).

Results
Genetic Algorithms Technique

The equations predicted from Petrophysical data, by Genetic Algorithms technique are*:*

a- Non-Linear Model:

In this Model, we have multiplier and exponential coefficients, which make it a Non-Linear form, where the Correlation coefficient between real Shear Wave and predicted Shear Wave Velocities, is equal to 0.84 and the Correlation coefficient between real Compressional Wave and predicted Compressional Wave Velocities is equal to 0.89.

For Vs, we have:

$$Vs(predicted) = 0.77Vp^{0.6} - 1.28Nphi^{0.12}$$
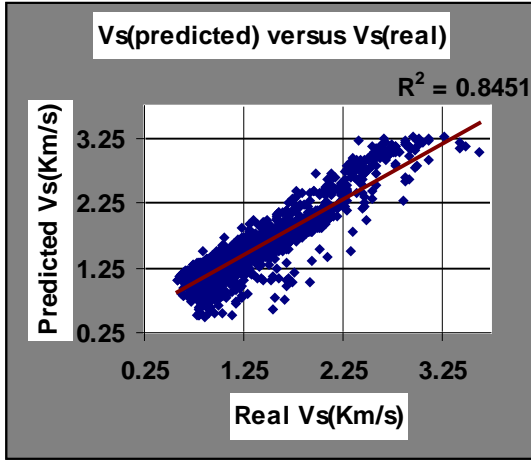$$+ 0.82Rhob^{1.01} - 0.02Rlld^{0.62} + 0.5Rlls^{0.16} \quad (28)$$
$$- 1.15$$

Figure 10: Predicted Shear Wave Velocity versus Real Shear Wave Velocity (Non-Linear Genetic Algorithms).

For Vp, we have:

$$Vp(predicted) = 1.47Vs^{0.79} + 0.66Rhob^{1.18} \quad (29)$$
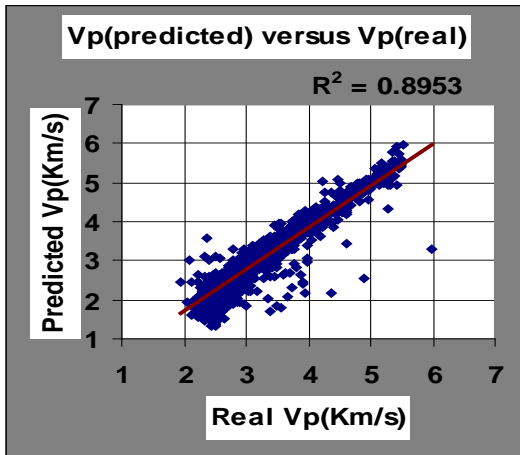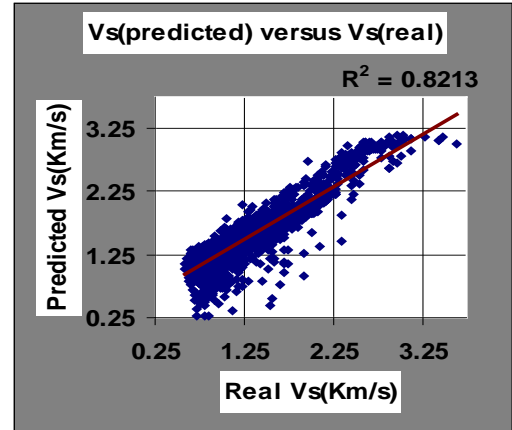$$- 0.88GR^{0.18} + 0.45PEF^{-0.001} + 0.54$$

Figure 11: Predicted Compressional Wave Velocity versus Real Compressional Wave Velocity (Non-Linear Genetic Algorithms).

b- Linear Model:
In this Model, we have multiplier coefficients, which make it a linear form, where the Correlation coefficient between real Shear Wave and predicted Shear Wave Velocities, is equal to 0.82 and the Correlation coefficient between real Compressional Wave and predicted Compressional Wave Velocities is equal to 0.88.
For Vs, we have:

$$Vs(predicted) = 0.3Vp - 1.09Nphi +$$
$$0.73Rhob - 0.00005Rlld - 0.00025Rlls \quad (30)$$
$$- 0.6$$

Figure 12: Predicted Shear Wave Velocity versus Real Shear Wave Velocity (Linear Genetic Algorithms).

For Vp, we have:

$$Vp(predicted) = 1.01Vs + 0.92Rhob$$
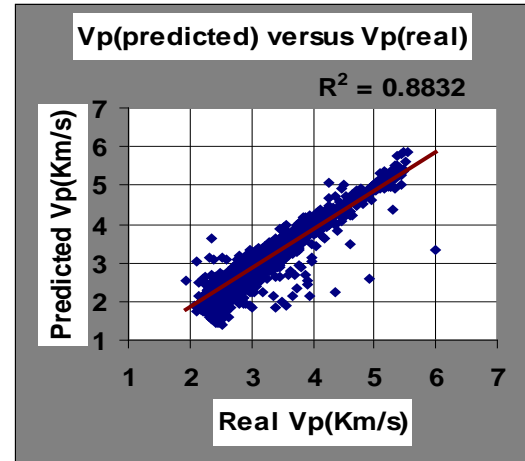$$- 0.007GR - 0.01PEF - 0.19 \quad (31)$$

Figure 13: Predicted Compressional Wave Velocity versus Real Compressional Wave Velocity (Linear Genetic Algorithms).

