A systematic approach for estimation of reservoir rock properties using Ant Colony Optimization

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Abstract

Optimization of reservoir parameters is an important issue in petroleum exploration and production. The Ant Colony Optimization (ACO) is a recent approach to solve discrete and continuous optimization problems. In this paper, the Ant Colony Optimization is used as an intelligent tool to estimate reservoir rock properties. The methodology is illustrated by using a case study on shear wave velocity estimation from petrophysical data by the linear and nonlinear ACO models. The results of this research show that the ACO is a fast, robust and cost-effective method for rock properties estimation. It is proposed that ant colony optimization aids in future reservoir characterization studies.

Keywords: *Ant Colony Optimization, Petrophysical Data, Rock Properties, Shear Wave Velocity.*

Introduction

Reservoir properties characterization plays an important role in the upstream sector of the petroleum industry. To date, many researchers have tried to establish a quantitative and qualitative correlation between them and a set of geosciences data such as geological, well logging and seismic data. For this purpose, intelligent systems such as neural networks and fuzzy systems have been utilized as routine tools for reservoir parameters estimation. For example, Kamali and Mirshady (2004) and Kadkhodaie-Ilkhchi *et al*. (2009) used expert systems including neural networks and neuro-fuzzy systems to estimate total organic carbon content from petrophysical data. Kadkhodaie-Ilkhchi *et al*. (2010) utilized techniques such as intelligent systems and Boosting technique for rock recognition from drilling sensor data. Several applications of expert system in rock property estimation are reported by Mohaghegh (2000), Nikravesh and Aminzadeh (2003), Rezaee *et al*. (2007) and many other researchers.

The optimization algorithms such as simulated annealing and genetic algorithms have become popular in reservoir parameters optimization. The Ant Colony Optimization (ACO) is a paradigm for designing metaheuristic algorithms based on real ants behavior. These ants deposit pheromones on the ground in order to mark some favorable path that should be followed by other members of the colony. The ant colony optimization exploits a similar mechanism for solving optimization problems (Dorigo *et al*., 2006). In recent years, the petroleum industry has witnessed rapid utilization of ACO in solving optimization problems. Zerafat *et al.* (2009) designed an ACO for Gas-lift Allocation Optimization. Razavi and Jalali-Farahani (2010) used ant colony algorithm for history matching, determining the optimum number of phase separators and separators pressure and maximizing oil production in petroleum reservoirs. Hajizadeh *et al*. (2011) developed an ACO for history matching and uncertainty quantification of reservoir models.

In this paper, the first application of the ACO in a systematic approach for rock properties estimation is reported. For this purpose, a modified Ant Colony Optimization algorithm was developed for the systematic estimation of shear wave velocity from petrophysical data. The methodology is applicable for any rock property estimation problem from a set of predefined inputs. The methodology presented in this paper is based on other researcher’s work which is not novel in their own right.

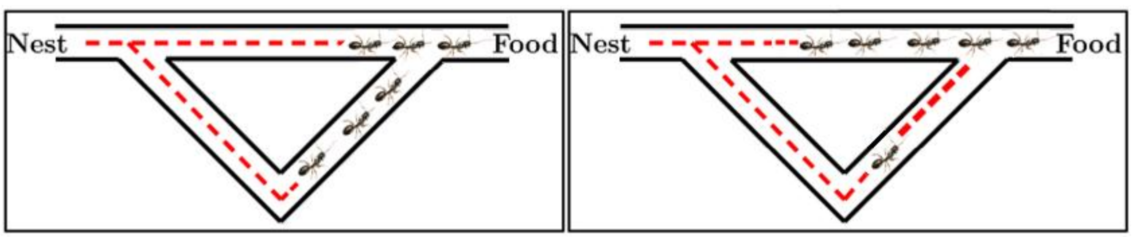
Ant Colony Optimization

The ant colony optimization is one of the most recent techniques for solving optimization problems. The inspiring source of ACO algorithms are real ant colonies. The behavior that provides the inspiration for the ACO is the ants’ foraging behavior, and in particular, how they can find the shortest paths between food sources and their nest.

When searching for food, ants initially explore the area surrounding their nest in a random manner and while moving, they leave pheromones on the ground which can smell. When choosing their path, they tend to choose in probability, paths marked by strong pheromone concentrations. As soon as an ant finds a food source, it evaluates the quantity and quality of the food and carries some of it back to the nest. During the return trip, the quantity of pheromone that an ant leaves on the ground may depend on the quantity and quality of the food. The pheromone trails will guide other ants to the food source (Blum, 2003). More details on the ACO could be found in Dorigo et al. (1996), Dorigo and Stutzle (2004) and Blum (2005). Figure 1 illustrates how communication among ants via pheromone trails enables them find the shortest paths between their nest and food sources.

a) All ants are in the nest. There is no pheromone in the environment.

b) The foraging starts. In probability, 50% of the ants take the short path and 50% take the long path to food source



c) The ants that have taken the short path have arrived earlier at the food source. Therefore, when returning, the probability to take again the short path is higher

d) The pheromone trail on the short path receives, in probability, a stronger reinforcement and the probability to take this path grows. Finally, due to the evaporation of the pheromone on the long path, the whole colony will, in probability, use the short path.

