



Prediction of shear wave velocity using empirical correlations and artificial intelligence methods



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Abstract Good understanding of mechanical properties of rock formations is essential during the development and production phases of a hydrocarbon reservoir. Conventionally, these properties are estimated from the petrophysical logs with compression and shear sonic data being the main input to the correlations. This is while in many cases the shear sonic data are not acquired during well logging, which may be for cost saving purposes. In this case, shear wave velocity is estimated using available empirical correlations or artificial intelligent methods proposed during the last few decades. In this paper, petrophysical logs corresponding to a well drilled in southern part of Iran were used to estimate the shear wave velocity using empirical correlations as well as two robust artificial intelligence methods known as Support Vector Regression (SVR) and Back-Propagation Neural Network (BPNN). Although the results obtained by SVR seem to be reliable, the estimated values are not very precise and considering the importance of shear sonic data as the input into different models, this study suggests acquiring shear sonic data during well logging. It is important to note that the benefits of having reliable shear sonic data for estimation of rock formation mechanical properties will compensate the possible additional costs for acquiring a shear log.

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1. Introduction

In rock engineering, methodologies based on wave velocity are increasingly used to determine the dynamic properties of rocks (Singh et al., 2012). In Petroleum engineering context, this is mainly due to very sparse or no borehole-based rock mechanical data being acquired during drilling phase. This is while having this information is essential for reservoir development,

management, and prospect evaluation in exploration areas (Ameen et al., 2009). The direct measurements of the geomechanical properties of formations need testing core samples in the lab. However, limited number of samples can be taken from the whole wellbore interval (of few thousands meter) due to cost and technical issues. In addition to the fact that lab experiments are time consuming and also expensive to be conducted, the results obtained from testing only few number of samples cannot provide a good estimation of mechanical properties of formations crossed by the wellbore. Indeed, it would be ideal to have continuous logs, similar to petrophysical logs, representing elastic and strength properties of different formations.

According to the studies carried out to estimate mechanical properties of subsurface layer, having shear velocity data is necessary to make reliable calculations (Ameen et al., 2009; Boonen et al., 1998; Eissa and Kazi, 1988; Rasouli et al., 2011; Zoback, 2007). However, in practice the shear sonic is not included in the set of acquired logs but only compressional sonic is available. In such occasions, several methodologies have been proposed to make an estimation of shear sonic data from other available data. For example, Wantland (1964) assumed Poisson's ratio for reservoir rocks and estimated shear wave velocities. However, Poisson's ratio is changing in a wide range in practice; hence the accuracy of estimated shear sonic data is questionable (Carroll, 1969). Another approach is to measure elastic properties of rocks through acoustic measurements of V_p and V_s using pulse transmission techniques in laboratory (Birch, 1960; Christensen, 1974; Kern, 1982; Burlini and Fountain, 1993; Ji and Salisbury, 1993; Watanabe et al., 2007). However, few lab data are available for V_s measurements compared to those of V_p (Ji et al., 2002). This is mainly due to the difficulties of V_s measurements at low pressures, as the transmission of shear wave through the sample requires a firm contact between the transducers and the end surfaces of the specimen. Since variations of shear wave velocity are related to the rock type, mechanical properties and loading conditions, the laboratory measurements cannot ideally simulate downhole field conditions (e.g. in situ stresses and fluid content). The use of a large range of empirical correlations has been reported during the last decades to estimate shear wave velocity from rock physical parameters (Castagna et al., 1993; Brocher, 2005, 2008; Ameen et al., 2009; Yasar and Erdogan, 2004). However, these correlations have been developed for a specific area and their use in other fields is subjected to uncertainties.

In recent years, artificial intelligence (AI) methods have been used widely for prediction purposes (Feng, 1995; Mohammadi and Rahmanejad, 2009; Zhang et al., 2009). Once the network has been trained, it can make prediction, based on its previous learning, about the output related to new input data set of similar pattern. Support Vector Regression (SVR) is usually used as an efficient machine learning methodology for prediction of rock properties (Annan and Chunian, 2008; Kang and Wang, 2010; Niu and Li, 2010; Rechlin et al., 2011; Wenlin et al., 2011). The SVR relies on the statistical learning theory enabling learning machines to generalize the unseen data. This technique has proven to have superior performances in a variety of problems due to its generalization abilities and robustness against noise and interferences (Steinwart, 2008). SVM is a device for finding a solution which uses the minimum possible energy of the data (Martinez-Ramon and Cristodoulou, 2006; Cristianini and Shawe-Taylor, 2000). In general, there are at

least three reasons for the success of SVM: its ability to learn well with only a very small number of parameters, robustness against the error of the model, and its computational efficiency compared with several other methods such as neural network and fuzzy network (Martinez-Ramon and Cristodoulou, 2006).

In this paper, petrophysical logs corresponding to a well drilled in the southern part of Iran are used to estimate the shear wave velocity using empirical correlations as well as novel AI techniques.

2. Geology of field

This study uses the data belonging to an oilfield located in the Iranian Province of Khuzestan, onshore of the Ahwaz region, near the Iran-Iraq frontier (see Fig. 1). The field is a North-South oriented gentle anticline, located in the Dezful Embayment, which is a sector associated with the closing of the Neo-Tethys sea and the Tertiary formation of the Zagros-Taurus Mountains. The oilfield is close to the Basrah area in the west. The structures in the Basrah area consist of gentle anticlines showing a North-South general trend which is the same to this field. The trend of these anticlines follows the old North-South oriented basement lines. The presence of Precambrian and Early Cambrian salt in Northern Persian Gulf area and Saudi Arabia is considered as a reason to explain the possible origin of these structures. However the development of these anticlines seems related to the reactivation of basement faults which can be responsible for their structural evolution. The structural growth of the field area may be already started during the Mesozoic or earlier and continued through the time.

The Fahliyan Formation is well exposed in the Zagros Mountains, in Fars province (James and Wynd, 1965). At the same time of the sedimentation of the Fahliyan, in the area located between the oilfield and the Khuzestan province, the intra-shelf basin of the Garau Formation takes place. The current oilfield area at the time of the Fahliyan sedimentation must have belonged to an articulate carbonate ramp complex, partly controlled by local tectonics, partly by sea level changes, probably limited Eastward by a more subsiding area underwent a deeper sedimentation. Argillaceous limestones and shales of deep environment also develop in Offshore Kuwait, suggesting that this area belonged to the same intra-shelf basin. The sedimentation of these units is related to the significant sea level rise started during the late Tithonian and continued into the early Berriasian (Sadooni, 1993). The shallow water sequences of Fahliyan and equivalent units of northern Persian Gulf underlay the shale and bioclastic limestone of the Ratawi Formation. Fig. 1 shows the approximate geographical location of the oil field in Iran.

