

A new artificial intelligence method for estimation of shear wave velocity and comparison of the results with rock physics models

Mina Shafiabadi

mina.shafiabadi@gmail.com

Shahrood University of Technology

Abolghasem Kamkar Rouhani

Shahrood University of Technology

Alireza Arab Amiri

Shahrood University of Technology

Manouchehr Sanei

Yazd University

Method Article

Keywords: Shear wave velocity, rock physics, Greenberg-Castagna, genetic algorithm, MLP algorithm

Posted Date: June 18th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-9822958/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

A new artificial intelligence method for estimation of shear wave velocity and comparison of the results with rock physics models

Mina Shafiabadi^{1*}, Abolghasem Kamkar Rouhani¹, Alireza Arab Amiri¹, Manouchehr Sanei²

¹ Department of Mining, Petroleum and Geophysics, Shahrood University of Technology, Shahrood, Iran

² Department of Mining and Metallurgical Engineering, Yazd University, Yazd, Iran

*Corresponding author: mina.shafiabadi@gmail.com

Abstract

Based on the extensive studies that have been conducted so far, there is no doubt that the role of shear wave velocity data in the evaluation of hydrocarbon reservoirs is vital. Shear wave velocity provides valuable information for determining the type of fluid present in the pores and measuring pore pressure, characterizing the lithology and determining the mechanical properties of the reservoir rock, which is a prerequisite for field development. Unfortunately, determining shear wave velocity using well logging recorders is expensive, and for this reason, shear wave velocity is not measured in most wells. The present study was conducted on a well from an oil field where shear wave velocity was measured along the well (for the purpose of validating the research). In this study, shear wave velocity was estimated using two methods: rock physics relations and neural networks, and the results were compared with the actual shear wave velocity measured in the same well. Using rock physics relationships, the correlation between estimated shear wave velocity values and measured values is about %96. This is while this correlation reaches about %98.7 when using artificial neural network methods such as GA-MLP. The obtained results confirm the suitability of using this method for estimating shear wave velocity in other wells in this field.

Keywords: Shear wave velocity, rock physics, Greenberg-Castagna, genetic algorithm, MLP algorithm

1. Introduction

Shear wave velocity is affected by various rock parameters (such as pressure wave velocity, pore fluid, clay percentage, etc.) and can indicate the physical properties of the rock. Therefore, shear wave velocity is used to determine the type of formation lithology, fluid within the formation (discovery of gas reservoirs), porosity, and to determine geomechanical parameters of the formation such as Poisson's ratio, shear modulus, bulk modulus, etc (Eskandari et al., 2004; Duffaut and Landrø, 2007). Shear wave velocity measurements are performed using a Dipole Shear Sonic Imager (DSI) or Laboratory measurements. Unfortunately, shear wave velocity is not measured in most wells due to its high cost and is not available, and only limited data such as density, compressional wave velocity, or porosity are measured. In such situations, shear wave estimation using empirical relationships based on rock physics can be a valuable tool

to supplement petrophysical data (Maleki et al, 2014). In the past few decades, estimating shear wave velocity based on physical parameters of rock has received attention, for this reason many researchers such as Pickett (1963), Milheland (1980), Thomson (1986), Gardner (1974), Crieff (1990), Fast (1953), Greenberg and Castagna (1992) and Hahn (1986) have worked in this field. Also, researchers who have estimated shear velocity data using neural network methods include: Rajabi et al. (2010) were able to estimate shear and Stoneley wave velocities using intelligent fuzzy logic, genetic, and neuro fuzzy methods. Motazedian et al. (2011) used genetic algorithms to estimate shear and compression wave velocities. Asodeh and Bagheripour (2012) used artificial neural networks, fuzzy logic, and neurofuzzy to predict compressional, shear, and Stoneley wave velocities. Akhoundi et al. (2014) estimated shear velocity log using multivariate regression and artificial neural networks in a carbonate reservoir. Kadkhodaei (2015) used ant colony optimization algorithm to predict shear wave velocity. Bagheripour et al. (2015) used support vector machine regression to predict shear wave velocity. Anmangli et al. (2017) estimated shear wave velocity using three intelligent network algorithms: LSSVM-COA, LSSVM-PSO, and LSSVM-GA. Elkatani et al. (2018) estimated the shear wave velocity using ANFIS and SVR algorithms. Mehrgini et al. (2019) estimated the shear wave velocity using artificial neural network methods. Dalvand and Falahat (2021) introduced a new rock physics method for estimating the shear wave velocity using compression wave velocity, density, bulk modulus of fluid. Nasrnia et al. (2023) estimated the shear rate diagram by combining intelligent systems and a rock physics model using a metaheuristic algorithm. Baghbani et al. (2023) used the CRRF algorithm to predict V_s and V_p in kaolin-sand and their results showed high prediction accuracy of the CRRF model with R^2 values for V_s equal to 0.963 and for V_p equal to 0.974. Ansari and Ansari (2023) compared the performance of seven AI-based models, including MLPANN, RF, DT, KNN, XGBoost, SVR and Ridge, for estimating shear wave velocity. The SVR model used in their study showed the best performance with R^2 value of 0.7220, followed by MLPANN, RF, XGBoost, Ridge and KNN with R^2 values of 0.7216, 0.7183, 0.7138, 0.7128 and 0.6970. Sanei et al. (2023) examined machine learning-based models such as GA-MLP and GA-RBF for predicting geomechanical parameters using log data. Mousavi et al. (2024a, 2024b) evaluated the performance of three machine learning models ANN, SVR, and GBR in predicting V_s . Among the three adopted algorithms, the ANN model showed the with R^2 values of 0.9918 and 0.9664 and MAE values of 4.1329 and 6.7406 for the train and test datasets, respectively. As mentioned above, shear wave velocity data are usually not available in many fields and must be estimated by other methods. The purpose of this research is to investigate the efficiency and capability of rock physics relationships in estimating shear wave velocity in areas without petrophysical diagrams and to compare their results with those obtained from RBF and MLP neural network methods and to combine these methods with genetic algorithms in order to select the most appropriate model for shear wave estimation.

2. Methodology

shear wave velocity can be measured using ultrasonic core tests under controlled conditions (Castagna et al, 1985). Another way to measure shear wave velocity is to use a dipole spectrometer (DSI). Each of these methods has its own advantages and disadvantages. Four groups of shear wave velocity estimation methods include 1. Empirical relationships (such as Castagna (1993), Picket (1963) and Brocher (2005), where compressional velocity, porosity and shale content are used to estimate shear wave velocity), 2. Multiple regression analysis (This method is used to fit the data as a linear function of the features, and to determine the coefficients of the equation, the gradient descent method is used by minimizing the error function), 3.

Intelligent methods and 4. Rock physics models (Nasrnia & Falahat, 2024).What is currently considered one of the most common methods for obtaining shear wave velocity is the use of rock physics models (Mavko et al, 1998).

2.1Estimation of shear wave velocity using rock physics relationships

Shear wave estimation using empirical relationships based on rock physics can be a valuable tool to supplement petrophysical data. To begin conducting rock physics studies at this stage, existing initial information is needed, including head formations and initial results of petrophysical evaluations. After reviewing and classifying the information and Available, this data is entered into the RokDoc software. The input data to the software includes corrected conventional logs along with petrophysical evaluation results, formation head depth, well path information including deviation angle and well azimuth. As can be seen in Figure 1, complete data is not available at most depths, so initial assessments of rock physics are only applicable within this range.

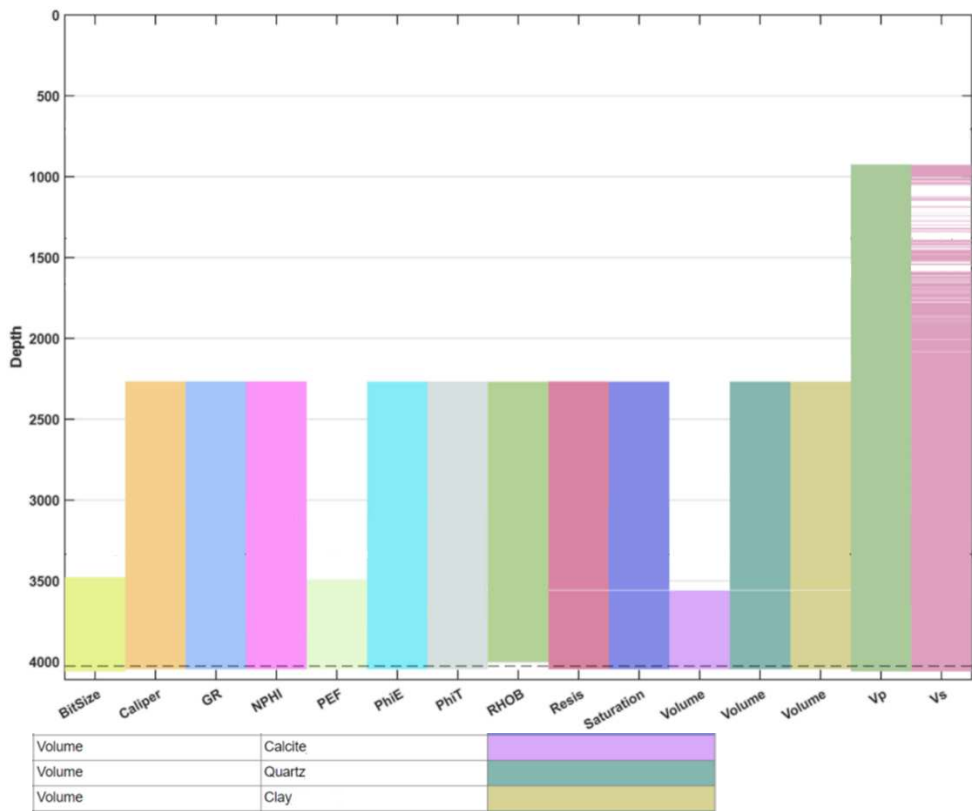


Figure 1. Display of data available along the well. From left to right, respectively, diagrams of bit size and caliper measurement, gamma, porosity, photoelectric, effective and total porosity, density, resistivity, mineral volume, compressional wave velocity, shear wave velocity.