Regression Analysis
The equations predicted from Petrophysical data by Regression Analysis are:
a- Non-Linear Model:
In this Model, we have multiplier and exponential coefficients, which make it a Non-Linear form, where the Correlation coefficient between real Shear Wave and predicted Shear Wave Velocities, is equal to 0.85 and the Correlation coefficient between real Compressional Wave and predicted Compressional Wave Velocities is equal to 0.89.

For Vs, we have:

$$Vs(predicted) = 1Vp^{0.53} - 0.96Nphi^{0.19}$$
$$+ 0.63Rhob^{1.15} - 0.05Rlld^{0.5} + 1Rlls^{0.107} \quad (32)$$
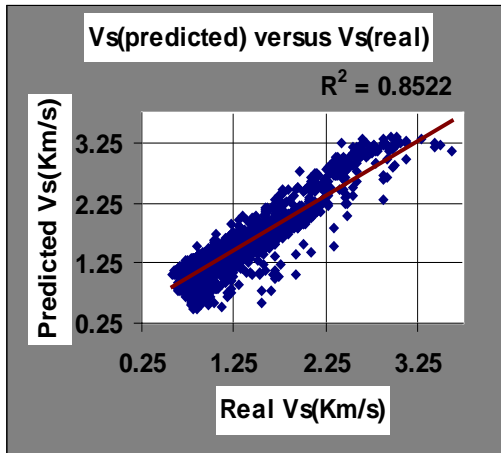$$- 2$$

Figure 14: Predicted Shear Wave Velocity versus Real Shear Wave Velocity (Non-Linear Regression).

For Vp, we have:

$$Vp(predicted) = 2Vs^{0.65} + 0.39Rhob^{1.5}$$
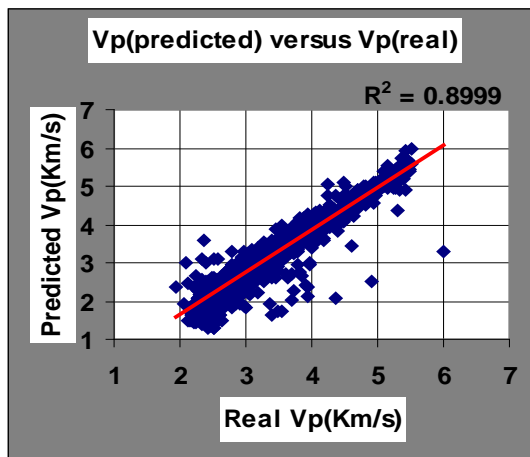$$- 1GR^{0.168} + 0.0001PEF^{-0.86} + 0.94 \quad (33)$$

Figure 15: Predicted Compressional Wave Velocity versus Real Compressional Wave Velocity (Non-Linear Regression).

b- Linear Model:
In this Model, we have multiplier coefficients, which make it a linear form, where the Correlation coefficient between real Shear Wave and predicted Shear Wave Velocities, is equal to 0.81 and the Correlation coefficient between real Compressional Wave and predicted Compressional Wave Velocities is equal to 0.88.

For Vs, we have:

$$Vs(predicted) = 0.29Vp - 0.97Nphi +$$
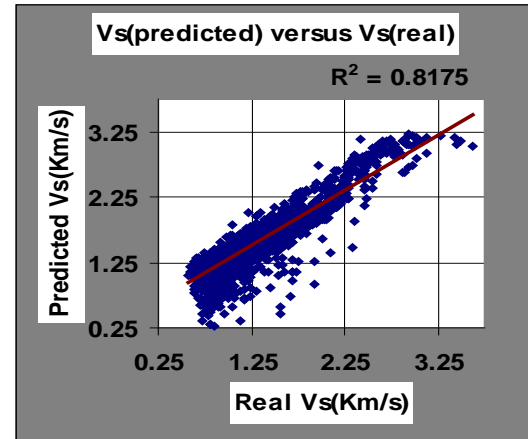$$0.806Rhob - 0.0007Rlld + 0.0019Rlls \quad (34)$$
$$- 0.76$$

Figure 16: Predicted Shear Wave Velocity versus Real Shear Wave Velocity (Linear Regression).