The middle and upper Cretaceous sediments of the Dezful Embayment form one of the richest petroleum systems in the Middle East, with the presence of the Gurpi, Khazdumi and Gadvan source rocks and the Lurestan, Asmari, Khuzestan and Khami/Bangestan reservoirs (see Fig. 2).

3. Well A

The available well log data of the current study are belonging to a vertical wellbore drilled into a carbonate reservoir in southern part of Iran. The digitized well logs consist of dipole shear sonic imager (DSI), compressional wave sonic log

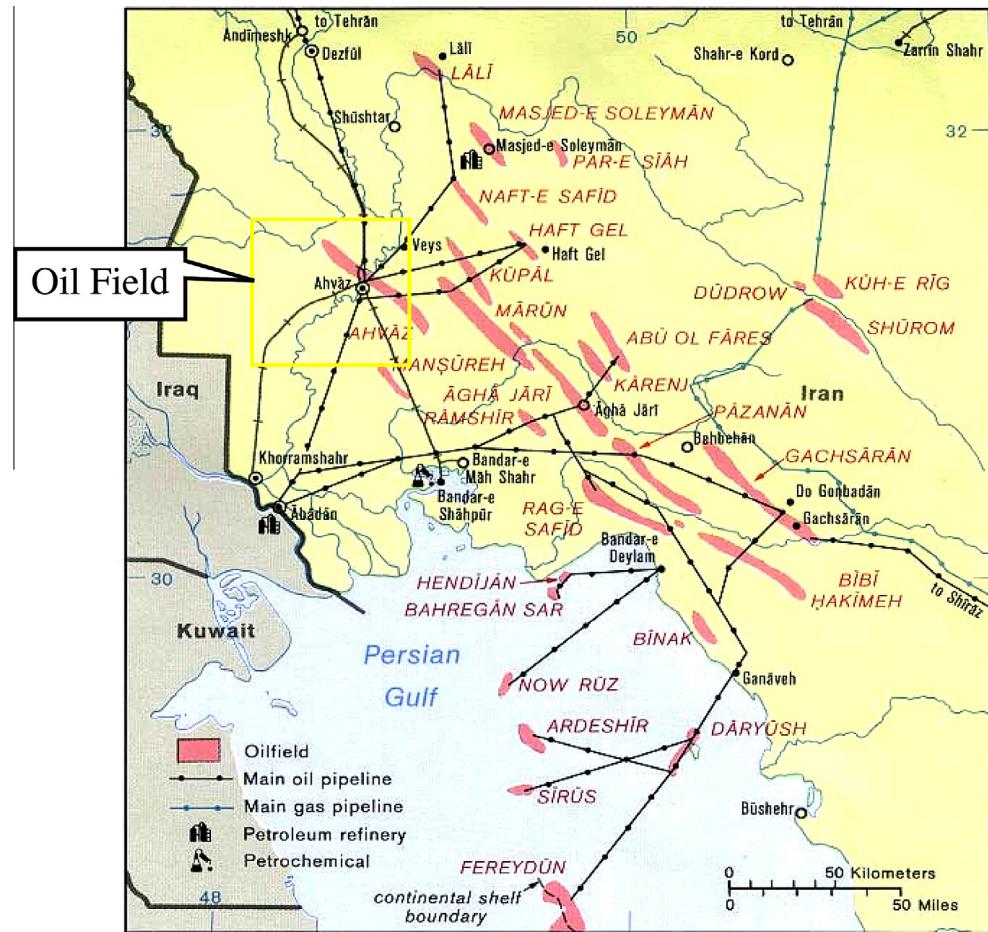


Fig. 1 Geographical location of the study area.

(DTCO), gamma ray log (CGR), density log (ROHZ), effective porosity (PHIT), true formation resistivity log (RT), and caliper logs (HCAL). Fig. 3 shows well logs used for the purpose of this study.

The plot of shear wave velocity versus different conventional well logs is shown in Figs. 4–6. As it is depicted in these figures, a fair correlation was found between shear velocity and density logs (Fig. 4). There was also a correlation coefficient of 0.39 obtained between shear wave velocities with gamma ray (Fig. 5) while a correlation coefficient of 0.94 was observed between shear and compressional wave velocities (Fig. 6).

It is obvious that there is a strong correlation between the shear and compressional wave velocity data of this well. Hence a correlation obtained by cross plotting of these two waves may have application for other wells located in this field where DSI data were not acquired for them. This correlation is presented as:

$$V_s = 0.4584 V_p + 0.3904 \quad (1)$$

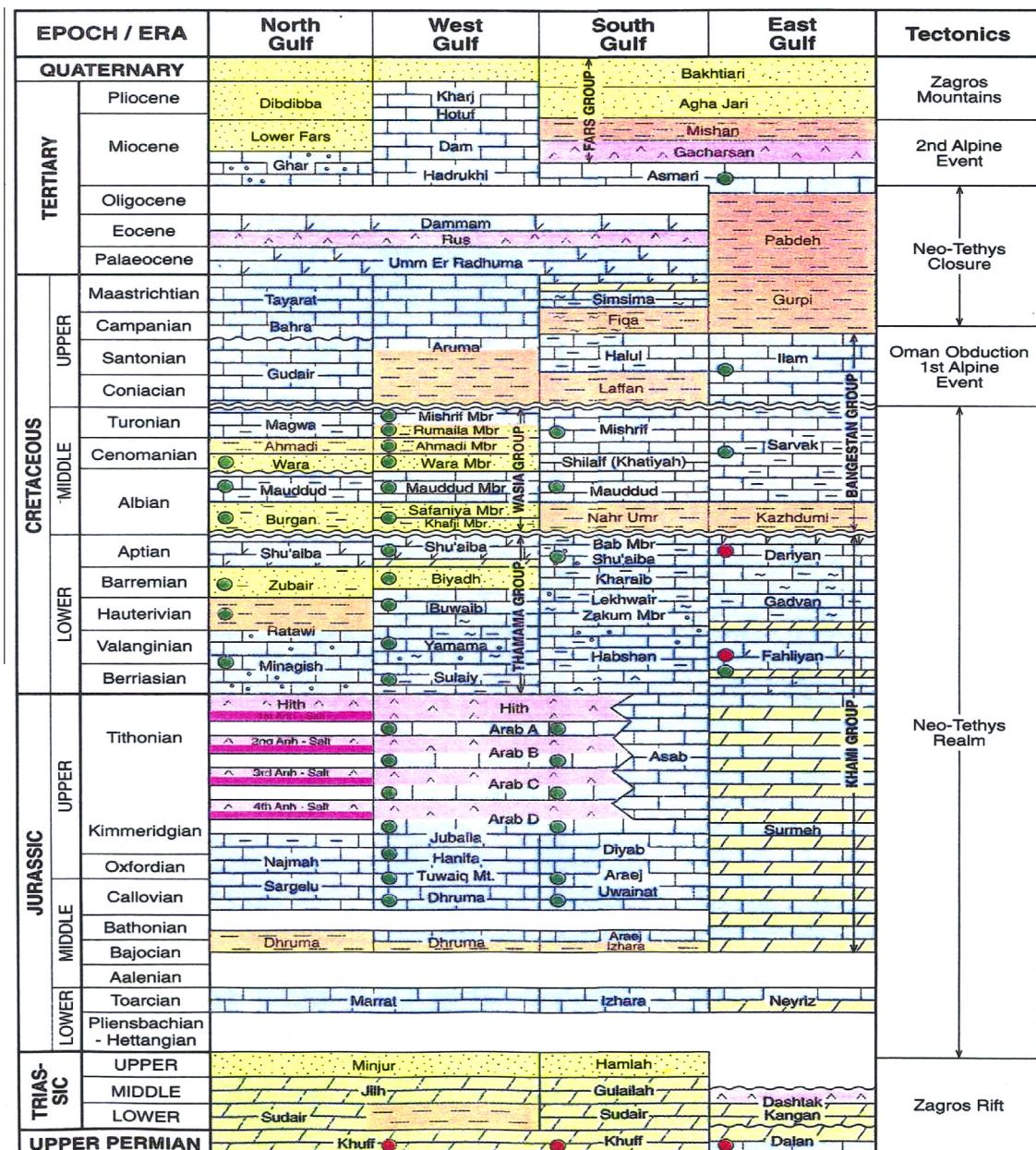
In this equation, V_s and V_p are, respectively, shear and compressional wave velocities and unit of V_s and V_p is km/s (kilometers to second).