Figure 1. An experimental setting that demonstrates the shortest path finding capability of ant colonies. Between the ants' nest and the only food source two paths of different lengths exist. In the four graphics, the pheromone trails are shown as dashed lines (modified after Blum, 2003).

ACO algorithm

To simply understand how the ACO algorithm works consider the schematic model explained in Figure 1 (Blum, 2003). The simple ant model consists of two points: *vs* (representing the ant's nest) and *vd* (representing food source). Assume two random links e_1 and e_2 between *vs* and *vd*. A length of l_1 is assigned to e_1 , and a length of l_2 to e_2 such that $l_2 > l_1$. e_1 represents the short path between *vs* and *vd* and e_1 represents the long path. As real ants deposit pheromone on their paths as they move, the chemical pheromone trails are modelled as follows:

An artificial pheromone value ${}^{2}{}_{i}$ is introduced for each of the two links e_i: $i=1, 2$. Such a value indicates the strength of the pheromone trail on the corresponding path. Finally, artificial ants, n_a, are introduced. Each ant behaves as follows:

Starting from *vs* (i.e. the nest), an ant chooses with probability:

$$p_i = \frac{{}^{2}{}_{i}}{{}^{2}{}_{1} + {}^{2}{}_{2}}, \quad i = 1, 2 \qquad (1)$$

between paths e_1 and e_2 for reaching the food source *vd*. Obviously, if ${}^{2}{}_{1} > {}^{2}{}_{2}$, the probability of choosing e_1 is higher, and vice versa. For returning from *vd* to *vs*, an ant uses the same path as it chose to reach *vd*, and it changes the artificial pheromone value associated to the used edge. Furthermore, having chosen edge e_i an ant changes the artificial pheromone ${}^{2}{}_{i}$ as follows (Blum, 2003):

$$^{2}{}_{i} \leftarrow {}^{2}{}_{i} + \frac{Q}{l_i}, \qquad (2)$$

where the positive constant Q is the parameter of the model.

In other words, the amount of artificial pheromone that is added depends on the length of the chosen path: the shorter the path, the higher the amount of added pheromone. The foraging of an ant colony is in this model iteratively simulated as follows:

At each step (or iteration) all the ants are initially placed in node, *vs* and then each ant moves from *vs* to *vd* as outlined above. As shown in Figure 1 (d), in nature the deposited pheromone is subject to evaporation over time. This pheromone is simulated in the artificial model as follows (Blum, 2003):

$$^{2}{}_{i} \leftarrow (1 - {}^{\circ}).{}^{2}{}_{i}, \; i = 1, 2 \qquad (3)$$

The parameter $^{\circ} \in (0,\ ]$ is a parameter that regulates pheromone evaporation. Finally, all ants conduct their trip and reinforce their chosen path as outlined above (Blum, 2003). As a result, ants will find the shortest path during time. This phenomenon forms the basis of solving discrete and continuous optimization problems.

In order to show the performance of the ACO algorithm, it was used to find the maximum points of the function "$f(x, y)=\cos(2\pi x).\cos(2\pi y)$". As shown in Figure 2a, 200 ants are initially generated on the surface of the function $f(x, y)$. The results of running the ACO algorithm are illustrated in Figure 2b where the maximum points of the function $f(x, y)$ are found using 200 ants after 50 iterations, successfully.

ACO model for rock properties estimation

In this section, a general scheme to estimate physical rock properties is presented by using ant colony systems. The general form of the ant colony optimization problem is $P=(S, f)$ in which are given a finite set of objects S (also called the search space) and an objective function $f: S \rightarrow R$ that assigns a cost value to each of the objects $s \in S$. The goal is to find an object of minimal cost value. The ACO problems could be defined in discrete or continuous domains. Here, a continuous form of the ant systems is used for rock properties estimation as follows.

Assuming that there are n inputs parameters x_i which are used to predict the target rock property y, then prediction error could be written as follows:

$$e=y-t(x_1, x_2, \dots x_n) \qquad (4)$$

where t is the rock property prediction and could be written in the linear and nonlinear forms as follows:

$$t(x_1, x_2, \dots x_n)=\alpha_1.x_1 + \alpha_2.x_2 + \dots .\alpha_n.x_n + \alpha_{n+1} \quad \text{(linear)} \qquad (5)$$

$$t(x_1, x_2, \dots x_n)= \alpha_1.x_1^{\beta 1} + \alpha_2.x_2^{\beta 2} + \dots .\alpha_n.x_n^{\beta n} + \alpha_{n+1} \quad \text{(nonlinear)} \qquad (6)$$

where α_1, α_2, … α_n, are coefficients of the equations and α_{n+1}, theconstant. Parameters β_1, β_2, β_n are exponents of the nonlinear equation.

The objective function for minimization by ACO as the mean squared error (MSE) of the rock properties predictions is defined as follows:

$$MSE = \frac{1}{m}\sum_{j=1}^{m}(\mathrm{y}_j\text{-t}(\mathrm{x}_{ij}))^2 \quad i=1, 2,\dots n \qquad (7)$$

where m is the number of predicted data samples and n is the number of input parameters for rock properties prediction. Running the ACO algorithm to minimize error function (7) results in coefficients, exponents and constants of the equations.