Empirical rock physics models are widely used in industry due to their simplicity. These models describe the relationships between reservoir properties and their elastic responses from measured data. They generally assume several functional forms, and their coefficients must be determined by fitting a function (either in linear or nonlinear form) to the data set through regression (Mavko, et al, 1998). The Faust model is an empirical rock physics model that relates compressional wave velocity to electrical resistivity. In fact, this empirical rock physics model can be used to estimate compressional wave velocity in areas without

data from electrical resistivity plots. Figure 2 shows the compressional velocity constructed using the Faust relationship alongside the measured compressional velocity plot.

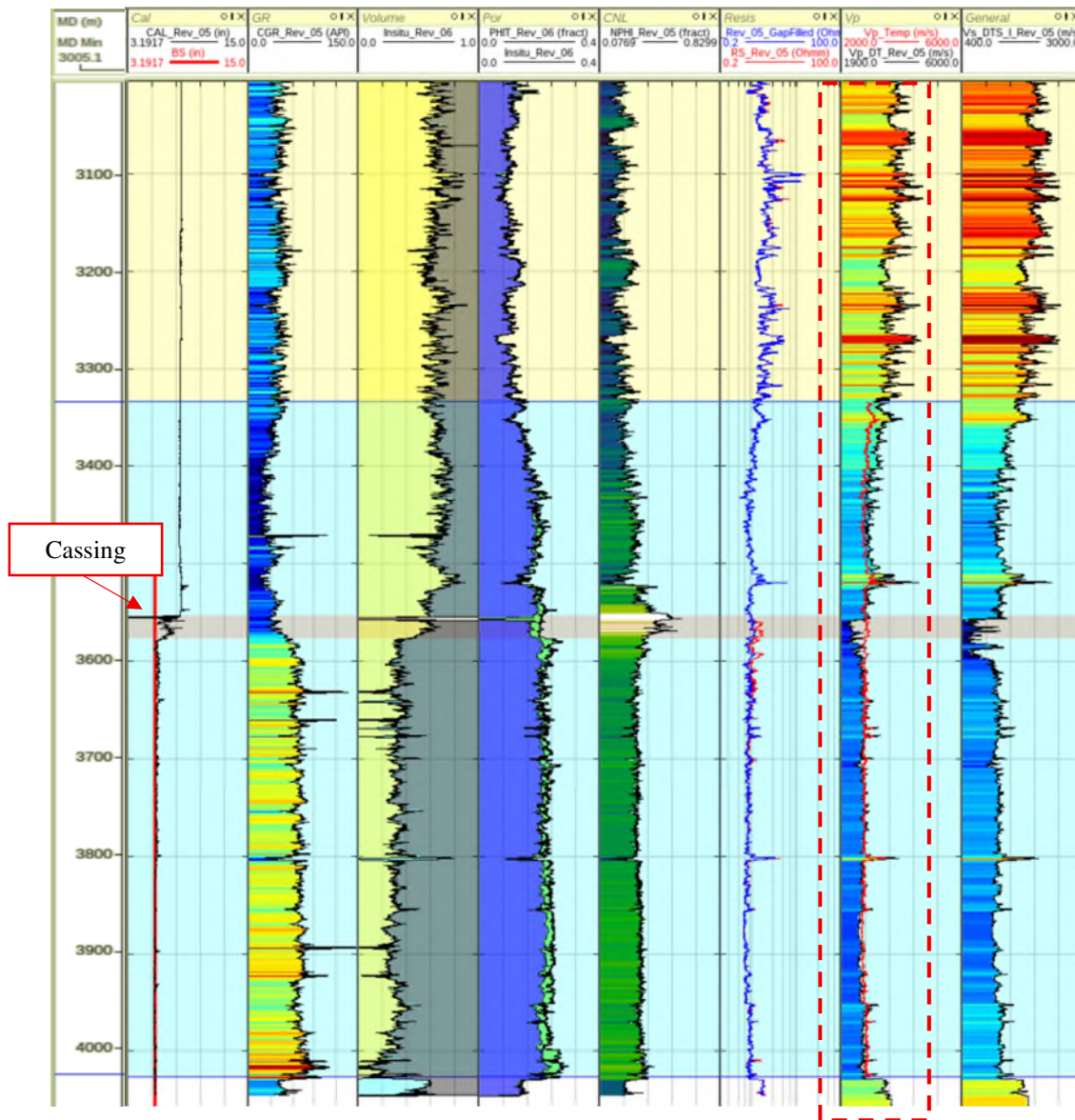


Figure 2. Display of the Faust equation with the obtained coefficients. The red graph in the seventh column from the left shows the compression rate constructed with the Faust equation next to the measured compression rate graph in this section.

The Gardner model is an empirical rock physics model that relates density to velocity (compressive or shear). Such a relationship is commonly constructed for various minerals found in the field. In this regard, due to the low percentage of calcite in this field, the Gardner model is only aligned for quartz and clay to relate density to compression wave velocity. In the first step, density and compression wave velocity data for clay content greater than 80% as a representative of clay were filtered and aligned by applying a power relationship. Figure 3 shows the result of this relationship. It should be noted that in addition to the

aforementioned filter, in all stages of Gardner model alignment, samples containing breakout have also been discarded.

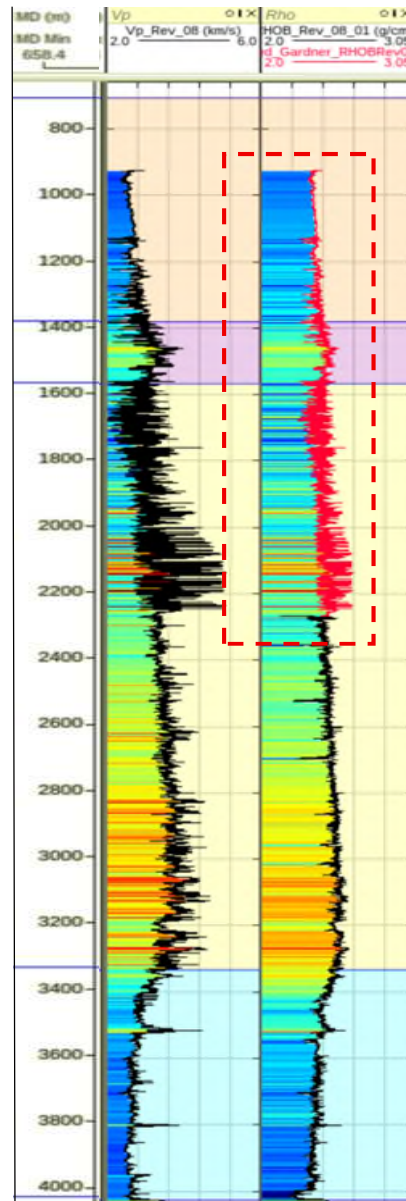


Figure 3. Density estimation (right curve) using the compression wave velocity plot (left curve) from the Gardner equation. The red curve shows the estimated area.

The Castagna model is a simple empirical rock physics model that is derived using only a linear regression. In contrast, the Greenberg-Castagna model is a more complete empirical model that also involves factors such as mineralogy and their volume percentage along with pore fluids to estimate shear wave velocity from compression wave velocity. The Castagna model is mainly used for areas without petrophysical information, and the Greenberg-Castagna model is used in areas with petrophysical information. The

Greenberg and Castagna model are expressed as follows in the case of fully saturated samples (Greenberg & Castagna, 1992):

$$V_s = \frac{1}{2} \left\{ \left[\sum_{i=1}^4 X_i \sum_{j=0}^2 a_{ij} V_p^j \right] + \left[\sum_{i=1}^4 X_i \left(\sum_{j=0}^2 a_{ij} V_p^j \right)^{-1} \right]^{-1} \right\} \quad (1)$$

In the above equation, X_i is the value of each lithological component in decimal form and V_p is the velocity of compressional waves. The coefficients a_{ij} are based on the type for sandstone, limestone, or dolomite and shale as shown in Table 1.