For Vp, we have:

$$Vp(predicted) = 1.01Vs + 0.94Rhob$$
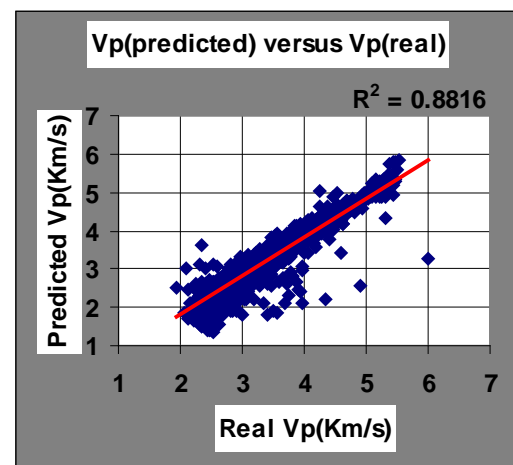$$- 0.007GR - 0.021PEF - 0.24 \quad (35)$$

Figure 17: Predicted Compressional Wave Velocity versus Real Compressional Wave Velocity (Linear Regression).

Discussion
Comparison of Non-Linear Models
Table 1, is a demonstration of Non-Linear Models (GA and RA) to predict coefficients in Shear Wave Velocity equation. In addition, Figure B-1 shows plots of Best Fitness and Selection Function derived from GA toolbox for Non-Linear GA.
As it can be inferred from the results, the Mean Squared Error in the Genetic Algorithms technique is almost equal to that of Regression Analysis.

Table 1: parameters given by Non-Linear Models to predict Shear Wave Velocity

Method / coefficient	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9	β_{10}	β_0	MSE	SSE	SSR	SST
Genetic Algorithms (Non-Linear)	0.77	0.6	-1.28	0.12	0.82	1.01	-0.02	0.62	0.5	0.16	-1.15	0.09	222.80	664.43	887.23
Regression (Non-Linear)	1	0.53	-0.96	0.19	0.63	1.15	-0.051	0.5	1	0.1	-2	0.08	230.02	727.07	957.09

Table 2: parameters given by Linear Models to predict Shear Wave Velocity

method/Coefficient	β_1	β_2	β_3	β_4	β_5	β_0	MSE	SSE	SSR	SST
Genetic Algorithms (Linear)	0.3	-1.09	0.73	-0.00005	-0.00025	-0.6	0.09	269.44	693.60	963.04
Regression (Linear)	0.29	-0.97	0.8	-0.0007	0.0019	-0.76	0.10	292.64	719.13	1011.77

Table 3, is a demonstration of Non-Linear Models (GA and RA) to predict coefficients in Compressional Wave Velocity equation. In addition, Figure B-2 shows plots of Best Fitness and Selection Function derived from GA toolbox for Non-Linear GA.

As it can be inferred from the results, there is a slight difference between the Mean Squared Error in Genetic Algorithms technique with Regression Analysis.

Table 3: parameters given by Non-Linear Models to predict Compressional Wave Velocity

method/ coefficient	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_0	MSE	SSE	SSR	SST
Genetic Algorithms (Non-Linear)	1.47	0.79	0.66	1.18	-0.88	0.18	0.45	-0.001	0.54	0.10	291.78	1598.44	1890.22
Regression (Non-Linear)	2	0.65	0.39	1.5	-1	0.16	0.0001	-0.86	0.94	0.13	378.57	1785.02	2163.52

Comparison of Linear Models

Table 2, is a demonstration of Linear Models (GA and RA) to predict Coefficients in Shear Wave Velocity modeled equation. In addition, Figure B-3 shows plots of Best Fitness and Selection Function derived from GA toolbox for Linear GA.

As it can be inferred from the results, there is a slight difference between the Mean Squared Error in Genetic Algorithms technique with Regression Analysis.

Table 4, is a demonstration of Linear Models (GA and RA) to predict coefficients in Compressional Wave Velocity equation. In addition, Figure B-4 shows plots of Best Fitness and Selection Function derived from GA toolbox for Linear GA.

As it can be inferred from the results, there is a slight difference between the Mean Squared Error in Genetic Algorithms technique with Regression Analysis.

Table 4: parameters given by Linear Models to predict Compressional Wave Velocity

method/Coefficient	β_1	β_2	β_3	β_4	β_0	MSE	SSE	SSR	SST
Genetic Algorithms (Linear)	1.01	0.92	-0.007	-0.01	-0.19	0.07	208.02	1369.42	1577.44
Regression (Linear)	1.01	0.94	-0.007	-0.021	-0.24	0.08	244.74	1398.95	1643.69

Conclusions

The Ghar member of Asmari formation in Hendijan field is slightly different in Lithology from that of Abuzar field, as in Hendijan field it is composed of sandstone, Dolomite and some thin layers of Shale but in Abuzar field it is composed of Sandstone, shale, limestone and Dolomite.