Case study

The prototype field of this study is located in South West Iran. The Asmari formation with limestone lithology forms one of the main reservoirs of the study area. In order to test the performance of the ant colony approach for rock property estimation, a case study is carried out on shear wave velocity estimation from well log data. Normally, almost all wells (even horizontal wells) are logged during or after drilling. Shear wave velocity (Vs) is measured using a DSI (Dipole Shear Sonic Imager) tool which is available for limited number of wells due to high costs of measurement. The Vs data play important role in reservoir characterization objectives such as lithology determination, identifying pore fluid type and geophysical interpretation.

Data for the study were obtained from two wells penetrated into the Asmari formation where both conventional well log data and DSI measurements are available. The first well with 329 data points was chosen for construction of the ACO models and data from the second well (263 data points) were used to evaluate the reliability of the models. Statistical analyses showed that there is a high correlation between Vs data and sonic (DT), neutron (NPHI) and density (RHOB) logs as predictor parameters. The linear and nonlinear ACO models were constructed as follows.

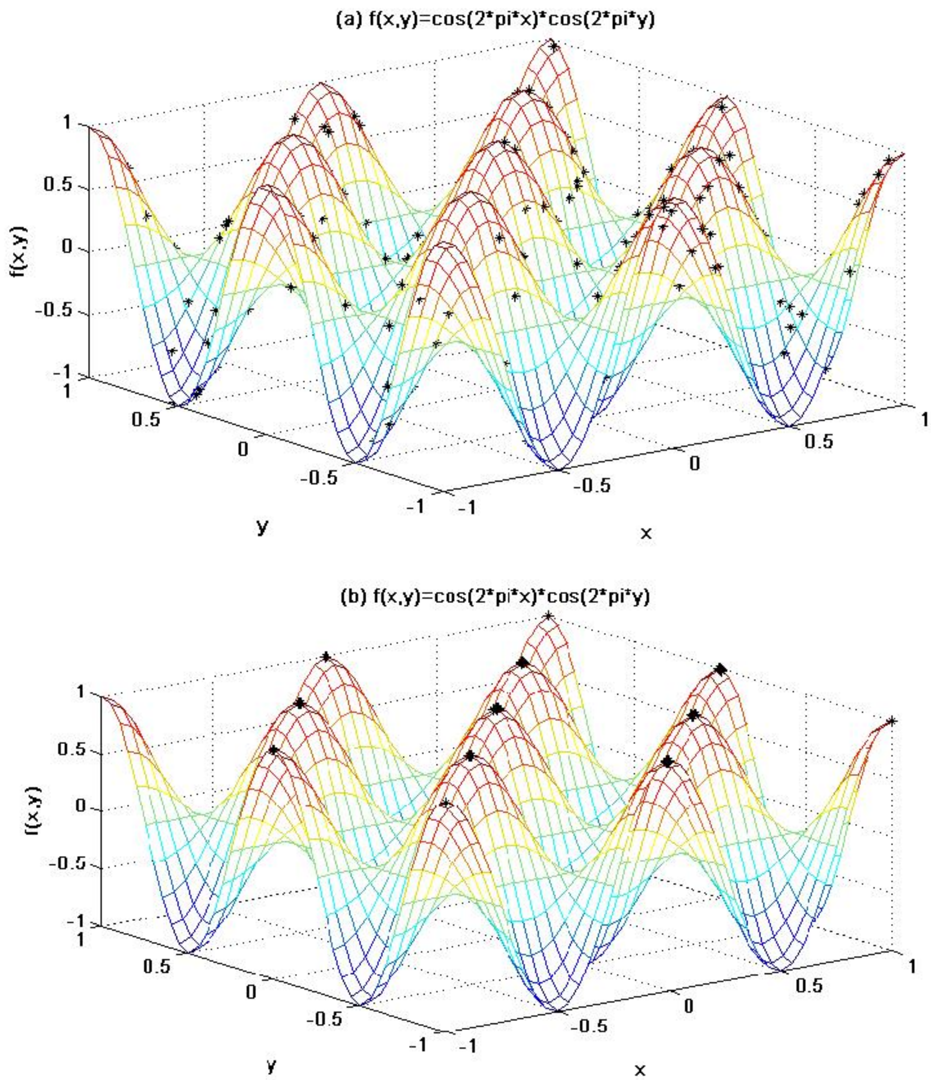


Figure 2. Ribbon plot showing the values of α_1, α_2, α_3 and α_4 for initial 200 ants generated in the range of [-1, 1]

Estimation of Vs using the linear ACO model

Equation 8 was used for the final estimation of Vs using the linear ACO model.

$$Vs_{ACO(LIN)} = \alpha_1 * Vp + \alpha_2 * NPHI + \alpha_3 * RHOB + \alpha_4 \quad (8)$$

In this equation, parameters α_1, α_2 and α_3 are coefficients corresponding to Vp, $NPHI$ and RHOB inputs, respectively. Parameter α_4 is constant for the equation. $Vs_{ACO(LIN)}$ is the estimated Vs for the linear ACO model.