4. Empirical correlations for shear-wave velocity estimation

Obtained results of specific shear wave velocities have shown that significant variations of shear wave velocity are related

to material type, their condition (compaction, strength) and structural loading conditions (Phil and Andy, 1990). To overcome the difficulty of determining the shear wave velocity or making an approximate value for it, laboratory measurement was introduced in the first place. The major disadvantage of determination of velocity on rock samples in the laboratory is that the values obtained are only representative of a small volume of the rocks. Unless the in situ conditions of stress, fluid content etc., of the rock samples are considered. Hence, measurements on samples in laboratory will differ significantly from those values existed in situ. This is because the acoustic properties of rock exhibit an environmental dependency particularly with respect to stress. Consequently, it is desirable to determine a method of estimating the shear wave velocity and at the same time avoid the associated cost of acquiring it. In this regard, various empirical correlations have been proposed based on regression analysis to predict shear wave velocity from compressional wave velocity (which is of course much easier to determine) or any other petrophysical data.

Regression analysis is one of the widely applied statistical tools for the investigation of relationships between a dependent variable of interest and a set of independent (related predictor) variables (Bailey, 1973). Regression equation gives an approximation to the actual functional relationship between the parameters of interest. Generally, regression analysis is applied to naturally-occurring variables (parameters), as opposed to experimentally gotten variables, although you can apply



Simplified Stratigraphy Petroleum Systems
And tectonics of the offshore of the Persian Gulf.
North Gulf Corresponds to Kuwait and Southeast
Iraq, West Gulf to Saudi Arabia and Bahrain, South
Gulf to the United Arab Emirates and Qatar, and
East Gulf to Iran's Offshore the Persian Gulf.

Fig. 2 Lithostratigraphic section of Iran (Khuzestan and Lurestan provinces) showing the distribution of the major source reservoir rocks.

regression to experimentally acquired variables (Montgomery et al., 2007). Regression analysis is either linear or non-linear. In linear regression, the data are modeled using linear independent variables or predictor functions, and unknown model variables are projected from the data. In non-linear regression data are modeled by a function which is a non-linear combination of the model parameters. This type of regression depends on one or more independent variables (Montgomery et al., 2007).

For the purpose of the current study, various empirical correlations proposed to predict shear wave velocity from petrophysical logs were used and two of them were selected as the best ones. In this section, these two correlations are presented and their results will be discussed in detail. In addition, a correlation is derived from the available data of the well logs which may have application for prediction of shear wave in gas shale formations.