Table 1. Regression coefficients for lithology presented by Castagna (Dvorkin, J.P., 2003)

X_i	a_{i0}	a_{i1}	a_{i2}
Sandstone	-0/85588	0/80416	0
Limestone	-1/03049	1/01677	-0/055088
Dolomite	-0/07775	0/58321	0
Shale	-0/86735	0/76969	0

First, the Greenberg-Castagna model coefficients need to be aligned for the minerals in this well. Figure 4 shows the estimated shear wave velocity (red curve) along with the measured shear wave velocity (black curve) and compression wave velocity.

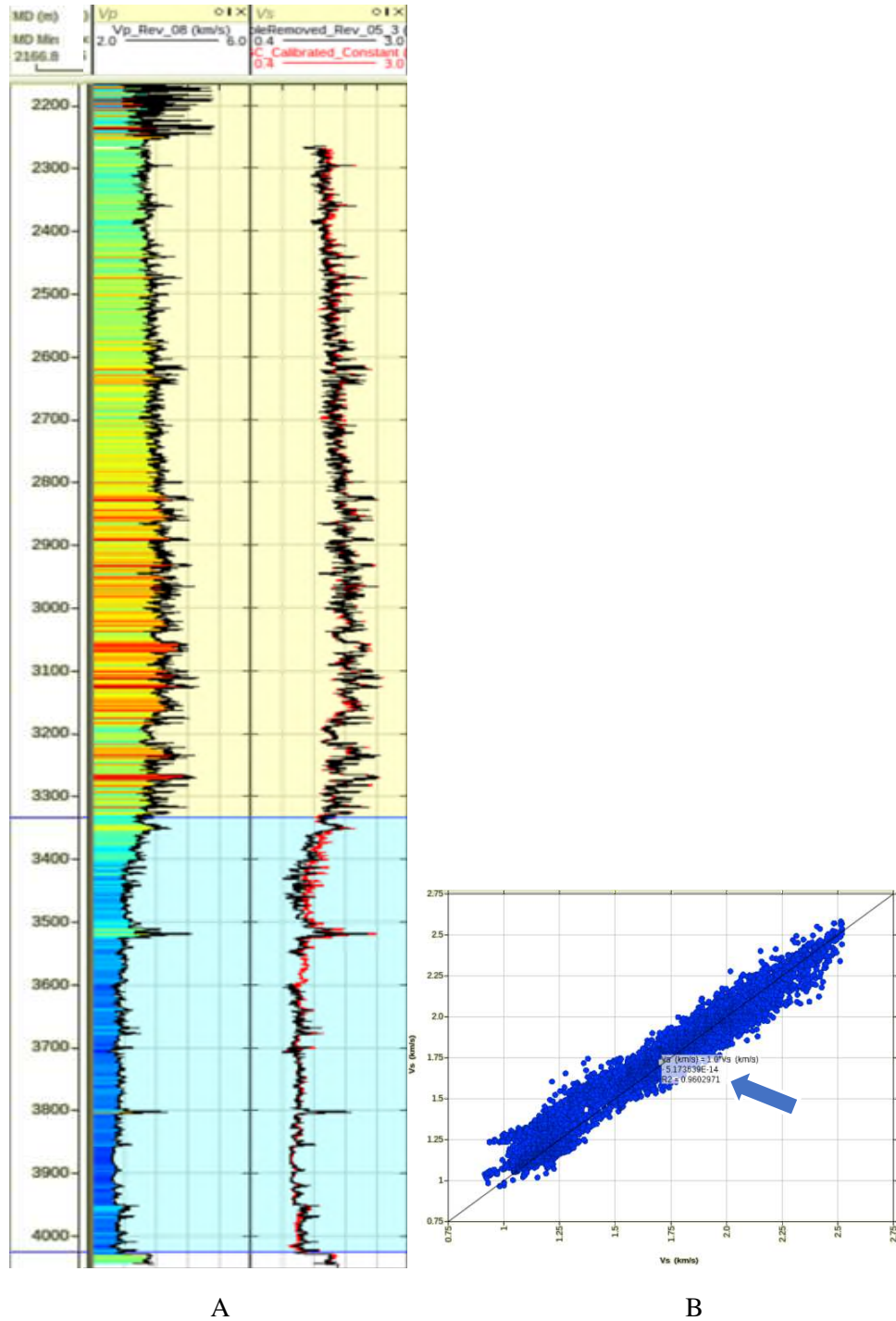


Figure 4. Estimated shear velocity (red curve in the second part from the left) by the Greenberg-Castagna model next to the measured shear wave velocity plot (black curve in the second part from the left) with the incorrect areas removed.

According to Figure 4, part A, the shear wave velocity was estimated in two depth ranges. In the depth range that lacked petrophysical information, the Castagna model and the compression wave velocity diagram were used. On the other hand, in the depth range, due to the presence of petrophysical evaluations,

the Greenberg-Castagna model was used. In addition, in Figure 4, part B, the correlation coefficient between the estimated and measured shear wave velocity can also be seen. The correlation coefficient in this range is about 96%.

Figure 5 shows the estimated shear wave velocity plot alongside the compression wave velocity, initial shear wave velocity, and density plots.

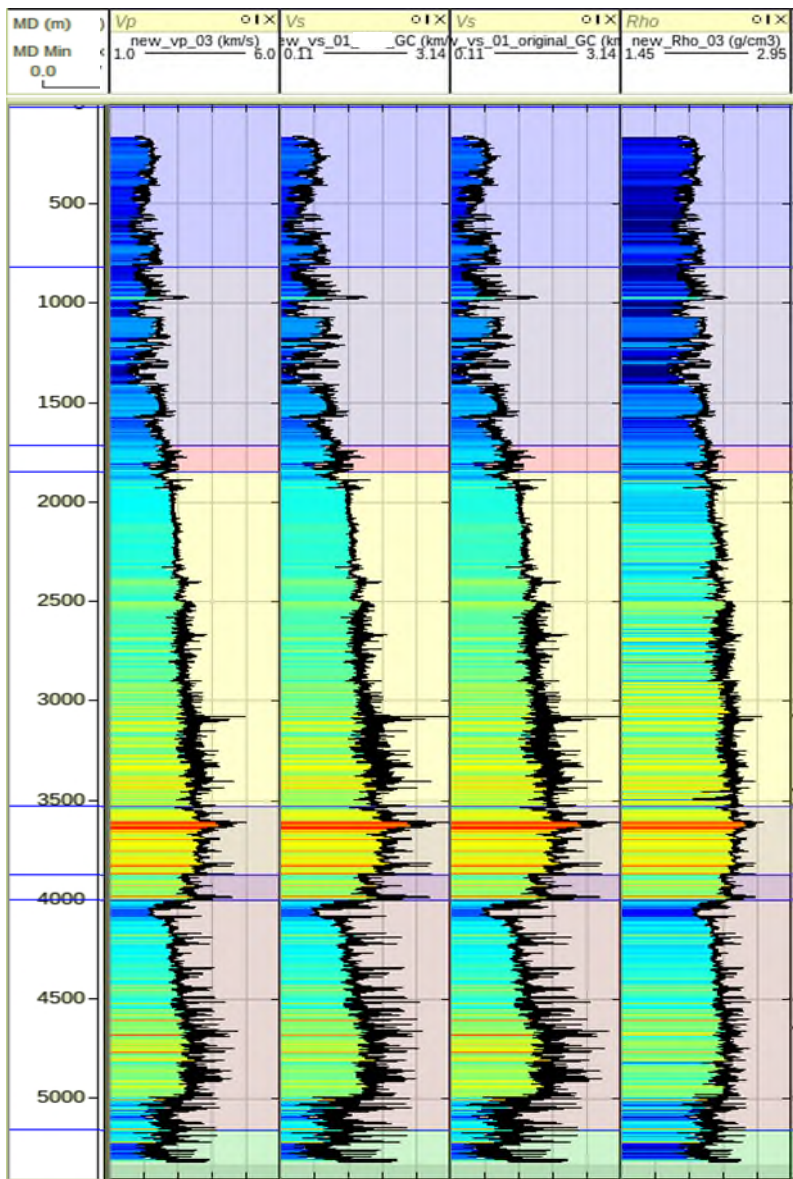


Figure 5. Estimated shear wave velocity diagram in the well. From left to right, the diagrams are: compression wave velocity, shear wave velocity estimated by the Greenberg-Castagna model, shear wave velocity estimated by the principal coefficients of the Greenberg-Castagna model, and density diagram

In this study, the shear wave velocity was estimated according to rock physics methods and the results were compared with the actual shear wave velocity measured in the same well. Using the correlation value of the

estimated and actual data obtained, the suitability of using the Greenberg-Castagna method for estimating shear wave velocity in other wells in this field is confirmed.