The objective function to be minimized by ACO was defined as MSE of the model data predictions (9):

$$MSE = \frac{1}{m}\sum_{i=1}^{N}(Vs_{ACO(LIN)} - Vs_{real})^2 \quad (9)$$

where m is the number of model data, MSE is the mean squared error and $Vs_{ACO(LIN)}$ is same as those of Equation (8). Vs is the target value (measured from DSI tool).

Firstly, 200 ants were generated and the initial pheromone value was set to 0.2. The initial search range was chosen between the range of -1, 1. Fitting coefficients of the linear Vs equation (α_1, α_2, α_3 and α_4) for the initial 200 ants are displayed in the ribbon plot of Figure 3.

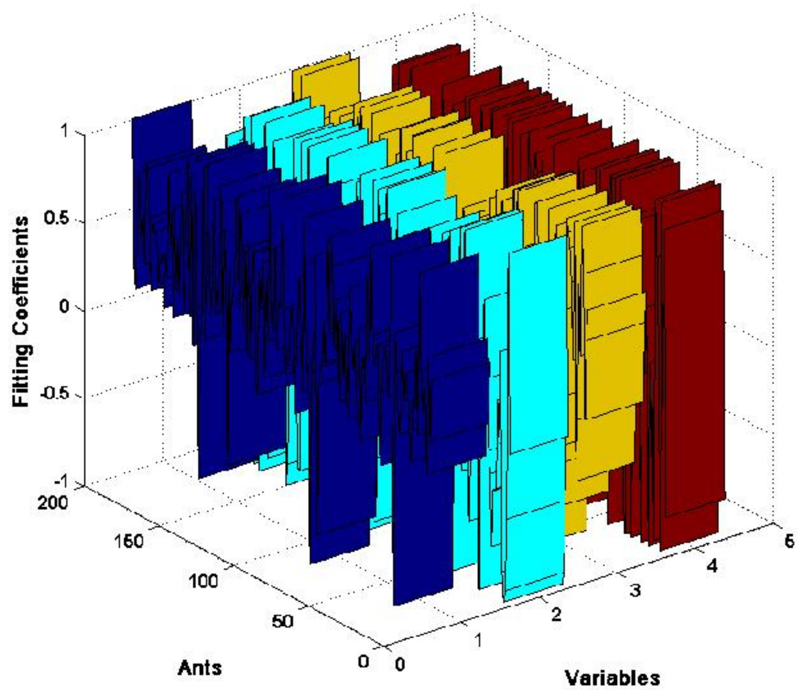


Figure 3. An example of minimizing *f(x, y)=cos(2πx).cos(2πy)* through ACO algorithm used in this study. Two hundred ants are initially generated on surface of function *f(x, y)* (a). Running ACO algorithm after 50 iterations returns maximum points of function *f(x, y)*. This example verifies performance of ACO developed in this study for rock property estimation.

Crossplots showing the correlation coefficient between Vs and input well log data including Vp (a), RHOB (b) and NPHI (c) are illustrated in Figure 4a-c.

After running the ACO algorithm, the optimized weight coefficients were applied to produce the final output. MSE values updates after 200 iterations are shown in Figure 5. As shown in Figure 5, the ant colony algorithm converges at 0.0187MSE. The ACO derived values for α_1, α_2 and α_3 corresponding to *Vp*, *NPHI* and *RHOB* estimations are *0.2116*, *-0.1445* and *0.9461*, respectively. Constant α_4 was derived as *-0.8378*. The overall estimation of *Vs* by the ACO for the test data was calculated as follows:

$$Vs_{ACO(LIN)} = 0.2116*Vp - 0.1445*NPHI + 0.9461*RHOB - 0.8378 \quad (10)$$

Estimation of Vs using the nonlinear ACO model

The Equation 11 was used for final estimation of Vs by the nonlinear ACO model.

$$Vs_{ACO(NLIN)} = \alpha_1 *Vp^{\beta 1} + \alpha_2 *NPHI^{\beta 2} + \alpha_3 *RHOB^{\beta 3} + \alpha_4 \quad (11)$$

In this equation parameters α_1, β_1, α_2, β_2, α_3 and β_3 are coefficients and exponents corresponding to *Vp*, NPHI and RHOB inputs, respectively. Parameter α_4 is constant for the equation. $Vs_{ACO(NLIN)}$ is the estimated Vs from the nonlinear ACO model. The objective function to be optimized by ACO was defined as follows:

$$MSE = \frac{1}{m}\sum_{i=1}^{m}(Vs_{ACO(NLIN)} - Vs_{real})^2 \quad (12)$$

where *m* is the number of model data, *MSE* is the mean squared error and $Vs_{ACO(NLIN)}$ is same as those of Equation 11. As with the linear model, 200 ants were generated and the initial pheromone value was set at 0.2. As shown in Figure 6 the ant colony algorithm converges at MSE.