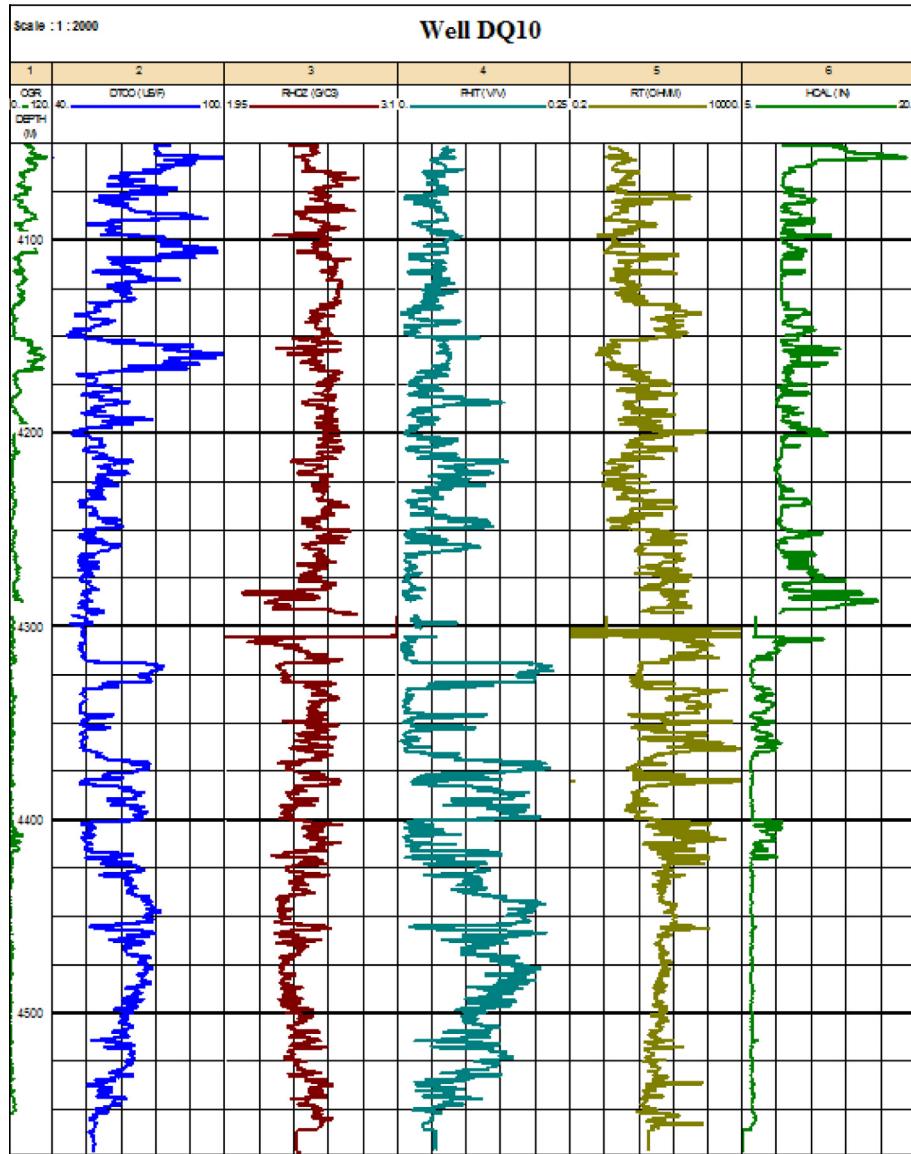


Fig. 3 Petrophysical logs used for this study.

4.1. Castagna equation

One of the most widely used correlations to predict shear wave velocity is Castagna equation. Castagna et al., 1993 proposed empirical equations for prediction of shear wave velocity in sandstone, limestone, shale and dolomite rocks. Since this study essentially considers carbonate formation, we use the equation proposed for carbonate rocks which is presented as:

$$V_s = -0.05509 V_p^2 + 1.0168 V_p - 1.0305 \quad (2)$$

In this equation, V_s and V_p are, respectively, shear and compressional wave velocities and unit of V_s and V_p is ft/us (foot to microsecond). The results obtained from utilizing Eq. (2) plotted against real shear wave velocity are shown in Fig. 7.

From Fig. 7, it is seen while Castagna correlation overestimates shear wave velocity, this is happening consistently which has resulted in a correlation coefficient of 0.96 between the real and predicted values. This means that this correlation results in a relatively high precise but low accurate estimation.

4.2. Brocher equation

Brocher (2005, 2008) plotted thousands of wave velocity data for a wide range of lithologies from unconsolidated sediments to very low porosity igneous rocks, and from non-welded volcanic tuffs to highly compact metamorphic rocks to draw a non-linear equation given as:

$$V_s = 0.7858 - 1.2344 V_p + 0.7949 V_p^2 - 0.1238 V_p^3 + 0.006 V_p^4 \quad (3)$$

This relation is valid for V_p between 1.5 and 8.5 km/s. where V_s and V_p are shear and compressional wave velocities respectively and unit of V_s and V_p is km/S (Kilometers to second). Fig. 8 shows the relationship and correlation coefficient obtained from Brocher equation.

From the above figure it can be concluded that this correlation is a good predictor of shear wave velocity. However the efficiency of Brocher equation in prediction of shear wave velocity is less than that of the Castagna equation.

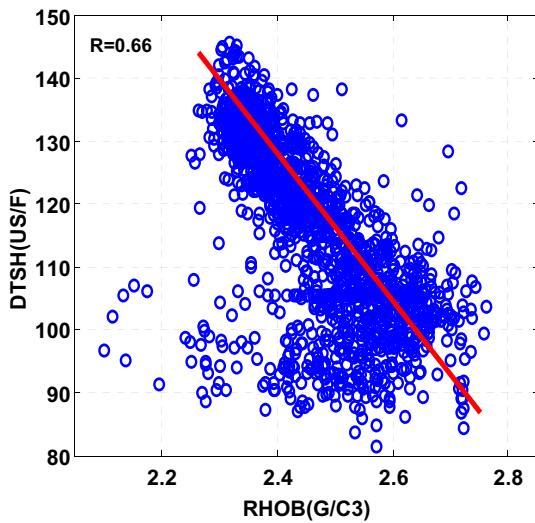


Fig. 4 Shear-wave velocity (US/F = microsecond to foot) versus density (RHOB).

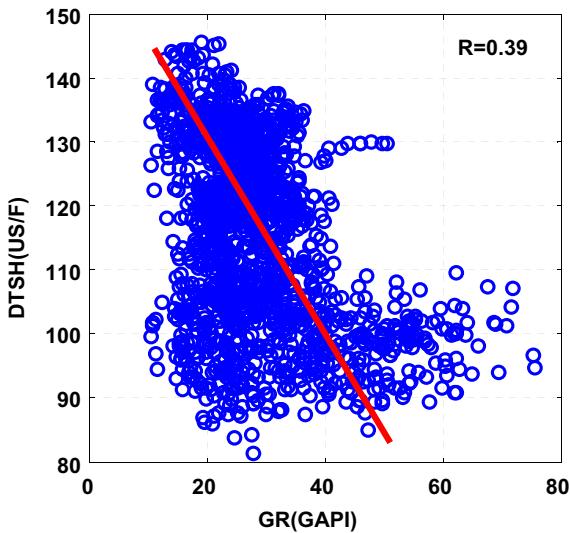


Fig. 5 Shear-wave velocity (US/F = microsecond to foot) versus gamma-ray.

4.3. Carroll equation

Carroll (1969) proposed the following empirical relation between compressional and shear wave velocities:

$$V_s = 1.09913326 \times V_p^{0.9238115336} \quad (4)$$

This correlation is valid for any rock having Poisson's ratio between 0.22 and 0.28 which implies based on elastic equations that the V_p/V_s ratio should be between 1.61 and 1.85 and unit of V_s and V_p is km/S. (Wadhwa et al., 2010). Fig. 9 shows the plot of shear wave velocity estimated from Carroll correlation versus real data.

The results obtained from Fig. 9 indicated that, in general, the estimated shear wave velocities using Carroll correlation are better than those of the Brocher. However, so far Castagna correlation seems to be the best correlation for prediction of

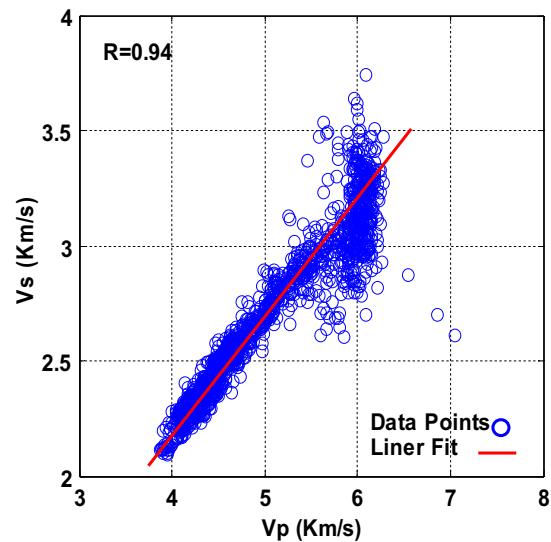


Fig. 6 Shear-wave velocity (km/S = Kilometers to second) versus compressional-wave velocity.

