Journal of Petroleum Science and Engineering 125 (2015) 95–99

Contents lists available at ScienceDirect

Journal of Petroleum Science and Engineering

journal homepage: www.elsevier.com/locate/petrol

Support vector regression based determination of shear wave velocity

Parisa Bagheripour [a], Amin Gholami [b], Mojtaba Asoodeh [a,*], Mohsen Vaezzadeh-Asadi [a]

[a] Department of Petroleum Engineering, Kharg Branch, Islamic Azad University, Kharg, Iran
[b] Abadan Faculty of Petroleum Engineering, Petroleum University of Technology, Abadan, Iran

ARTICLE INFO

Article history:
Received 19 April 2013
Accepted 24 November 2014
Available online 4 December 2014

Keywords:
Shear wave velocity
Support vector regression (SVR)
Structural risk minimization (SRM)
Empirical risk minimization (ERM)
Conventional well logs
Rock mechanics

ABSTRACT

Shear wave velocity in the company of compressional wave velocity add up to an invaluable source of information for geomechanical and geophysical studies. Although compressional wave velocity measurements exist in almost all wells, shear wave velocity is not recorded for most of elderly wells due to lack of technologic tools in those days and incapability of recent tools in cased holes. Furthermore, measurement of shear wave velocity is to some extent costly. This study proposes a novel methodology to remove aforementioned problems by use of support vector regression tool originally invented by Vapnik (1995, The Nature of Statistical Learning Theory. Springer, New York, NY). Support vector regression (SVR) is a supervised learning algorithm plant based on statistical learning (SLT) theory. It is used in this study to formulate conventional well log data into shear wave velocity in a quick, cheap, and accurate manner. SVR is preferred for model construction because it utilizes structural risk minimization (SRM) principle which is superior to empirical risk minimization (ERM) theory, used in traditional learning algorithms such as neural networks. A group of 2879 data points was used for model construction and 1176 data points were employed for assessment of SVR model. A comparison between measured and SVR predicted data showed SVR was capable of accurately extract shear wave velocity, hidden in conventional well log data. Finally, a comparison among SVR, neural network, and four well-known empirical correlations demonstrated SVR model outperformed other methods. This strategy was successfully applied in one of carbonate reservoir rocks of Iran Gas-Fields.

1. Introduction

Sonic measurements in hydrocarbon wells provide precious information for rock mechanical and geophysical studies. Compressional wave velocity is easily recorded and is available for all wells. However, measurement of shear wave velocity is more complicated and these measurements are not available in old wells owing to lack of technologic tools in those days. Run of recent tools in old wells is not practical for most of them due to prevailing casing completion. Therefore, a quantitative formulation between conventional well logs (available in all wells) and shear wave velocity eliminates the mentioned problems and makes it possible to perform geophysical and geomechanical studies. Combination of shear and compressional wave velocities measurements adds up to invaluable source of information for lithology identification (Pickett, 1963), rock mechanical properties calculation (Eaton, 1972; Kumar, 1976; Chang et al., 2006; Ameen et al., 2009), and pore type identification (Eberli et al., 2003). Due to significance of subject several researchers have tried to establish empirical correlations estimating shear wave velocity (Pickett, 1963; Tosaya and Nur, 1982; Castagna et al., 1985; Han, 1986; Eberhart-Phillips, 1989; Castagna et al., 1993; Anselmetti and Eberli, 1993; Eskandari et al., 2004; Brocher, 2005).

Recent studies have proved the superiority of intelligent systems to empirical and statistical approaches in geosciences and petroleum related problems. A growing tendency is observed among researchers to utilize intelligent systems in solving their problems of various fields (Mohaghegh et al., 2000; Saggaf and Nebrija 2003; Artun et al., 2005; Kadkhodaei-Illkchi et al., 2008; Asoodeh and Bagheripour, 2012a). Several researchers suggested estimation of shear wave velocity from conventional well logs using traditional learning algorithm such as neural networks which use empirical risk minimization (ERM) principle (Rezaee et al., 2006; Rajabi et al., 2009; Asoodeh and Bagheripour, 2012b). In this study, shear wave velocity is estimated from conventional well log data using support vector regression (SVR). SVR utilizes structural risk minimization (SRM) in conjunction with ERM. Therefore, it produces more reliable results compared with neural networks that solely use ERM principle. SVR model was compared with neural network and four well-known empirical correlations. Results confirm superiority of SVR to other methods. This methodology was successfully implemented to Asmari carbonate reservoir rocks, the major reservoir of Iranian Oil Fields. Top of the reservoir formation is varying in range of 2983 m to

* Corresponding author. Tel.: +98 93 9516 1149.
E-mail address: Asoodeh.mojtaba@gmail.com (M. Asoodeh).

http://dx.doi.org/10.1016/j.petrol.2014.11.025
0920-4105/

2996 m in field of our study. Therefore, there is a compaction knowing approximate 1 psi/ft overburden pressure.