Unlike Shear wave velocity data Compressional wave velocity data and other conventional log data such as Neutron porosity, Density and Resistivity data are more frequent in Old Wells. These logs have mathematical and physical relations with Shear wave velocity data, and as in Reservoir Intervals, Shear wave velocity data are important in Geophysical studies such as AVO and VSP, Lithology and Fluid Type identification, interpretation of Elastic parameters and Rock mechanical properties calculation, by using conventional log data and finding logical relations between these data and Shear wave velocity data, we can Estimate Shear wave velocity in equivalent and partially similar intervals or wells with no Shear wave velocity data. The reason for predicting Compressional Wave Velocity in this study was to validate the reliability of Genetic Algorithms Technique as an Optimization Method for predicting Parameters such as Vs. According to the results of GA and RA methods, we can conclude some major points:

1- The Training Model gives the best results when it is in match with the Test Model in Lithology, Fluid Properties and Petrophysical Characteristics (figures A-1 to A-8).

2- The Genetic Algorithms Technique has been successful as one of the best Stochastic Optimization Methods in predicting Compressional and Shear Wave Velocities from Petrophysical data. The Correlation Coefficient and the Mean Squared Error (MSE) between Real and Predicted Shear Wave Velocity by Non-Linear Genetic Algorithms are respectively 0.85 and 0.07; and by Linear Genetic Algorithms, the Correlation Coefficient and the Mean Squared Error are respectively 0.81 and 0.09.

The Correlation Coefficient and the Mean Squared Error (MSE) between Real Compressional Velocity and Predicted Compressional Wave Velocity resulted by Non-Linear Genetic Algorithms are respectively 0.89 and 0.10; and the Correlation Coefficient and the Mean Squared Error (MSE) resulted by Linear Genetic Algorithms, are respectively 0.88 and 0.07.

3- The predicted Shear Wave and Compressional Wave Velocities by Regression Analysis support the results achieved by Genetic Algorithms technique. The Correlation Coefficient and the MSE between Real and Predicted Shear Wave Velocity resulted by Non-Linear Regression Analysis are respectively 0.85 and 0.08; and the Correlation coefficient and the MSE resulted by Linear Regression are respectively 0.81 and 0.10.

The Correlation Coefficient and the Mean Squared Error (MSE), between Real Compressional Wave Velocity and Predicted Compressional Wave Velocity resulted by Non-Linear Regression Analysis are respectively 0.89 and 0.13; and the Correlation coefficient and the Mean Squared Error (MSE), resulted by Linear Regression Analysis are respectively 0.88 and 0.08.

4- The Optimization Techniques are not imperative, but for Predicting Models they are the best methods. Genetic Algorithms Technique, which is a subset of Intelligent Systems, is one of the best techniques in optimizing simple, non-linear and more complex equations in petroleum industry.

5- Regression Analysis is one of the best Methods to be used as a validating technique to be compared with GA Optimization technique; hence if the Results of the two methods are almost the same, it clarifies the validity of GA but not its equality with RA. In fact GA is more powerful than RA, as it can be used for different Optimization methods and solving more complicated problems.

Appendix A
The Training Model gives the best results when it matches with the test Model in Lithology, Fluid properties and Petrophysical characteristics, so as can be seen in figures A-1 to A-8, the distance between Hendijan And Abuzar fields in Persian Gulf results in a slight difference in these properties and the consequence of this difference is the Correlation Coefficients ranging from 81% to 89% depending on the method used in Predicting Models.
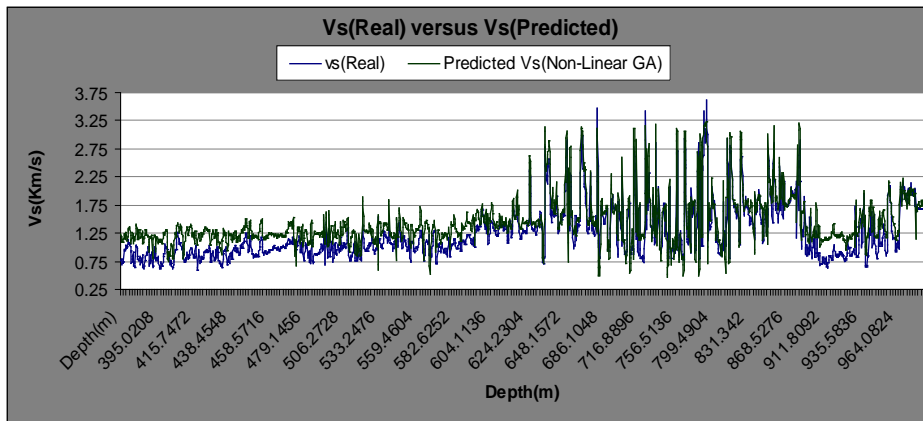
Figure A-1: Comparison of Predicted Vs (Non-Liner GA Parameters) and Real Vs with $R^2 = 0.85$
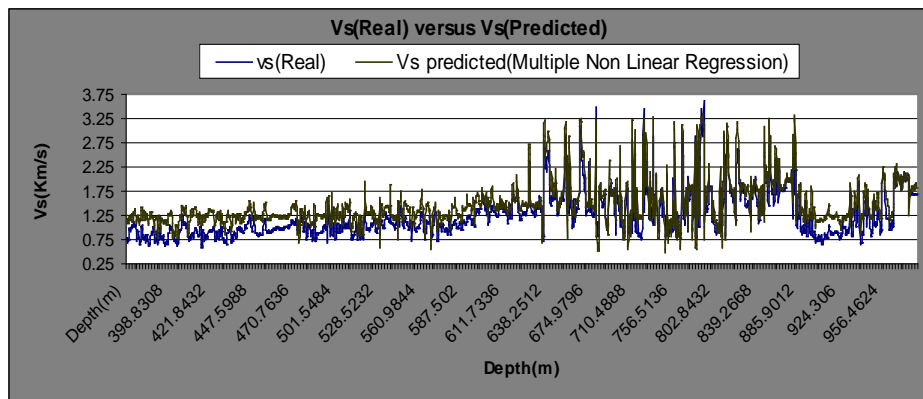