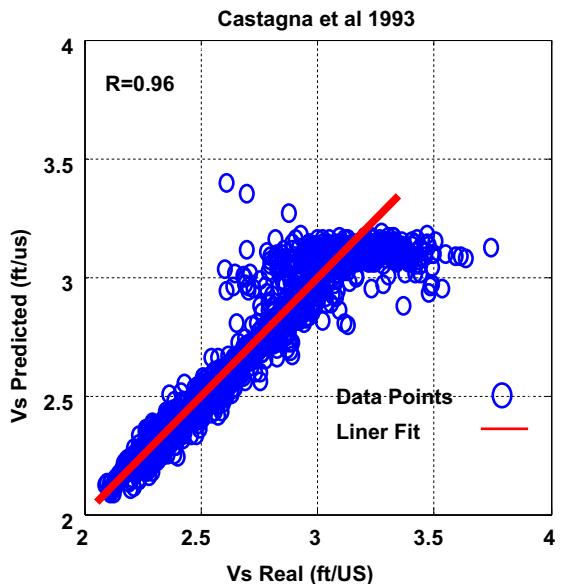


Fig. 7 Comparison of real versus predicted shear wave velocity (using Castagna correlation) in the studied wellbore (ft/us (foot to microsecond).

shear wave velocity. In any of the empirical correlations used in this paper there needs a shift to be applied in order to obtain better estimation of shear velocity values. However, different amounts of corrections may be required in different cases, which makes the use of these correlations difficult and subjected to uncertainties. This indicates that available correlations (as the results of three mostly popular ones shown here) are not good enough to extract a reliable shear velocity log. This stresses the importance and benefit of acquiring shear sonic data as part of the wire-line logging program during the drilling phase.

In the next section, application of two robust artificial intelligence algorithms is presented in order to show how much

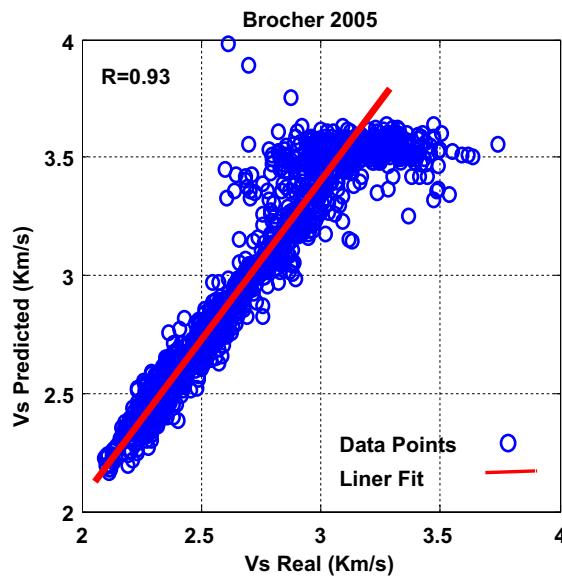


Fig. 8 Comparison of real versus predicted shear wave velocity (using Brocher correlation) in the studied wellbore (km/S = Kilometers to second).

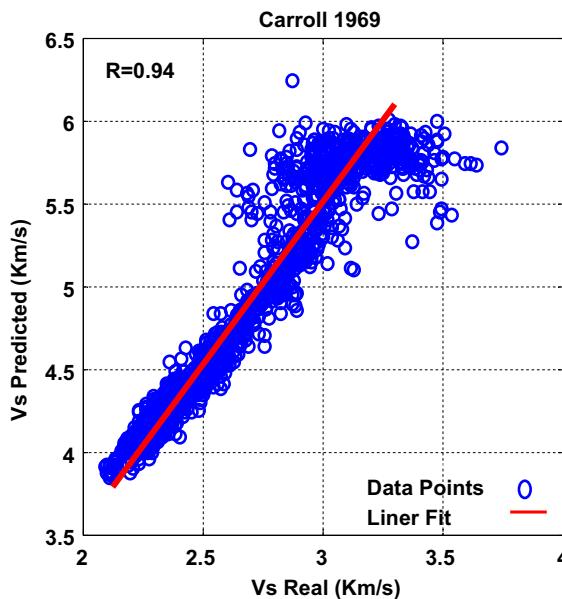


Fig. 9 Comparison of real versus predicted shear wave velocity (using Carroll correlation) in the studied wellbore (km/S = Kilometers to second).

accurate these methods may be in the prediction of shear wave velocity.

5. Regression based algorithms

In this section two robust artificial intelligence algorithms known as Support Vector Regression (SVR) and Back-Propagation Neural Network (BPNN) are used to estimate shear wave velocity using different petrophysical logs. These two networks have been extensively introduced in the

literatures so presenting their mathematical equations is beyond the scope of the current paper. In addition, to optimize the parameters involved in the structures of these two networks used for prediction of the shear velocity, genetic algorithm (GA) is used. Hence, in the following sections, a brief introduction to the SVR, BPNN and GA is given which is followed by discussing the steps involved in the development of the models.

5.1. Support Vector Regression

Support Vector Machine (SVM) used for regression analysis is called the Support Vector Regression (SVR). The aim of the SVR is to find a function for approximation of the output according to the available dataset (Cristianini and Shawe-Taylor, 2000). To estimate a function, a small fraction of training samples called support vectors (SVs) is taken into account. In addition, a specific loss function called ϵ -insensitive is used to create a sparseness property for SVR algorithm. The basis of the theory has been developed based on a regression algorithm as well as the inner product of two vectors in Hilbert space (i.e. a space in which inner product of two vectors has a real value). To control the risk minimization simultaneous control of the complexity and the error of the model are taken into consideration. This is the basic idea used to improve the generalization ability of the SVR (Martinez-Ramon and Cristodoulou, 2006). However, to get a better generalization in non-linear cases, the data points are mapped into a space called feature space (i.e., Hilbert or inner product space) through utilizing a function known as kernel function (Steinwart, 2008). Selecting a suitable kernel makes it possible to separate the data in the feature space while the original input space is still non-linear. Thus while data for n -parity are not separated by a hyper plane in input space, it can be separated in the feature space by a proper kernel (Scholkopf et al., 1998; Walczak and Massart, 1996). According to the definition of kernel, the non-linear regression estimation problem of SVR can be proposed and utilized for solving any regression analysis (Sanchez, 2003).