2.2 Shear wave velocity estimation using neural network methods

An artificial neural network is a collection of artificial neurons that perform data processing operations in groups and in parallel. An artificial neural network consists of three layers: input layers, output layers, and hidden (processing) layers. Inside each neuron is a specific weight that affects the input values to the neuron. The weighted values are then fed into the transfer functions, and the output function finds the original values for itself, and depending on whether a suitable answer has been obtained, these values are compared with the target vector, and in case of a difference with the target vector, it is returned to the previous steps to select more appropriate weights for those vectors (Demuth.H., Beale.M., 1993; Galushkin, 2007; Nasrnia & Falahat, 2024).

Several metrics have been considered to evaluate the efficiency and accuracy of models. These metrics include the coefficient of determination (R^2), root mean square error (RMSE), and standard deviation (SD), which can evaluate the overall performance of the model. Equations 2 to 4 are used to calculate these parameters:

$$R^2 = \frac{(\sum_{i=1}^n (M_m - \bar{M}_m)(M_p - \bar{M}_p))^2}{\sum_{i=1}^n (M_m - \bar{M}_m)^2 \sum_{i=1}^n (M_p - \bar{M}_p)^2} \quad (2)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (M_p - \bar{M}_m)^2}{n}} \quad (3)$$

$$SD = \sqrt{\frac{\sum_{i=1}^n (x_i - \mu)^2}{m - 1}} \quad (4)$$

According to the above equation, M_m and M_p are the measured and predicted values, respectively, and $\bar{M}_m$ and $\bar{M}_p$ are the averages of the measured and predicted values, respectively. m represents the number of samples and μ represents the mean of x_i .

2.2.1 Data Processing

Genetic algorithms are a computational method inspired by nature that is used in the field of artificial intelligence to solve complex problems and optimization. For example, in the neural network optimization approach, the structure and parameters of the neural network are represented as chromosomes. Using crossover and mutation operators, new structures of neural networks are generated, and the fit function evaluates the performance of each network. By repeating this process, more optimal neural networks are obtained that perform better in machine learning problems (Davis and Coombs, 1987; Goldberg, 1989). In this study, the input data for the neural network includes Gamma ray (GR), compressional wave transmission time (DT), density (RHOB), coordinate X, coordinate Y, coordinate Z and neutron porosity (NPHI), which are trained by the Levenberg-Marquardt algorithm and divided into three categories: 70% of the data as train data, 15% as test data, and 15% as validation data. A section of the data of well are showed in Table 2.

Table 2. A section of the data bank extracted from well in present study.

MD	X	Y	Z	SigmaV	Hydrostat Pressure	CAL	GR	DT	NPHI	RHOB
3097.7	435118.8	6479318	2812.546	53.33450406	28.9646788	8.3916	33.7093	82.1824	0.237	2.5628
3097.8	435118.8	6479318	2812.612	53.33573109	28.96534518	8.3899	36.0976	82.4785	0.2468	2.5575
3097.9	435118.7	6479318	2812.678	53.33695813	28.96601155	8.3836	40.4929	82.9046	0.2577	2.5558
3098	435118.6	6479318	2812.744	53.33818517	28.96667793	8.3822	44.634	83.41	0.2654	2.5591
3098.1	435118.6	6479318	2812.81	53.33941221	28.9673443	8.3875	45.0298	83.5862	0.2674	2.5624
3098.2	435118.5	6479318	2812.876	53.34063924	28.96801067	8.3977	42.6943	82.8604	0.2649	2.5615
3098.3	435118.4	6479318	2812.942	53.34186628	28.96867705	8.404	41.3058	81.3384	0.2584	2.5579
3098.4	435118.4	6479318	2813.008	53.34309332	28.96934342	8.401	41.1918	79.4419	0.2498	2.558
3098.5	435118.3	6479318	2813.074	53.34432036	28.9700098	8.3946	41.0254	77.6853	0.2415	2.5669
3098.6	435118.2	6479318	2813.14	53.34554739	28.97067617	8.3903	39.87	76.3011	0.2334	2.5822

The working method of GA–MLP and GA–RBF algorithms in the present study is shown in Figure 6.

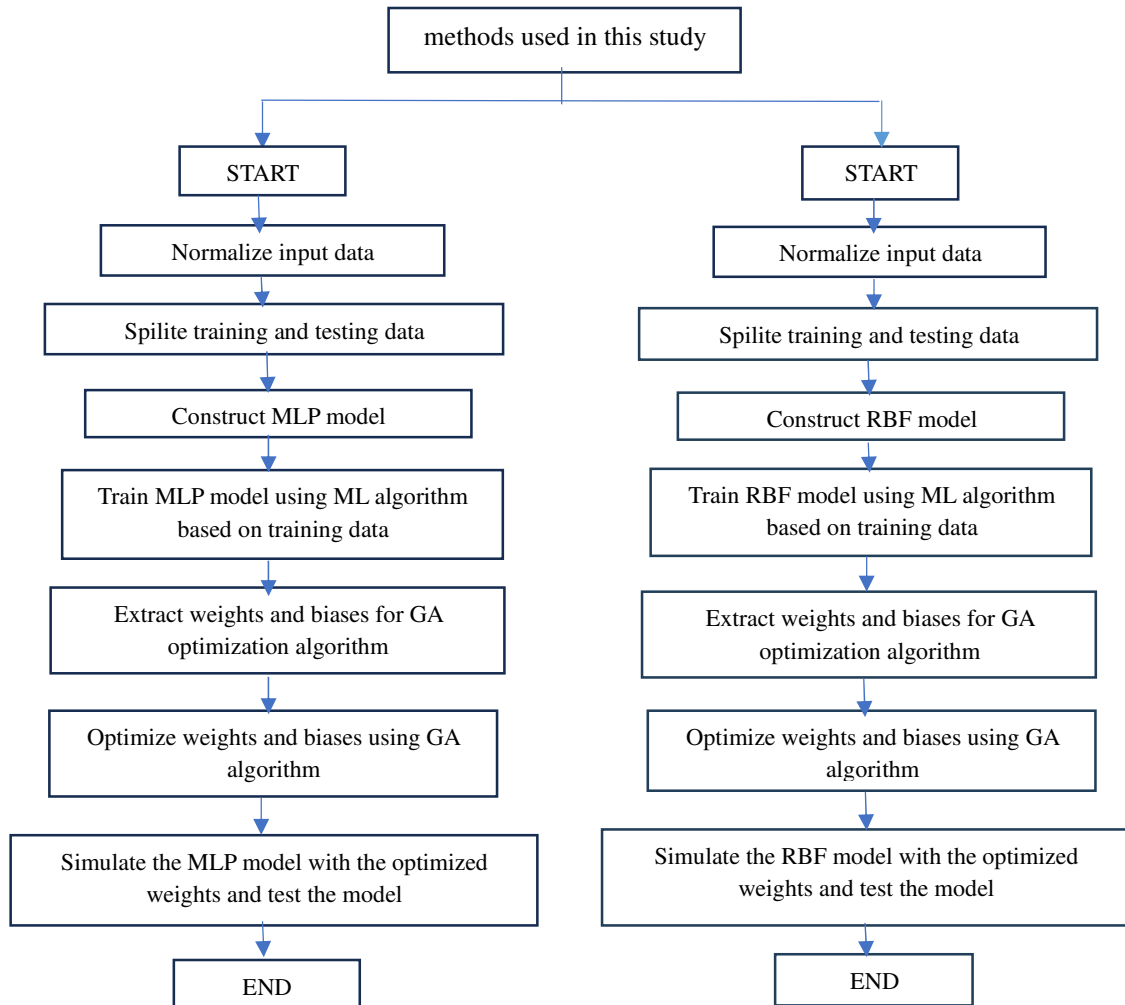


Fig 6. Flowchart GA–MLP algorithm (Left) and GA–RBF algorithm (Right)

2.2.2MLP algorithm

The performance of the Multilayer Perceptron (MLP) neural network model depends on the number of hidden layers and the number of neurons, and the problem is that the more layers and hidden neurons, the more computational time. Then optimizing the MLP structure can increase the efficiency and accuracy of this model. Trial and error learning method can be a suitable method to calculate the number of hidden layers, but it is complicated (Ham and Kostanic 2001). Figure 7 shows the outline of the different stages of the MLP model.