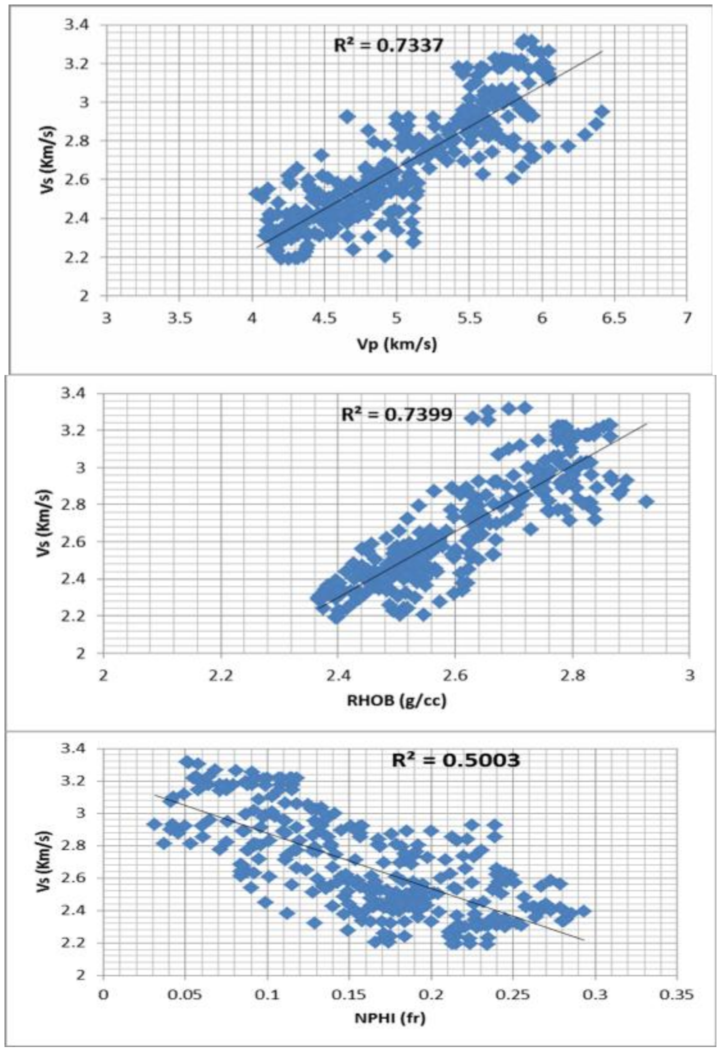


Figure 4. Crossplots showing the correlation coefficient between Vs and input well log data including Vp (a), RHOB (b) and NPHI (c) in the training well

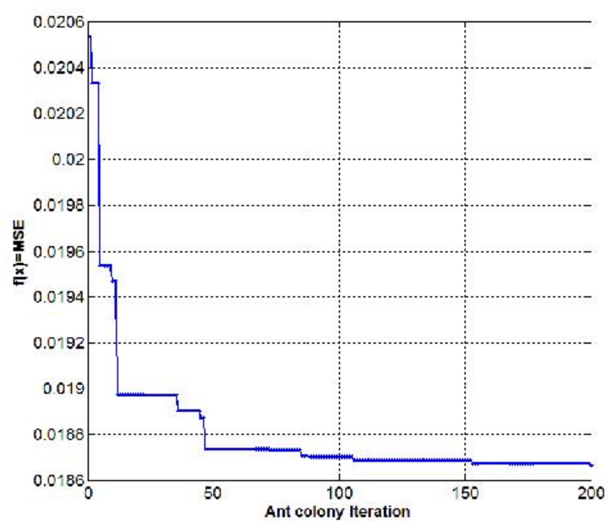


Figure 5. Graph showing changes in MSE values of objective function versus Ant Colony algorithm iterations for linear model. ACO algorithm is converged at MSE of 0.6143.

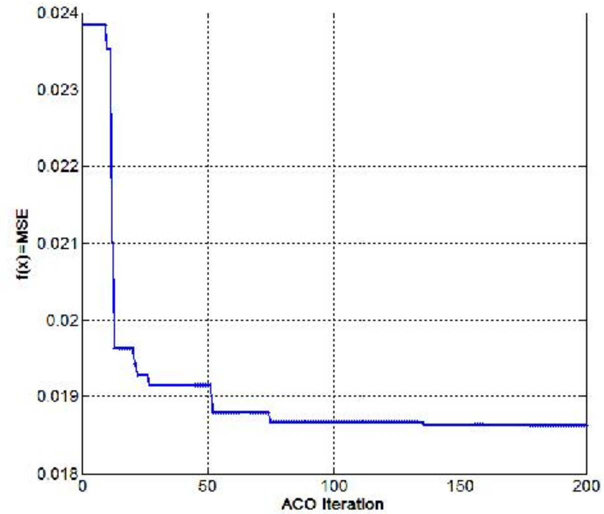


Figure 6. Graph showing changes in MSE values of objective function versus Ant Colony algorithm iterations for nonlinear model. ACO algorithm is converged at MSE of 0.6129.

After 200 iterations the ant colony derived values for α_1, β_1, α_2, β_2, α_3 and β_3 are *0.0445*, *1.6391*, *0.0552*, *1.6239*, *1.5133* and *0.8321*, respectively. Constant α_4 was derived as *-1.3229*.

The overall estimation of *Vs* by ACO for testing data was calculated using Equation 13.

$$Vs_{ACO(NLIN)}= 0.0445*Vp^{1.6391} +0.0552 *NPHI^{1.6239} +1.5133 *RHOB^{0.8321} -1.3229 \quad (13)$$

Results and Discussion

In this study, an ACO algorithm was developed for rock property estimation from a set of available input data. In order to show the performance of the ACO algorithm, a case study of shear wave velocity estimation from petrophysical inputs was carried out. The ACO models were constructed in both linear and nonlinear forms.