5.2. Back-Propagation Neural Network

The goal of Artificial Neural Network (ANN) research is to develop a mathematical model of biological events in order to imitate the capability of biological neural structures in purpose of designing an intelligent information processing system. Back-propagation neural network (BPNN) is an active research topic in the recent years because of its efficiency in modeling non-linear dynamic systems (Narendra and Parthasarathy, 1990; Kolen, 2001). Numerous applications can be found in various papers indicating the ability of this typical neural network (Haykin, 1999; Plett, 2003). BPNN is usually recognized for its prediction capabilities and ability to generalize well on a wide variety of problems. For example, Liang and Gupta studied the stability of dynamic back propagation training algorithm by the Lyapunov method (Liang and Gupta, 1999). This network is a supervised type of network which means that it should be trained with both input and target output data. During the training, the network tries to match the outputs with the desired target values. Learning starts with the assignment of random weights. The output is then calculated and the error is estimated. This error is used to update the weights until the

stopping criterion is reached. It should be noted that the stopping criterion is usually the average error of epoch.

5.3. Genetic algorithm

Genetic algorithm (GA) is an appropriate method principally based on natural selection of genes. It was firstly introduced by John Holland in the early 1975s for simulation of natural evolution processes observed in the human body. Generally, GA works on a set of possible solutions of a specific problem when they are encoded into chromosome. Regarding their performance in solving the problem, some of the solutions are chosen and subsequently used to create a new set of possible solutions. This process is repeated several times until the criterion defined is met. In biological terms, possible or potential solutions are christened chromosomes which are binary strings. Chromosomes can form population and problems that need to be solved are represented by fitness functions. Selection of individuals is carried out in a process called selection. Genetic operators including crossover and mutation are particular operators used to create a new population. Crossover, in this regard, is an operator working to vary information among individuals and mutation works to ensure desirable diversity (Reformat, 1997). Fig. 10 shows a general flowchart showing combined use of GA and artificial intelligence techniques. According to the typical procedure of search performed by GA, search for optimal input well log combination includes the following steps:

- **Coding process:** The number of genes in chromosome would be equal to the number of extracted features. In other words, genes are coded by binary number and a locus corresponds to an input parameter for prediction. If the value of a gene is equal to 1, its corresponding feature is considered in the combination while the value equal to 0 indicates that corresponding feature is not included in combination.
- **Initial population generation:** Conventionally, initial population is generated by random sampling from the input parameter combinations existed in the database. It should be noted that, the population size would have a profound effect on the calculation efficiency as well as prediction precision.

- **Fitness function evaluation:** Fitness function is a measure to evaluate estimation performance of the individual chromosomes (well logs) used in combination. The fitness function can be calculated and evaluated by artificial intelligence algorithms.

- **Selecting the best structure for GA:** Genetic operators in a GA consist of selection, crossover and mutation. Selection helps GA to reproduce high-grade individuals and eliminate bad individuals included in population. In crossover, new individuals are generated by exchanging part genes of old individuals resulting in a high improvement in search ability. Mutation reverses the binary code of genes to maintain diversity of population. Frequency of crossover and mutation of individuals mainly depend on crossover and mutation probabilities. According to repeated genetic operation, the best input parameter combinations corresponding to minimum fitness error are selected as an optimal combination for prediction purpose.

Requirements of applying GA in optimizing the Artificial Neural Network (ANN) parameters have been addressed by many research works (Hegazy et al., 1994). In fact, it was shown that GA is a useful method when selecting the best inputs and structure for ANN is hard to find. Van-Rooij et al. (1996) and Vonk et al. (1997) proposed a robust computation approach based on utilizing the GA in the field of ANN for generation of both structure and weights of ANN. Miller et al. (1989) supported this proposal and optimized the connection weights and the architecture of ANN using GA. In this paper GA is used in conjunction of SVR and BPNN to select both optimum structure and input parameters for prediction of shear wave velocity.

5.4. Data preparation and normalization

Before starting the training process, input and output data were scaled to be between the upper and lower bounds of transfer functions (usually between zero and one or negative one and one). Normalization of data helps artificial networks to better understand the relationship between input and output data as well as increasing the accuracy of prediction so high efficiency will be achieved during testing step. The normalization process for the raw inputs has great effect on preparing

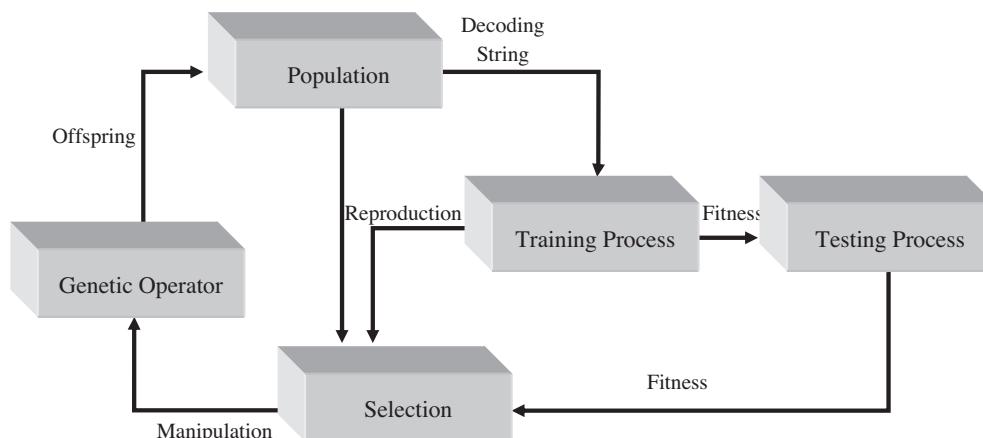


Fig. 10 A general flowchart showing combined use of GA and artificial intelligence techniques (Saemi et al., 2007).

the data to be suitable for the training. Without this normalization, training the networks would have been very slow. It can be used to scale the data in the same range of values for each input feature in order to minimize bias within the networks from one feature to another. Data normalization can also speed up training time by starting the training process for each feature within the same scale. It is especially useful for modeling application where the inputs are generally on widely different scales (Jayalakshmi and Santhakumaran, 2011). There are many different types of normalization usually used to scale data including Z-Score Normalization, Min–Max normalization, Sigmoid normalization, Statistical column normalization, etc. For the purpose of this study, to transform and normalize the data, among various normalization techniques, Min–Max normalization method (Eq. (4)) was considered as it is very simple but a very sophisticated method:

$$p_n = 2 \frac{p - p_{\min}}{p_{\max} - p_{\min}} - 1 \quad (4)$$

In the above equation, p_n is the normalized parameter, p is the actual parameter and p_{\min} and p_{\max} are the minimum and maximum of the actual parameters, respectively. (Jayalakshmi and Santhakumaran, 2011).