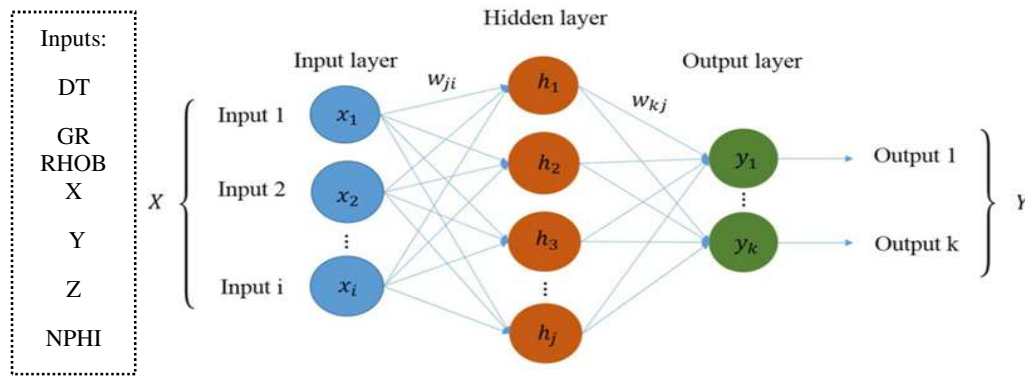


Figure 7. Schematic of the MLP algorithm.

In this study, the GA algorithm is used to calculate the number of hidden layers of MLP and the number of neurons in each layer. Table 3 shows the values of the control parameters of the GA-MLP algorithm that are necessary to optimize the number of layers and neurons.

Table 3. Control parameters of the GA-MLP algorithm

MLP		GA	
Control parameter	Value/Options	Control parameter	Value/Options
Number of inputs	7	Population	60
Number of hidden layers	1	Selection method	Roulette wheel
Number of input layer neurons	40	Crossover	Uniform, ($p = 1$)
Number of output layer neurons	1	Mutation	Uniform, ($p = 0.05$)
		Mutation rate	0.11
		Selection pressure for Roulette wheel	2

In MLP, neurons in the neural network are connected through feedforward type. The Sigmoid tangent transfer function is applied to the hidden layer and the linear function is applied to the output layer. The Levenberg-Marquardt algorithm is applied to train the network. The results obtained from the test, train and validation of the GA-MLP method are in the form of figures 8 to 11.

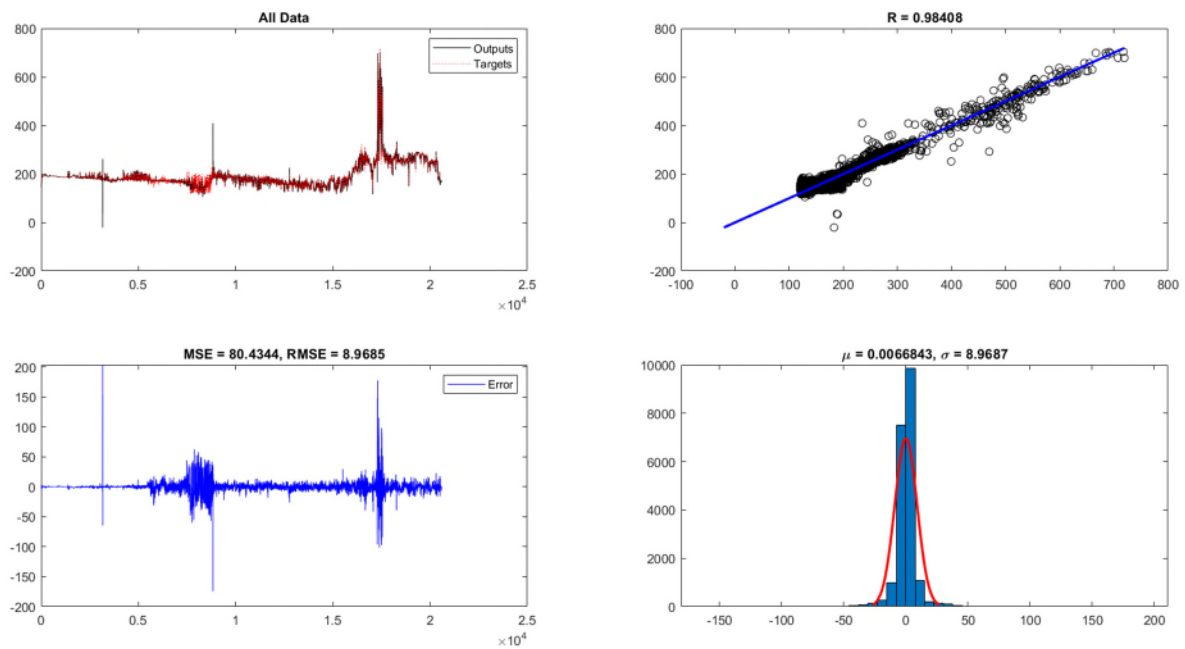


Figure 8. Results of all data in the GA-MLP algorithm in the studied well.

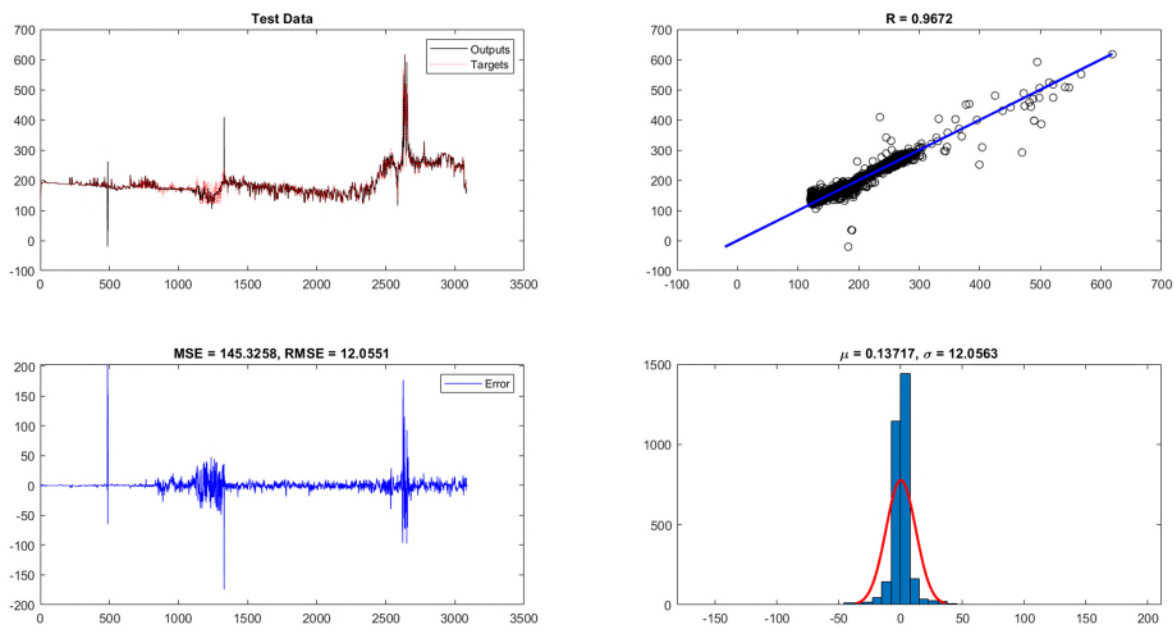


Figure 9. Test results of the GA-MLP algorithm in the studied well.

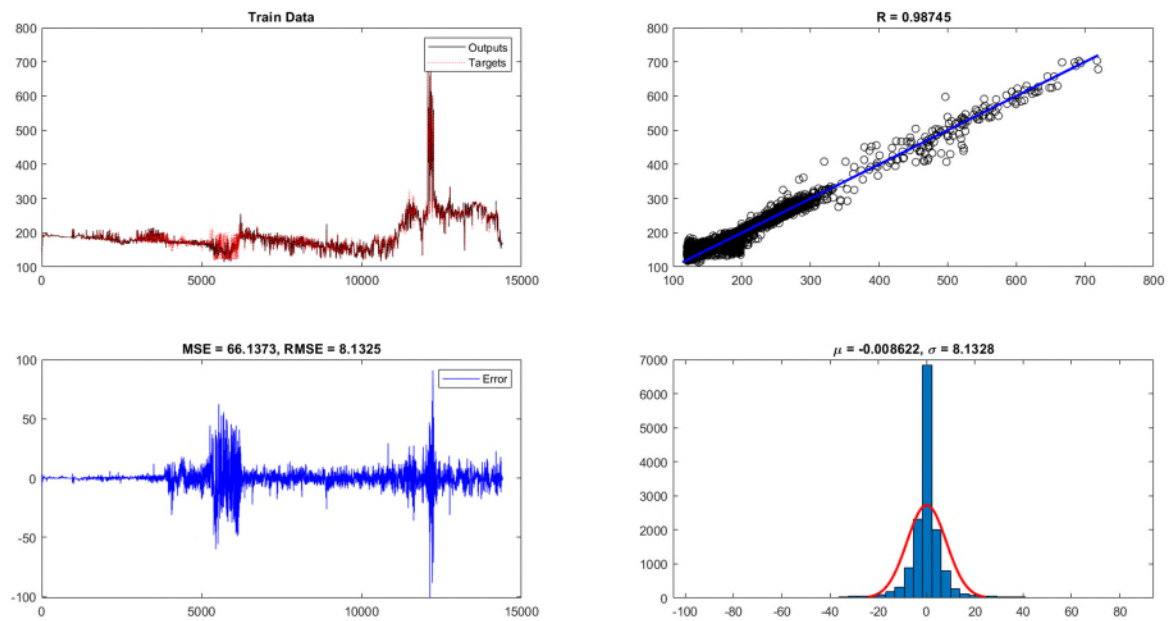


Figure 10. Train Results of the GA-MLP algorithm in the studied well.