Figure A-2: Comparison of Predicted Vs (Multiple Non-Liner Regression) and Real Vs with $R^2 = 0.85$
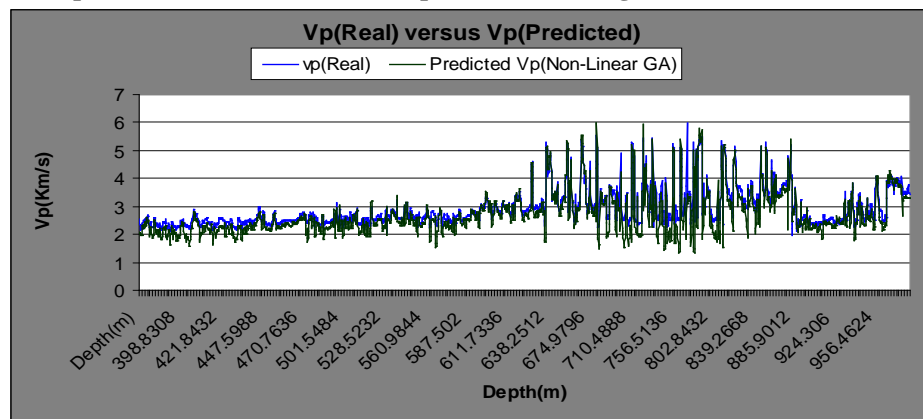

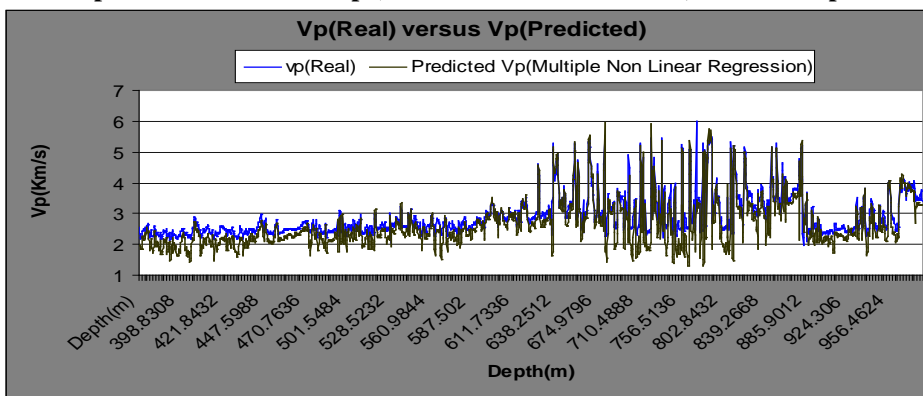**Figure A-3: Comparison of Predicted Vp (Non-Liner GA Parameters) and Real Vp with $R^2 = 0.89$**