MSE of the linear ACO model for Vs estimation in the testing data was 0.0087 which corresponds to the correlation coefficient value of 0.943 (Fig. 7a). Graphical comparison between the measured and simulated Vs values for the testing data using the linear ACO model is shown in Figure 8.

MSE of the nonlinear ACO model for the test data is 0.0084 which corresponds to the correlation coefficient value of 0.944 (Fig. 7b). A graphical comparison between the measured and simulated Vs values for the testing data using the nonlinear ACO model is shown in Figure 9.

The results show that the performance of the linear and nonlinear ACO models for Vs estimation is close to each other. The study successfully estimated the Vs with correlation coefficient of 0.94 from sonic, neutron and density logs which are available for almost all drilled wells.

The objective function to be minimized needs to be written in the form of error in rock property estimation. The ACO algorithm can determine coefficients, exponents and constants of the rock property equations when the error reaches its minimum value.

Neural networks are complex and advanced type of regression equations. In order to make a comparison with the ant colony system, a three layered perceptron was employed to estimate Vs from the same predictors used in the ACO model. As shown in Figure 10, perceptron training stops at epoch 7 where the validation error starts to increase. The correlation coefficient between the measured and neural network estimated Vs is 0.940 (Fig. 7c). The corresponding mean squared error for neural network estimations is equal to 0.0092 (Fig. 11).

The ANN and ACO have quite different basics and concepts; however, they reached closed and high accuracy results for Vs estimation problem which is a good confirmation in validating their computational algorithms.

The ACO is a robust, fast and easy method to solve for fitting coefficients of predetermined linear and nonlinear Vs equations. In spite of the neural networks in which many parameters need to be set (e.g. number of hidden layers and their associated neurons, transfer function, learning rate, training algorithm, etc.), ACO requires a limited number of parameters to be chosen. Thus, the only requirement for the algorithm is setting the number of ants and their associated initial pheromone fractions.

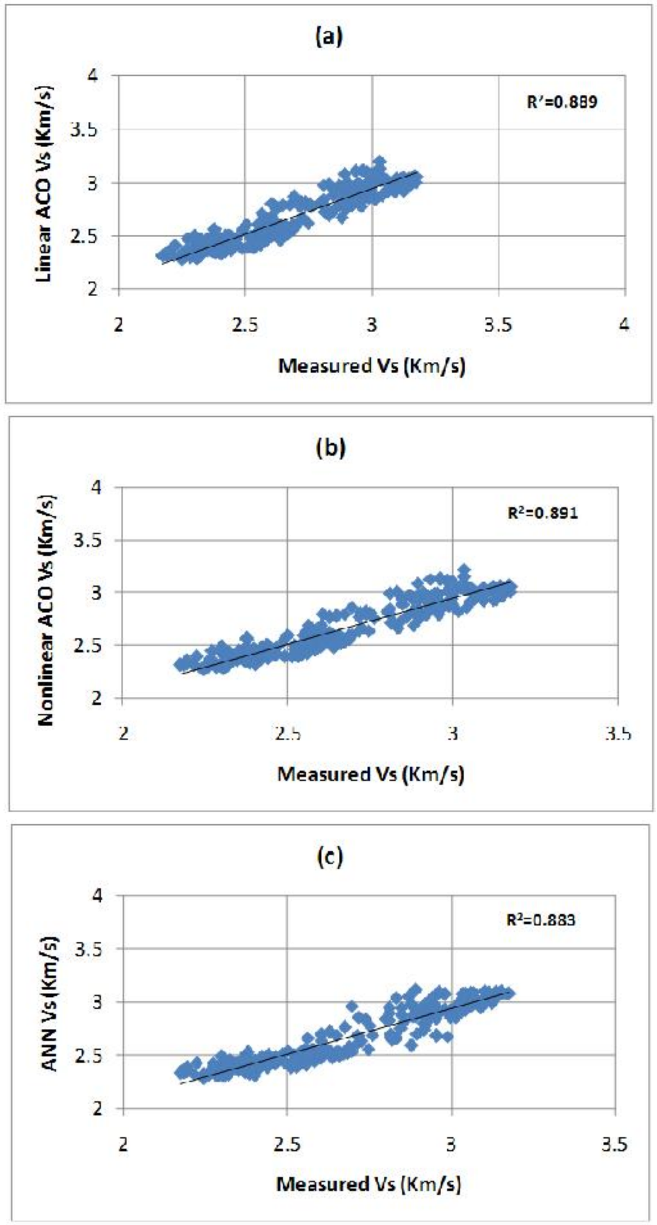


Figure 7. Crossplots showing correlation coefficient between measured Vs and estimated Vs from linear ACO model (a), nonlinear ACO model (b) and neural network (c) in the testing well

As with the neural networks, genetic algorithms have many parameters to be chosen correctly. Any inaccuracy in setting parameters such as initial guess, selection function, mutation function, crossover function, crossover fraction, stopping criteria, etc. will increase the risk of falling into local minima. However, the ant systems, due to simplicity of parameter setting and less model parameters have a higher chance of obtaining global minima.