2. Method: Support vector regression

Support vector regression was introduced as a machine learning technique by Vapnik (1995). SVR has been deemed as an arresting tool featuring promising applications owing to its superior capability in successfully solving large variety of nonlinear regression problems. SVR method utilizes structural risk minimization principle in addition to supplanted empirical risk minimization principle that traditionally has been used by neural networks with a view to developing an accurate model (Al-Anazi and Gates, 2010a; El-Sebakhy, 2009; Jiang and Zhao 2013; Liao et al., 2011;Ustun et al., 2005; Wu and Law 2010). An elaboration on SVR underlying structure is brought as follows. In SVR regression, the ultimate goal is to find linear relation between n-dimensional input vectors $x \in R^n$ and output variables $y \in R$ as follow:

$$f(x) = w^T x + b \tag{1}$$

Where w and b are the slope and offset of the regression line, respectively. For determining the values of b and w, it is necessary to minimize following equation:

$$R = \frac{1}{2}||w||^2 + \frac{C}{l}\sum_{i=1}^{l} |y_i - f(x_i)|_{\varepsilon} \tag{2}$$

Loss function, used in SVR is ε-insensitive which has been introduced by Vapnik (1995) as below:

$$|y_i - f(x_i)|_{\varepsilon} = \begin{cases} 0 & \text{if} \quad |y_i - f(x_i)| \le \varepsilon \\ |y_i - f(x_i)| - \varepsilon & \text{Otherwise} \end{cases} \tag{3}$$

This problem can be reformulated in a dual space by:

$$\text{Maximize} \quad L_p(\alpha_i, \alpha_i^*) = -\frac{1}{2}\sum_{i,j=1}^{l} (\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*) x_i^T x_j - \varepsilon \sum_{i=1}^{l} (\alpha_i + \alpha_i^*) + \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) y_i \tag{4}$$

$$\text{Subject to} \begin{cases} \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) = 0 \\ 0 \le \alpha_i \le C, \quad i = 1, \ldots, l \\ 0 \le \alpha_i^* \le C, \quad i = 1, \ldots, l \end{cases} \tag{5}$$

where $\alpha_i, \alpha_i^* \ge 0$ are positive Lagrange multipliers. C is regulated positive parameter which determines trade-off between approximation error and the weight vector norm$||w||$. After calculation of Lagrange multipliers α_i and α_i^*, training data points, those meeting the conditions $\alpha_i - \alpha_i^* \ne 0$, will be employed to construct the decision function. Hence, the best linear hyper surface regression is given by:

$$f(x) = w_o^T x + b = \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) x_i^T x + b \tag{6}$$

Which desired weight vector of the regression hyper plane is given by:

$$w_o = \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) x_i \tag{7}$$

In nonlinear regression, Kernel function is employed for mapping input data onto higher dimensional feature space in order to generate a linear regression hyper plane. Polynomial, radial basis function (RBF), and sigmoid are the common kernel functions in SVR. In the case of the nonlinear regression, the learning problem is again formulated in the same way as in a linear case, i.e., the nonlinear hyperplane regression function becomes:

$$f(x) = \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) K(x_i, x) + b \tag{8}$$

In above equation, $K(x_i, x)$ is kernel function which is defined as follow:

$$k(x_i, x_j) = \Phi^T(x_i)\Phi(x_j) \quad i, j = 1, \ldots, l \tag{9}$$

where $\Phi(x_i)$ and $\Phi(x_j)$ are projection of the x_i and x_j in feature space, respectively. For simplicity, a brief description of SVR was explained. More detailed studies about SVR are provided in several papers and reviews which readers can refer to (Al-Anazi and Gates, 2010b; Kecman 2005, 2006;Mousavi et al., 2013; Vogt and Kecman, 2005).

3. Input selection by sensitivity analysis

Using a back-propagation neural network, Dutta and Gupta (2010) suggested a stable method based on partial derivative of output with respect to ith input to find relative contribution of each input in estimating output. Partial derivative of output with respect to ith input is evaluated using following equation:

$$\frac{\partial V_s}{\partial xi} = \sum_j Woj\left(1 - hj^2\right) Wji \tag{10}$$

where $\partial V_s/\partial xi$ is partial derivative of shear wave velocity with respect to ith input, Woj is weight between output neuron and jth hidden neuron and hj is the response of jth neuron in the hidden layer. Relative contribution of back-propagation neural network inputs is calculated by sum of the squares of the partial derivatives (S) as follow:

$$S_i = \sum_{j=1}^{N} \left[\left(\frac{\partial V_s}{\partial x_i} \right) \right]_j \tag{11}$$

$$RCi = \frac{S_i}{\sum_i S_i} \times 100 \tag{12}$$

where RCi is relative contribution of ith input.

To achieve influence of each input in estimation of shear wave velocity, an improved strategy was followed and subsequently optimal number of inputs was evaluated. First, a feed forward back-propagation neural network was constructed using all available well logs and a sensitivity analysis was performed to compute RC value for each input as is shown in Table 1. In spite of correlation coefficient which is a qualitative criterion for illustrating dependency between inputs and output, sensitivity results are quantitative norms and are more reliable. In next step, RC values were used for ranking inputs. In SVR model, optimal number of introduced inputs is a crucial design factor. Therefore, conventional well logs were introduced into SVR model one by one according to their RC values and performance of SVR model was evaluated for each set of

Table 1
Relative contribution of each input in shear wave velocity estimation, based on sensitivity analysis and correlation coefficient concept.

Conventional well logs	Relative contribution (%)	Correlation coefficient
Compressional wave slowness (DT)	41.03	0.76
Bulk density (RHOB)	23.73	0.51
Neutron porosity (NPHI)	18	0.31
True resistivity (RT)	12.41	0.19
Photoelectric factor (PEF)	2.53	0.23
Shallow resistivity (RS)	1.84	0.04
Gamma ray (GR)	0.46	0.11