Figure A-4: Comparison of Predicted Vp (Multiple Non-Liner Regression) and Real Vp with $R^2 = 0.89$
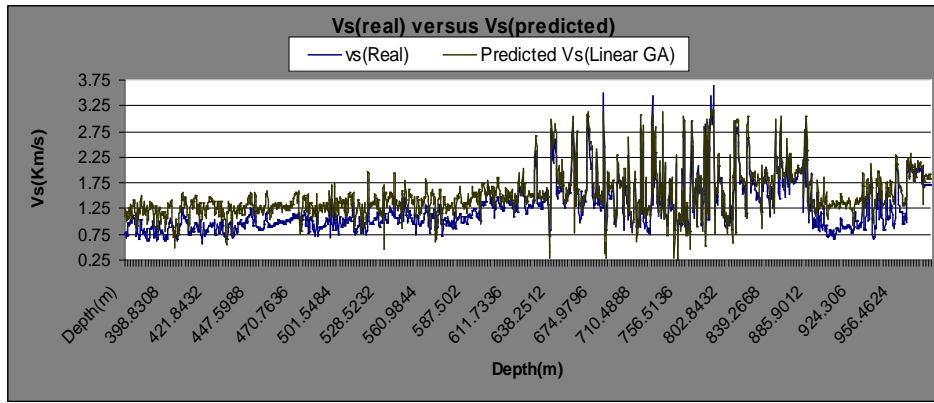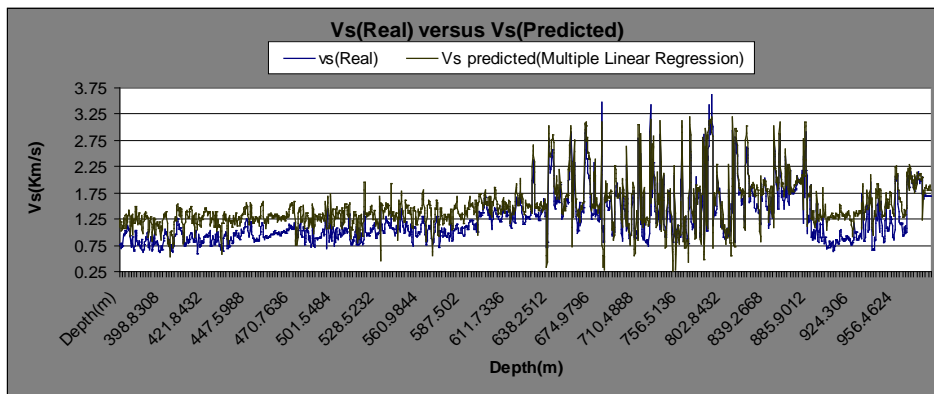
Figure A-5: Comparison of Predicted Vs (Liner GA Parameters) and Real Vs with $R^2 = 0.81$

Figure A-6: Comparison of Predicted Vs (Multiple Liner Regression) and Real Vs with $R^2 = 0.81$
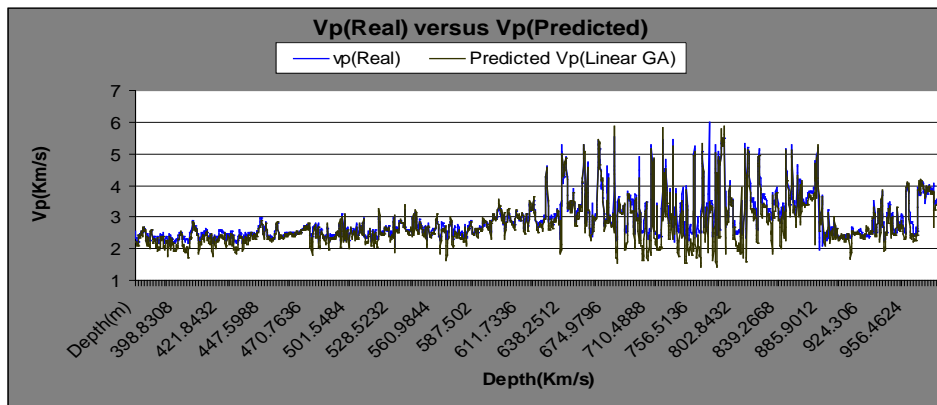

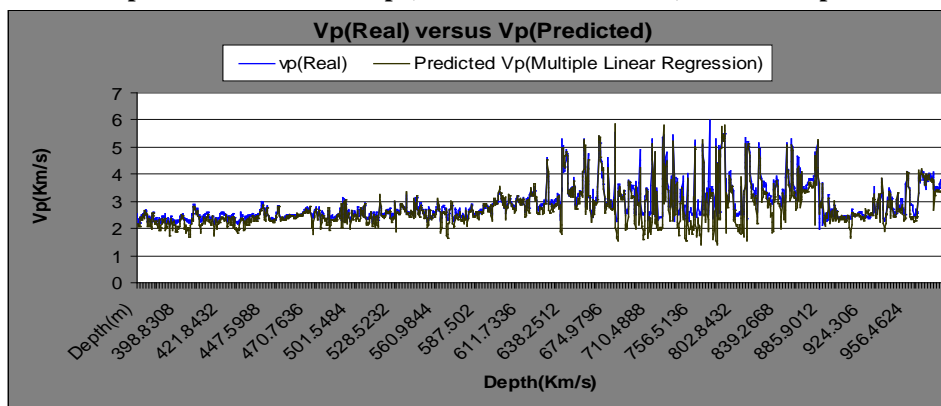**Figure A-7: Comparison of Predicted Vp (Linear GA Parameters) and Real Vp with** $R^2 = 0.88$

Figure A-8: Comparison of Predicted Vp (Multiple Liner Regression) and Real Vp with
$R^2 = 0.88$