It is expected that the artificial ants approach be considered as a robust technique in future rock properties estimation and optimization of reservoir problems such as dynamic simulation, reservoir monitoring and well placement.

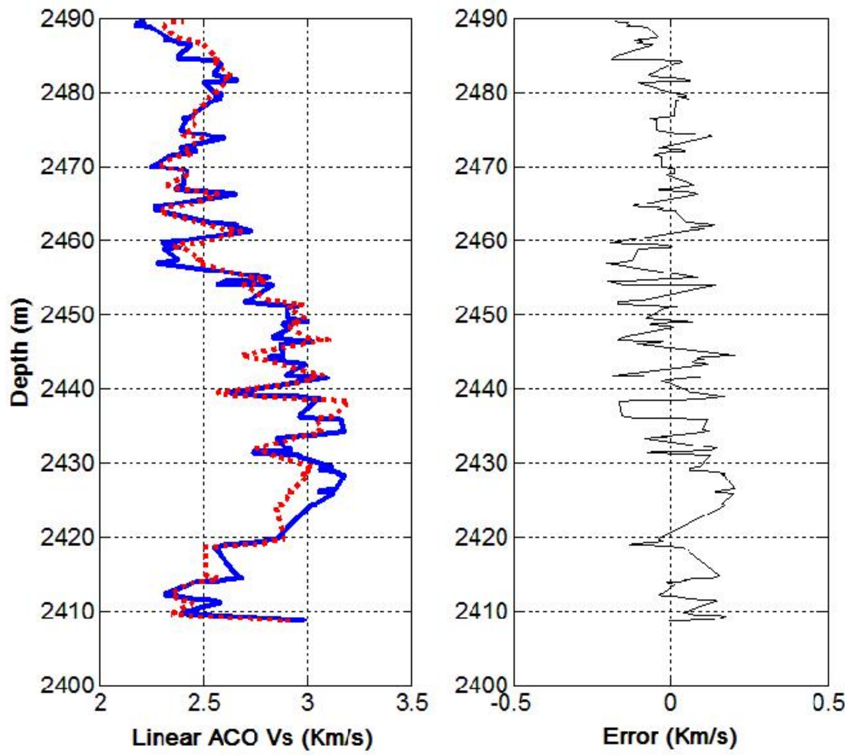


Figure 8. A graphical comparison between measured and estimated Vs from linear ACO model versus depth (left track) for testing well. The corresponding error in Vs estimation is plotted in right track.

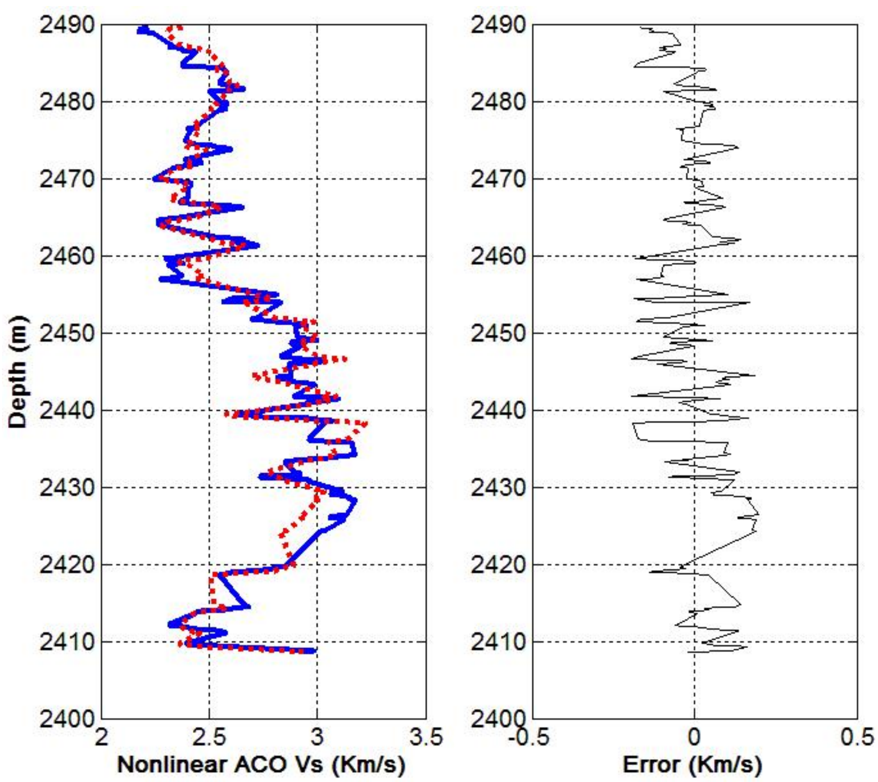


Figure 9. A graphical comparison between measured and estimated Vs from nonlinear ACO model versus depth (left track) for testing well. The corresponding error in Vs estimation is plotted in right track.