5.5. Model development

The first step in the construction of a SVR is to find their corresponding optimum kernel function (i.e. K parameter). According to recommendation given in many literatures, we chose Radial Basis Function kernel (also called Gaussian kernel) due to its theoretical and computational efficiency (Keerthi and Lin, 2003; Lin and Lin, 2003; Schölkopf and Smola, 2002). This kernel has the following mathematical formula:

$$K(x_i, x_j) = e^{-\|x_i - x_j\|^2/2\sigma^2} \quad (5)$$

We also need to find appropriate values for additional parameters of each network. For the SVR, parameters like σ (which controls the amplitude and error of Gaussian kernel), C (regularization parameter controlling the trade-off between maximizing the margin and minimizing the training error) and ε (determines the margin and controls the error) need to be determined before the training phase. Selection of parameter C is vital since choosing a small value for C can cause inappropriate training convergence whereas a large value for C will result in over-fitting of the algorithm through training process. Parameter ε is also critically important as it prevents the entire training set meeting boundary conditions. On the other hand, BPNN algorithm has parameters like momentum and learning rates that should be determined prior to training the network.

In this paper, two codes were developed in MATLAB multipurpose software for finding the best structure for the networks. In both of these codes, GA was used in conjunction with networks to optimize the values allocated to model parameters as well as selecting the best inputs for training step. Developed codes were able to automatically select the chromosome length used for an optimal search so it became possible to tune the relative parameters of each network using individual chromosomes generated in population generation step. In GA algorithm, number of gens is selected according to the number of training parameters of each network. Thus, SVR

had three gens consisting of σ , ε and C whereas BPNN had two genes including learning and momentum rates.

According to computational experiences and the literature, a uniform cross-over and mutation operators were used for the GA and probability of the cross-over and mutation operators were selected to be 0.5 and 0.01, respectively. Genetic algorithm was started with 100 randomly generated chromosomes containing gene structures of each network. There is no unified role to determine the population size of GA as it has profound effect on the training time because the fitness value of every chromosome must be evaluated in every generation. However, population sizes of 50–100 are commonly used for GA so the initial population value was set to be 50 chromosomes in the present study. Tests were performed to represent combination of different levels for crossover rate, mutation rate, and population size. The obtained values were based on both computational experiences and those found in the literature. Accordingly, a uniform cross-over and uniform mutation operators were used and their probabilities were adjusted at 0.5 and 0.01, respectively. Also the genetic algorithm was started with 50 randomly generated chromosomes, with gene structures as described above. Chromosome population size and number of generations usually influence the training time as the fitness value of each chromosome must be evaluated in every generation. There are no general rules for determining the population size. However, population sizes of 50–100 are commonly used for the GA (Saemi et al., 2007). Once the population size is chosen, the initial population is randomly generated. In the present study, the initial population value was set to be 50 chromosomes. GA starts its evolution in initially random population of solutions via picking those individuals (solutions) which will live on and/or mate into the next generation. In this process, the GA assesses the finesse using procedures relevant to the problem. The fitter individuals reproduce and the cycle starts again with the resulting population of the last generation. Generation of new populations is repeated until a satisfactory solution is reached, or specific termination criteria are met (Bandyopadhyay and Pal, 2007). Genetic operators modify individuals to produce a new individual for test-

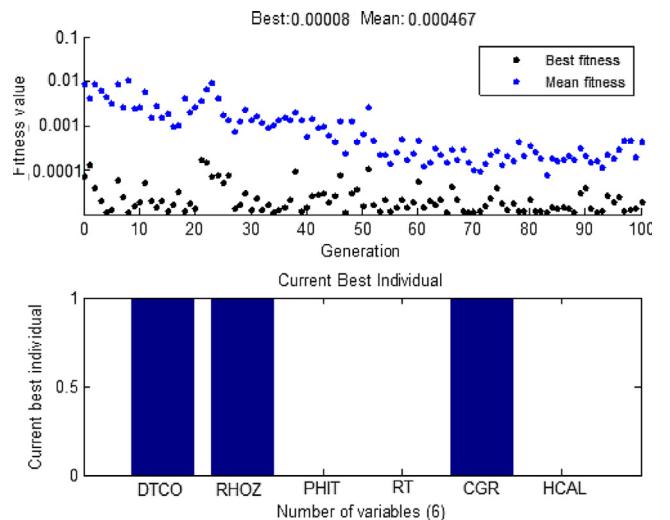


Fig. 11 Selection of the best relevant input logs using the GA-SVR algorithm.

ing and evaluation. In this, cross-over and mutation are by far the most important genetic operators. The cross-over operator gives two chromosomes for producing two new chromosomes, and accelerates the process of reaching the optimal solution (Bandyopadhyay and Pal, 2007).

In this study, a chromosome is represented by a binary string in feature selection. Hence, crossover can be performed by arbitrarily choosing a point called cross-over point, at which two chromosomes exchange their parts to create two new chromosomes. The mutation operator increases the variability of the population and provides a solution to escape getting into the local optimal area. During the mutation process, each bit of the chromosomes can take a value of 0 or 1 based on predetermined mutation rate. After the cross-over and mutation operations are completed, a new population is generated and evaluated using the fitness function. Selection is a process in which individual chromosomes are copied regarding their fitness value. In this hybrid system, selection is performed using the roulette wheel method. Hence, the probability of

selecting a chromosome for inclusion in the mating pool is proportional to its fitness value. As a result, only a desired, predefined number of the best chromosomes survive to produce next generation.

6. Analysis and results

In this study, at the end of running the GA-SVR and the GA-BPNN, the optimum values of σ and ε were selected to be 0.55, and 0.19, respectively. Wang et al. (2003) indicated that prediction error of SVR and RVR was scarcely influenced by parameter C . Hence to make the learning process stable, a large value should be considered for C (e.g., $C = 100$). In the case of BPNN, the optimum networks include one input layer consisting of 6 neurons (one for each input log), one hidden layer of sigmoidal function comprising 12 neurons and an output layer containing only one neuron (Shear wave velocity). Having all of these parameters selected, the most relevant input variables for predicting the shear wave velocity were indicated by GA. The results obtained from the GA-SVR and the GA-BPNN were the same and showed that three logs including DTCO (Best Individual No. 1), RHOZ (Best Individual No. 2) and CGR (Best Individual No. 2) are the most suitable input parameters needed to be used to reach the best fitness. Fig. 11 shows the selected input parameters (i.e. best individuals) during the training of the GA-SVR algorithm.