Appendix B

Demonstration of Best Fitness Plots derived from GA toolbox for Non-Linear and Linear Models predicting Shear and Compressional Wave Velocities. It should be noted that GA parameters were set the same in all runs for Non-Linear and Linear Parameters so that a better comparison could be made between different Models.
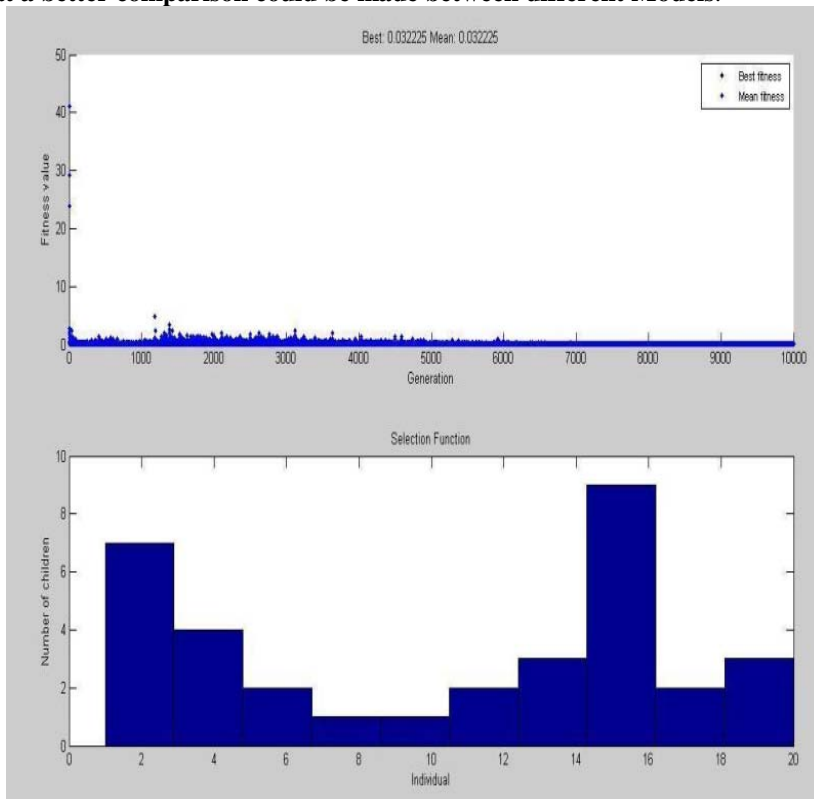

Figure B-1:Best Fitness and Selection Function Plots of Non Linear Parameters for prediction of Shear Wave Velocity by Genetic Algorithms Technique
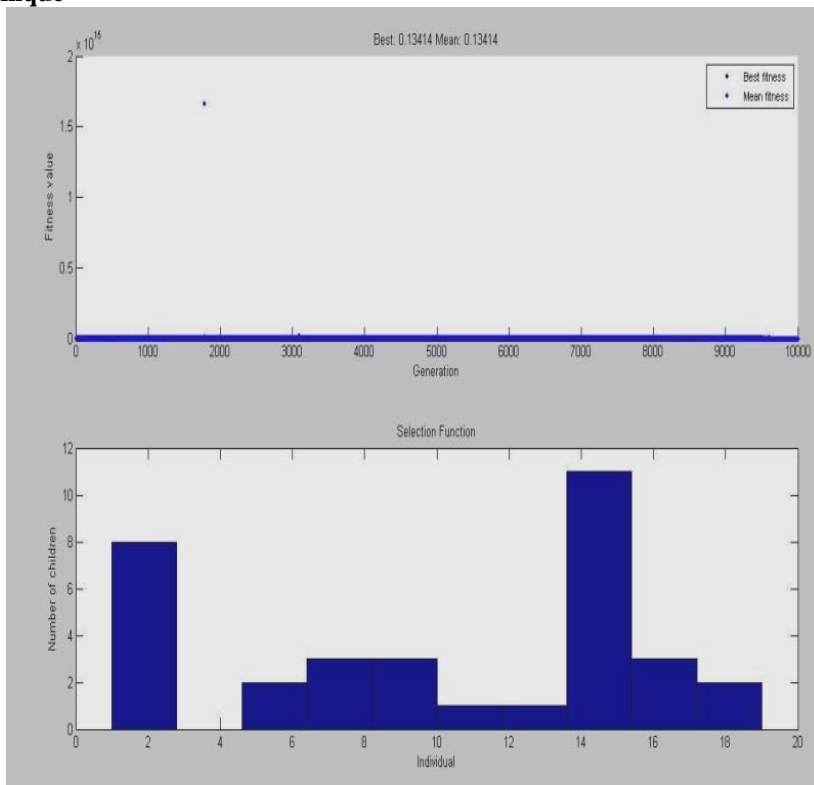