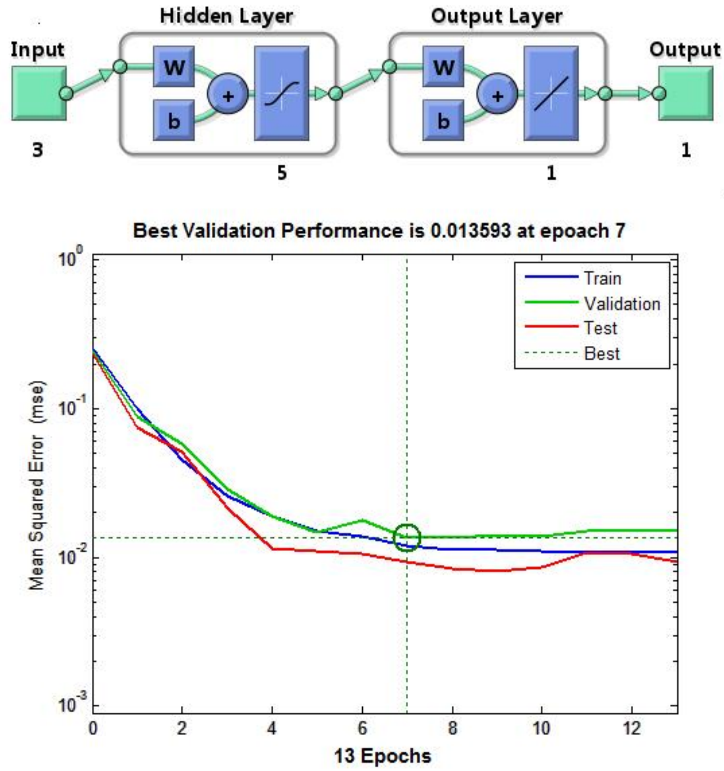


Figure 10. Updates in MSE of training, validation and testing samples versus network epochs for a three layered perceptron with five hidden neurons. Validation error starts to increase at epoch 17 and training is fixed in MSE=0.0136.

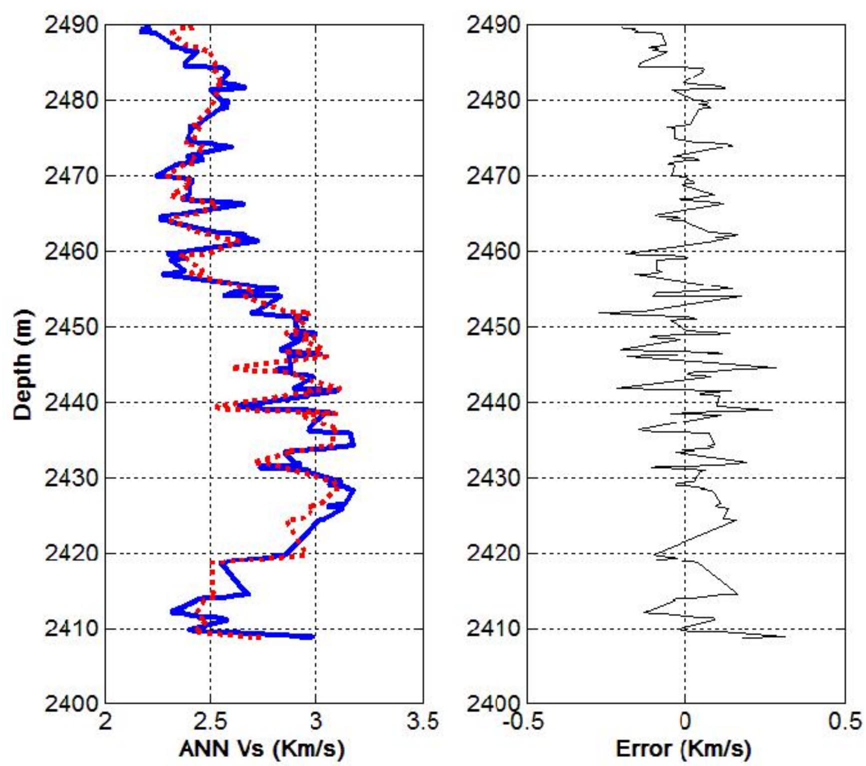


Figure 11. A graphical comparison between measured and estimated Vs from neural network model versus depth (left track) for testing well. The corresponding mean squared error in Vs estimation is plotted in the right track.

Conclusion

In this study, a systematic approach is introduced to estimate rock properties from a set of predetermined available well log data. In this study, the linear and nonlinear ant colony optimization algorithms were developed for shear wave velocity estimation from the available well log data including sonic, neutron and density.

Normally, what intelligent system (ACO) is to strengthen the relationships between dependent-independent variables and to construct an intelligent model which act much better than a single regression with only dependent parameters. The ACO model used in this study derived optimal weights for each of the inputs used and provides a more robust model to predict Vs by a combination of input well logs.

Actually, rock physics models are developed for specific formation in the world and they may not be suitable to use for any other formation. To achieve more realistic results, some tunings and optimal parameter setting need to be carried out. ACO model acts similarly to rock physics models only with the difference that it derives the optimal coefficients of S-wave velocity prediction equation through using swarm intelligence which could be considered as an alternative and robust model. The ACO successfully derives fitting coefficients for predetermined rock property equations. The ACO models were compared to a neural network approach. The ACO models with limited number of parameters obtained high accuracy results in comparison to the neural network approach in which many parameters need to be optimized. The results show that ACO is a robust, quick and easy method to predict rock properties.

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