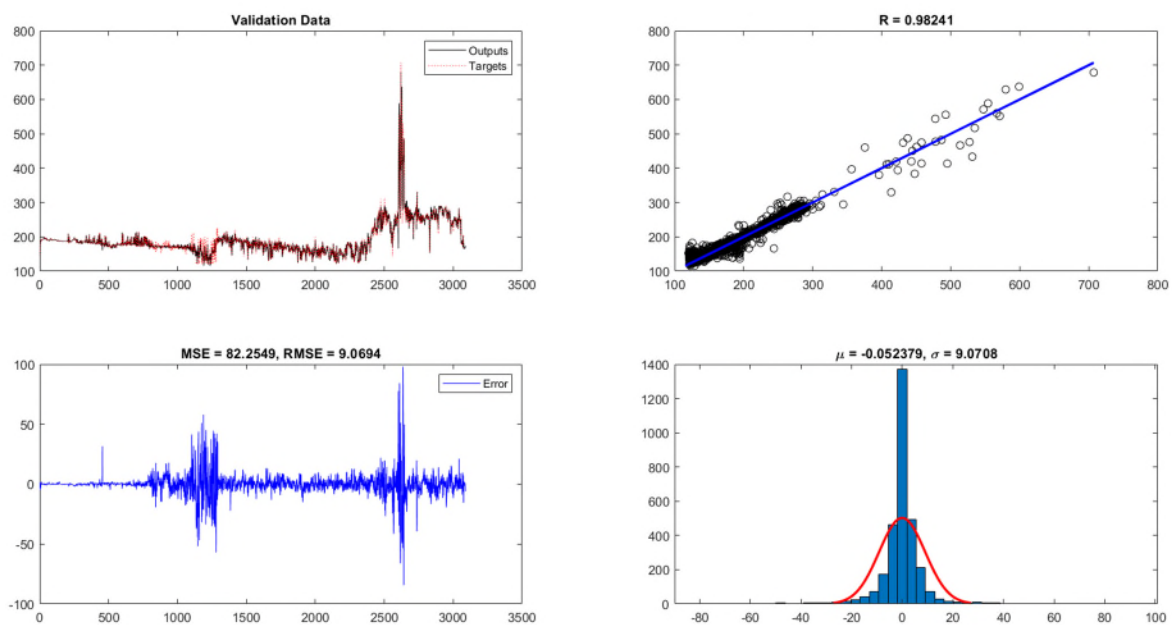


Figure 11. Validation results in the GA-MLP algorithm in the studied well.

2.2.3 RBF algorithm

Radial basis function (RBF) network has a simple structure and fast training process. Selecting a sufficient number of neurons for a hidden layer in RBF is necessary to satisfy the specific mean square error (Wu et al. 2012). Optimization of the RBF structure can increase the efficiency and accuracy of this method. Figure 12 shows the outline of the different stages of the RBF model.

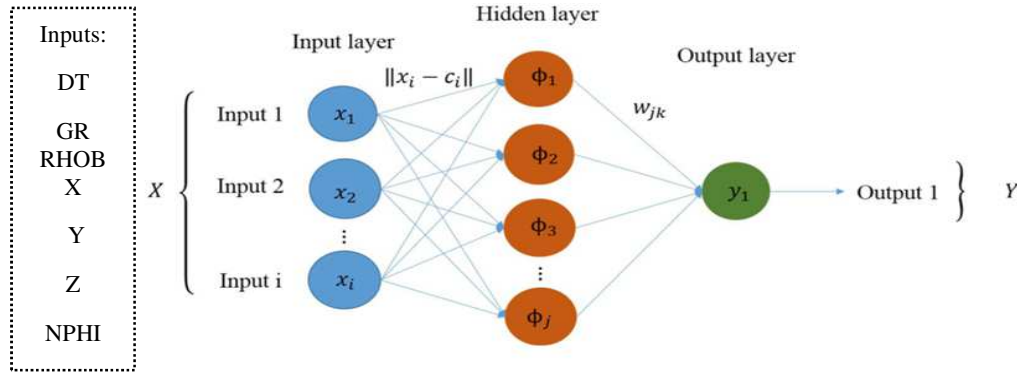


Figure 12. Schematic of the RBF algorithm.

Table 4 shows the values of the control parameters of the GA-RBF algorithm that are necessary and useful for optimizing the number of spreads and neurons.

Table 4. Control parameters of the GA-RBF algorithm.

RBF		GA	
Control parameter	Value/Options	Control parameter	Value/Options
Number of inputs	7	Population	60
Number of spreads	4	Selection method	Roulette wheel
Number of input layer neurons	800	Crossover	Uniform, ($p = 1$)
Number of output layer neurons	1	Mutation	Uniform, ($p = 0.05$)
		Mutation rate	0.11
		Selection pressure for Roulette wheel	2

The activation functions in the RBF method are implemented using Gaussian functions. The radial basis function is applied to the hidden layer and the linear function is applied to the output layer. The results of the implementation of the GA-RBF model are shown in Figures 13 to 15.

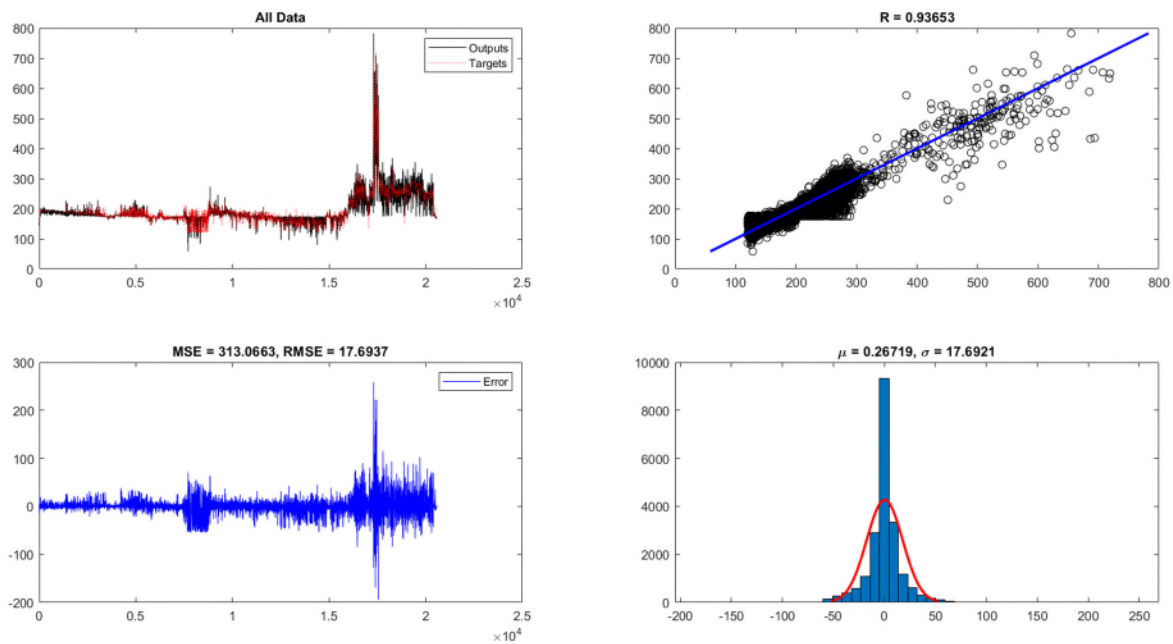


Figure 13. Results of all data in the GA-RBF algorithm in the studied well.