Figure B-2: Best Fitness and Selection Function Plots of Non Linear Parameters for prediction of Compressional Wave Velocity by Genetic Algorithms Technique
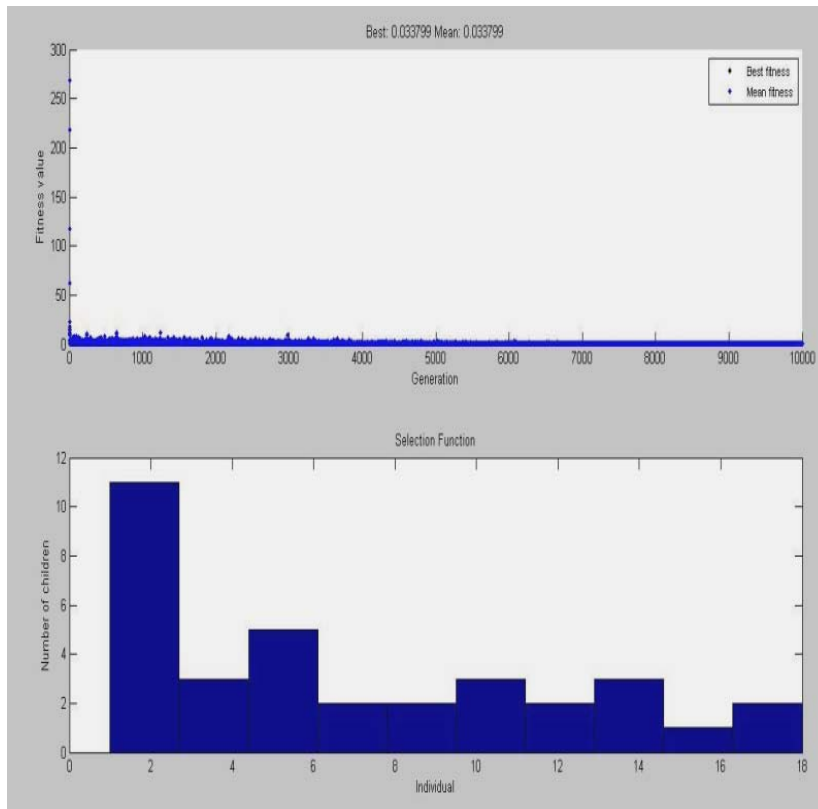
Figure B-3: Best Fitness and Selection Function Plots of Linear Parameters for prediction of Shear Wave Velocity by Genetic Algorithms Technique
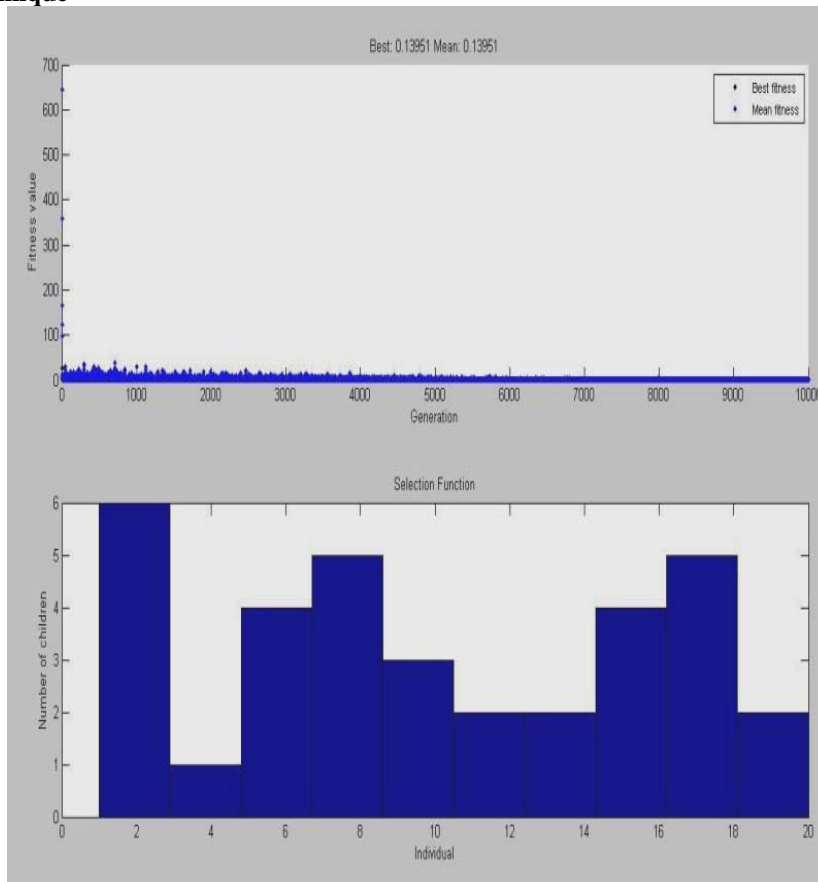

Figure B-4- Best Fitness and Selection Function Plots of Linear Parameters for prediction of Compressional Wave Velocity by Genetic Algorithms Technique

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