Table 1 Best and mean fitness and selected input parameters in two networks used in this study.

Method	Best fitness	Mean fitness	Best input parameters selected
GA-SVR	0.00008	0.000467	DTCO, RHOZ, CGR
GA-BPNN	0.00018	0.001034	DTCO, RHOZ, CGR

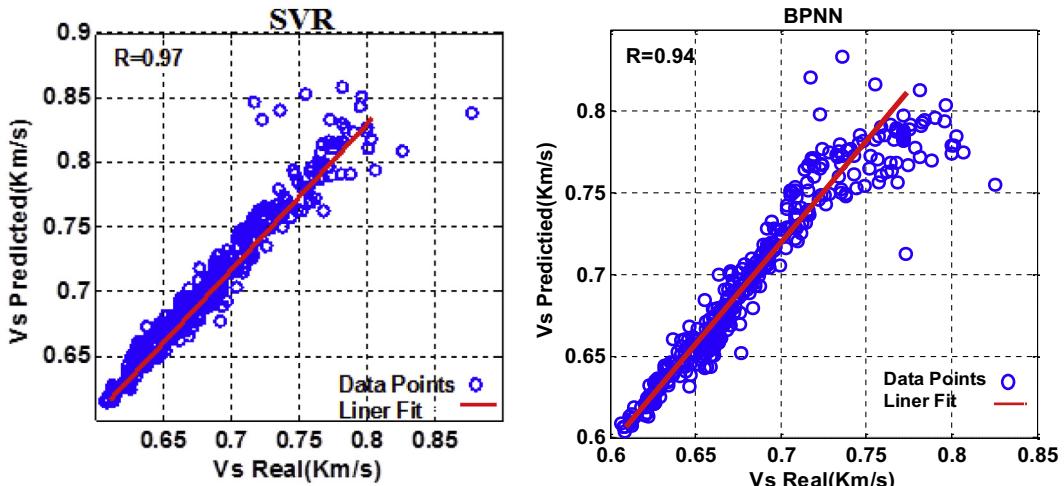


Fig. 12 Comparison of real versus predicted shear wave velocity using the SVR (left) and the BPNN (right).

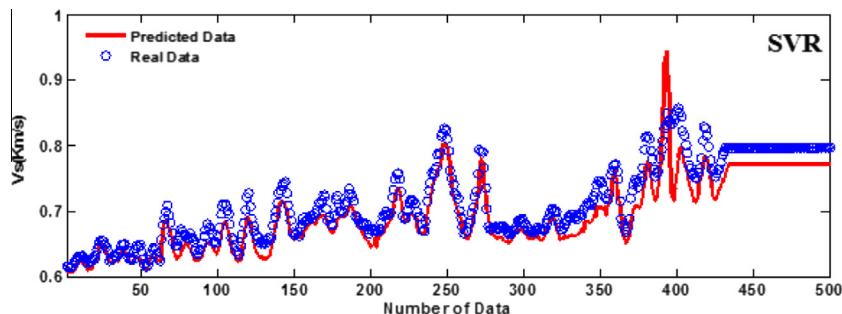


Fig. 13 Demonstrating the errors of shear wave velocity estimation using SVR.

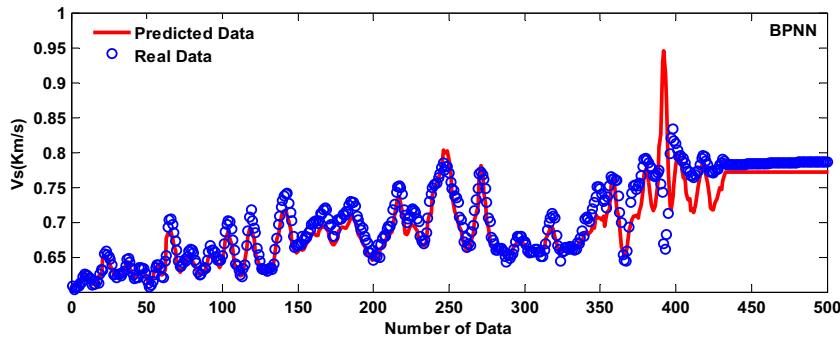


Fig. 14 Demonstrating the errors of shear wave velocity estimation using BPNN.

Table 2 Statistical indicator (R^2 and RMSE) values corresponding to correlations and AI based algorithms applied to estimate shear wave velocity log in this study.

Method	RMSE	R^2
Castagna correlation	41.25	0.96
Brocher correlation	65.12	0.93
Carroll correlation	51.24	0.94
SVR algorithm	26.68	0.97
BPNN algorithm	50.51	0.94

Table 1 reports the best and mean fitness values corresponding to the two networks used for this study together with their selected input. From this Table, it is seen that both networks are similar but their best and mean fitness values are different.

The predicted values for the shear wave velocities using the SVR and BPNN algorithms are shown against the real values in **Fig. 12**. The results show a relatively high correlation coefficient of 0.97 for the SVR and 0.94 for the BPNN. Generally speaking, SVR gives more accuracy and precision prediction compared to those of the BPNN. **Figs. 13 and 14** compare the accuracy of the networks. From the above discussion, it can be indicated that SVR is the best approach for prediction of shear wave velocity. Generally, it appears after SVR, Castagna correlation is the best approach for prediction of shear wave velocity. **Table 2** gives the correlation coefficients (R) and the root mean square error (RMSE) values corresponding to all five predictive methods used for prediction of shear wave velocity in this study.

7. Conclusions

In this paper, shear wave velocity was estimated from the petrophysical logs in a well drilled in carbonate formation by using correlations and artificial intelligence methods. Castagna, Brocher and Carroll empirical correlations were the correlations used to estimate shear wave velocity whereas Support Vector Regression (SVR) and Back-Propagation Neural Network (BPNN) were the two artificial intelligence methods applied for such purpose.

The results indicated that Castagna correlation is the best approach for prediction of shear wave as it presents a higher correlation coefficient and carries less RMSE. Between the SVR and BPNN methods, it is seen that the first algorithm

is a better predictor in the case of the data studied here. From the running time perspective, the SVR showed to be a faster method compared to the BPNN. Altogether, the results of this study indicated that among the five methods used the SVR method is better predictor for estimation of the shear wave velocity than correlations. However, the presented results for all methods demonstrated that none of them are capable of making a reliable estimation of the shear wave velocity. This indicates the necessity of acquiring real shear velocity data when possible. Running the shear velocity log during the wire-line logging does not infer that much extra cost but would provide valuable data for future well design and better understanding of the reservoir performance. The results indicated that the estimated shear velocities through different methods are valid to a limited extent and acquiring shear sonic log as part of wire-line logging program is highly recommended.

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