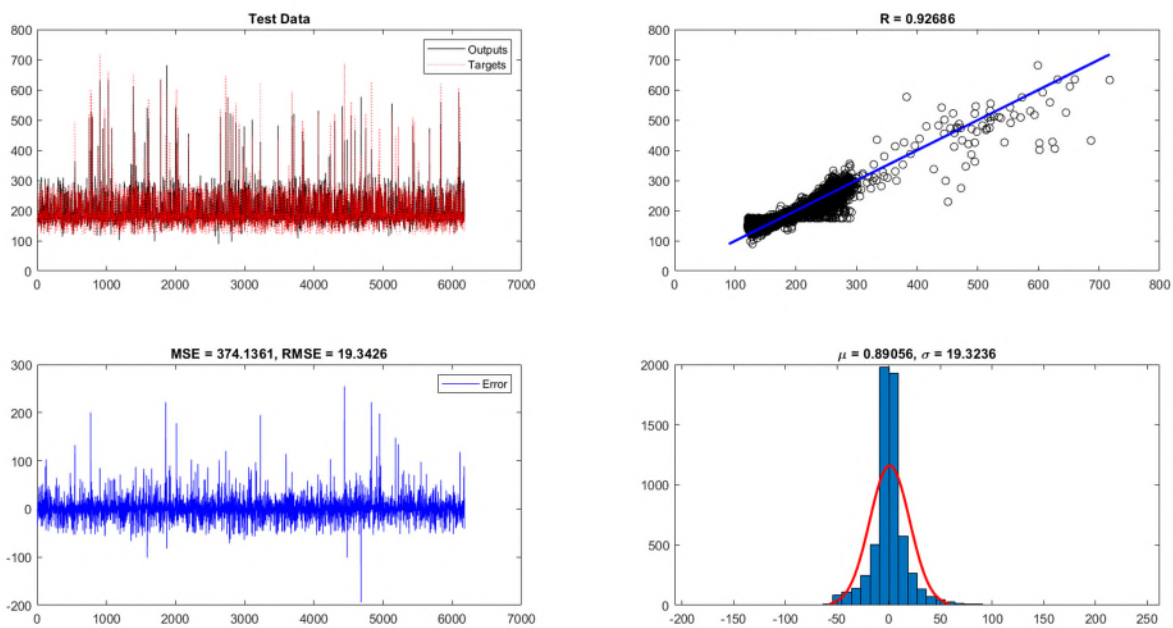


Figure 14. Test results of the GA-RBF algorithm in the studied well.

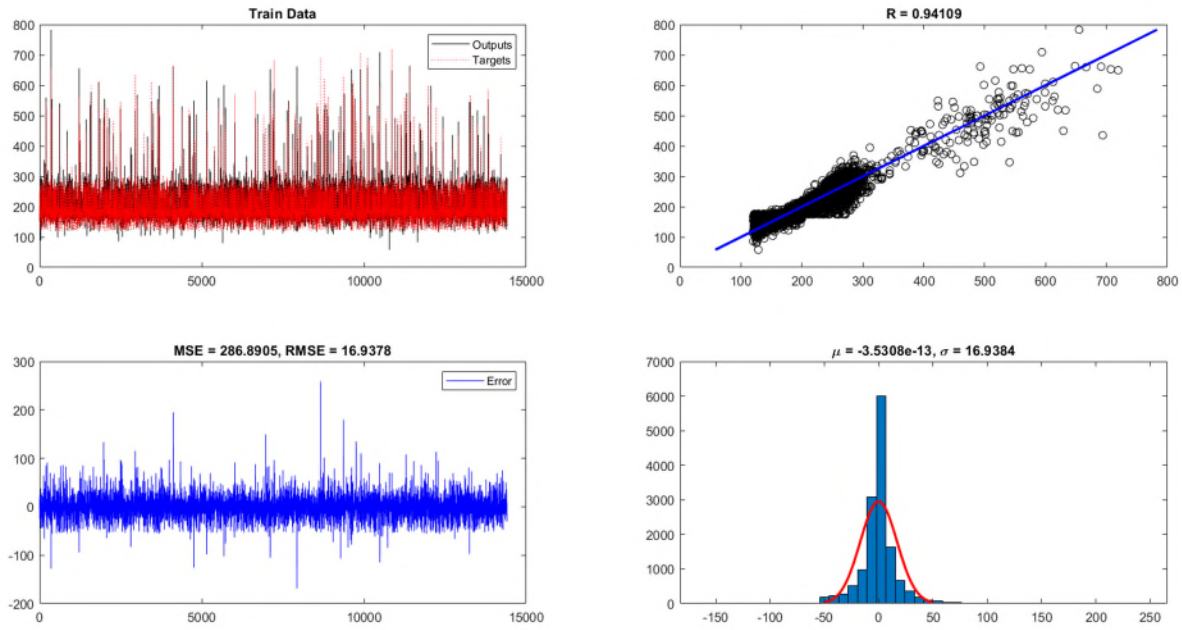


Figure 15. Train Results of the GA-RBF algorithm in the studied well.

3. Results of GA–MLP and GA–RBF Algorithms

The evaluation of current research models is evaluated using statistical measures such as coefficient of determination (R^2), root mean square error (RMSE), and mean square error (MSE). Table 5 compares the performance of the two methods used in this study.

Table 5. Results obtained from GA-MLP and GA-RBF methods.

Predicated name	R^2			RMSE			MSE		
	Train	Test	Validation	Train	Test	Validation	Train	Test	Validation
GA-MLP	0.9872	0.9672	0.9824	8.13	12.055	9,06	66.13	145.32	82.25
GA-RBF	0.9410	0.9268	0.9388	16.93	19.34	17.70	286.89	374.13	304.288

As we know, a model has acceptable performance when its R^2 value is the highest and close to 1 and its error values are the lowest and close to zero. According to the results obtained for the coefficient of determination and RMSE values presented in Table 5, the efficiency of the GA-MLP model is proven. To provide the estimation accuracy, the results of GA-MLP and GA-RBF are compared with each other and shown in Figure 16 and Figure 17.

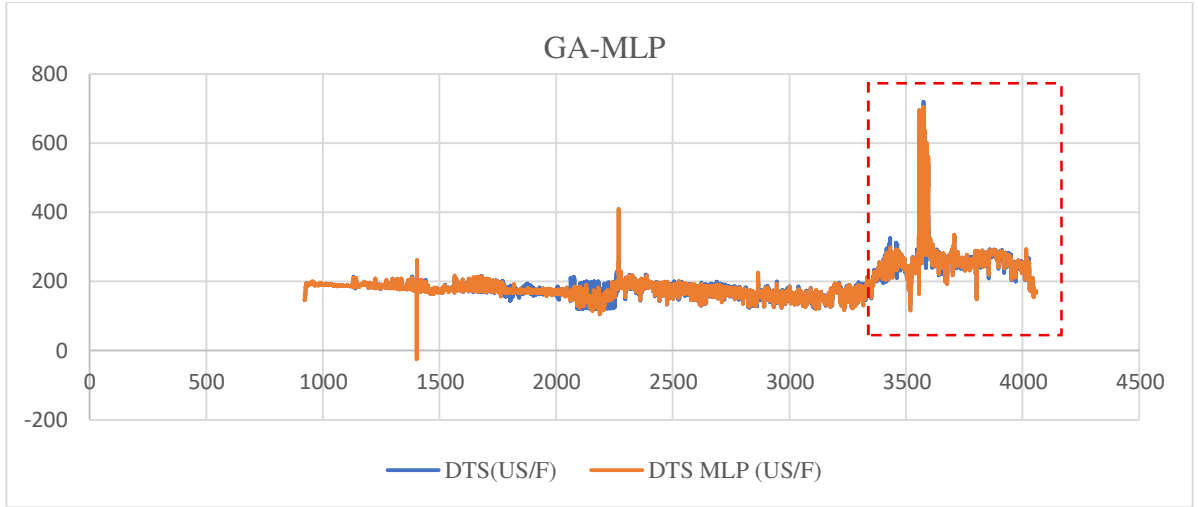


Figure 16. Validation of the initial shear wave velocity log with the obtained in the GA-MLP method log.

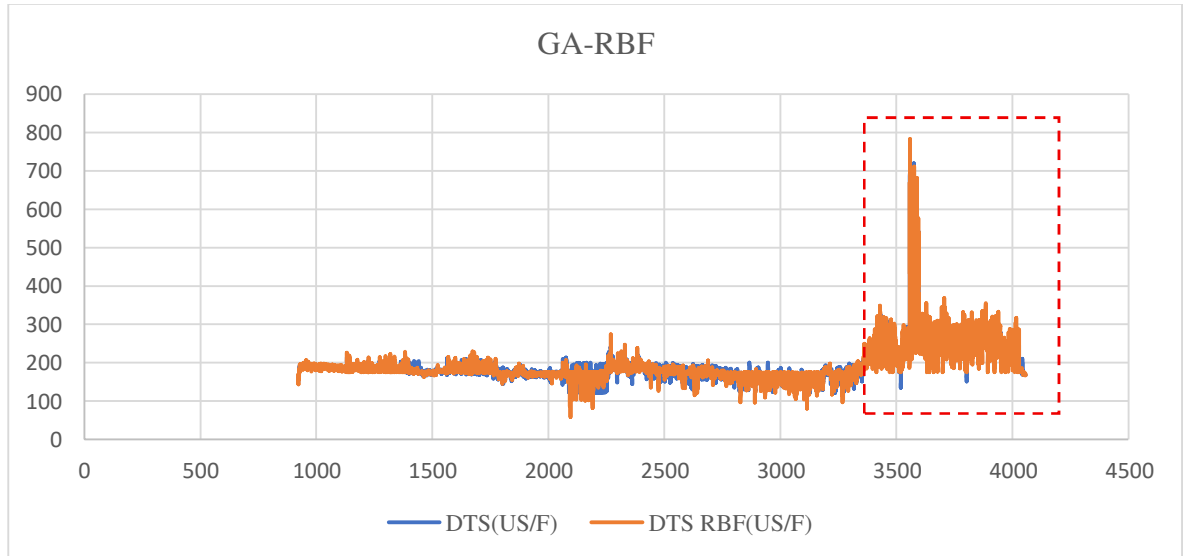


Figure 17. Validation of the initial shear wave velocity log with the obtained in the GA-RBF method log.

According to the red box in Figures 16 and 17, it can be seen that the GA-MLP algorithm has been able to provide a better fit to the original log in many places than the GA-RBF algorithm.

4. Conclusion

The aim of this paper is to investigate the efficiency and capability of neural network compared to other methods. Considering the good agreement between the rock physics and intelligent methods, it can be stated that the method proposed in this paper can be used as a practical method for estimating shear wave velocity without spending much money and more time. In the first step of the study, the shear wave diagram was estimated using rock physics relations such as Greenberg-Castagna for the depth range containing petrophysical information. In the second step of this study, for areas lacking petrophysical evaluations, the Castagna linear relation was used to estimate the shear wave velocity from the compression wave velocity, and finally these two diagrams were merged together. For areas lacking petrophysical information and

evaluations, the density diagram was aligned using the Gardner relation and the compression wave velocity diagram was estimated. Then this estimated diagram was combined with the density diagram available in the depth interval containing the information to obtain a complete density diagram. Also, for the area without data in the compression wave velocity diagram, the aligned Faust model was used to estimate the compression wave velocity in this interval. In the last step of this research, the genetic algorithm method was inoculated with MLP and RBF. The results of this study showed that the Greenberg-Castagna rock physics model has a correlation coefficient of about %96 in estimating shear wave velocity. As a result, apply the genetic algorithm to MLP and RBF neural networks as GA-MLP and GA-RBF for estimating shear wave velocity showed that GA-MLP has a correlation coefficient of %98.7 with the measured values.

Reference

- Ansary M.A., Ansary M. (2023). Use of SPT and depth for estimating shear-wave velocity using optimised machine learning models.
- Asoodeh, M., Bagheripour, P. (2012). Prediction of compressional, shear, and stoneley wave velocities from conventional well log data using a committee machine with intelligent systems. *Rock mechanics and rock engineering*, 45(1), 45-63.
- Akhundi, H., Ghafoori, M., Lashkaripour, G.R. (2014). Prediction of shear wave velocity using artificial neural network technique, multiple regression and petrophysical data: a case study in Asmari reservoir (SW Iran). *Open J. Geol.* 4, 303–313.
- Anemangely, M., Ramezanzadeh, A., Behzad, T. (2017). Shear wave travel time estimation from petrophysical logs using ANFIS-PSO algorithm: a case study from Ab-Teymour Oilfield. *J. Nat. Gas Sci. Eng.* 38, 373–387.
- Baghbani A., Abuel-Naga H., Shirani Faradonbeh R., Costa S., Almasoudi R. (2023). Ultrasonic characterization of compacted salty kaolin–sand mixtures under nearly zero vertical stress using experimental study and machine learning.
- Bagheripour, P., Gholami, A., Asoodeh, M., Vaezzadeh-Asadi, M. (2015). Support vector regression-based determination of shear wave velocity. *Journal of Petroleum Science and Engineering*, 125, 95-99.
- Brocher, T. M., (2005). Empirical Relations between Elastic Wave speeds and Density in the Earth's Crust, *Bulletin of the seismological Society of America*, 95, 6, pp. 2081–2092.
- Castagna, J.P., Batzle, M.L., Eastwood, R.L. (1985). Relationship between compressional and shear wave velocities in silicate rocks", *Geophysics* 50, 571–581.
- Castagna, J.P., Batzle, M.L., Kan, T.K. (1993). Rock physics—the link between rock properties and AVO response, in: Castagna, J.P., Backus, M.M. (Eds.), *Offset-Dependent Reflectivity—Theory and Practice of AVO Analysis*. Soc. Expl. Geophysics, pp. 124–157.
- Dalvand, M and falahat, R. (2021), A New Rock Physics Model to Estimate Shear Velocity Log, *Journal of Petroleum Science and Engineering*.
- Duffaut, K., Landrø, M. (2007). V_p/V_s ratio versus differential stress and rock consolidation—A comparison between rock models and time-lapse AVO data. *Geophysics*, 72(5), C81-C94.

Elkatatny, S., Tariq, Z., Mahmoud, M., Mohamed, I., Abdulraheem, A. (2018). Development of New Mathematical Model for Compressional and Shear Sonic Times from Wireline Log Data Using Artificial Intelligence Neural Networks (White Box), Arab J Sci Eng, 43, pp. 6375–6389.

Greenberg, M.L., Castagna, J.P. (1992). Shear wave velocity estimation in porous rocks: theoretical formulation, preliminary verification and applications, Geophys. Prospect. 40, 195–209.

Davis, L., Coombs, S. (1987). Genetic algorithms and communication link speed design: Theoretical considerations. Genetic Algorithms and Their Applications: Proceedings of the Second International Conference on Genetic Algorithms (pp. 252-256). Cambridge, MA: Lawrence Erlbaum.

Dvorkin, J.P. (2003). Velocity and Porosity Empirical and Theoretical Models.

Demuth, H., Beale, M. (1993). Neural network toolbox for use with MATLAB.

Eskandari, H., Rezaee, M.R., Mohammadnia, M. (2004). Application of multiple regression and artificial neural network techniques to predict shear wave velocity from well log data for a carbonate reservoir, south-west Iran. CSEG RECORDER, pp. 42–48.

Galushkin, A.I. (2007). Neural networks theory, Springer, New York.

Goldberg, D. E. (1989). Genetic algorithms in search, optimization, and machine learning. Reading, MA: Addison-Wesley.

Han, D., Nur, A., Morgan, D. (1986). Effects of porosity and clay content on wave velocities in sandstones", Geophysics, 51, 2093-2107.

Pickett, G.R. (1963). Acoustic character logs and their application in formation evaluation. Pet. Technol. 15, 650–667.

Rajabi M., Bohloli B., Ahangar E.G. (2010). Intelligent approaches for prediction of compressional, shear and Stoneley wave velocities from conventional well log data: A case study from the Sarvak carbonate reservoir in the Abadan Plain (Southwestern Iran). Computers & Geosciences, Vol: 36, No:5, P: 647-664.

Kadkhodaie-Ilkhchi, A. (2015). A systematic approach for estimation of reservoir rock properties using Ant Colony Optimization. Geopersia, 5(1), 7-17.

Maleki, S., Moradzadeh, A., Riabi, R. G., Gholami, R., Sadeghzadeh, F. (2014). Prediction of shear wave velocity using empirical correlations and artificial intelligence methods. NRIAG Journal of Astronomy and Geophysics, 3(1), 70-81.

Mavko, G., Mukerji, T., Dvorkin, J. (1998). The Rock Physics Handbook, Cambridge University Press, ISBN 0521-62068- 6.

Mehrgini, B., Izadi, H., and Memarian, H. (2019). Shear Wave Velocity Prediction Using Elman Artificial Neural Network, Carbonates Evaporites, 34, pp. 1281–1291.

Milholand, P., Manghnani, M.H., Schlanger, S.O., Sutton, G.H. (1980). Geoacoustic modeling of deepsea carbonate sediments, J. Acoust. Soc. Am., 68: PP. 1351-1360.

Moatazadian, I., Rahimpour-Bonab, H., Kadkhodaie-Ilkhchi, A., Rajoli, M. (2011). 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. Geopersia, 1(1), 1-17.

Mousavi, Z., Bayat, M., Feng W. (2024 a). Machine learning models for predicting shear wave velocity of soils IOP Conf. Ser. Earth Environ. Sci., 1334, Article 012039.

Mousavi, Z., Bayat M., Yang, J., Feng, W. (2024 b). Evaluation of empirical and machine learning models for predicting shear wave velocity of granular soils based on laboratory element tests Soil Dynam. Earthq. Eng., 183, Article 108805.

Nasrnia B., Falahat R., Kadkhodaie A., Gholami-Vijouyeh, A. (2023). A committee machine-based estimation of shear velocity log by combining intelligent systems and rock-physics model using metaheuristic algorithms. Eng Appl Artif Intell 126:106821.

Nasrnia, B., Falahat, R. (2024). Introducing a simplified rock physics model to estimate shear velocity to consider the geometry of pore spaces and minerals. *Acta Geophysica*, 72(5), 3223-3235.

Sanei, M., Ramezanzadeh, A, Delavar, M. (2023). Applied machine learning-based models for predicting the geomechanical parameters using logging data, Journal of Petroleum Exploration and Production Technology.

Thomsen, L. (1986). Weak elastic anisotropy, *Geophys*, 51: P. 1654-1966.

Krief, M., Garat, J., Stellingwerf, J., Venter, J. (1990). A petrophysical interpretation using the velocities of P and S waves (full wave from sonic), *Log Anal*. 31, 35–369.