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Log Data-Driven Prediction of Rock Strength Using Least-Square Support Vector Machine Approach: Case Study of a Gas Well Reservoir

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Abstract

An accurate estimation of uniaxial compressive rock strength (UCS) is crucial for wellbore failure analysis to protect a gas well blowout during drilling operation, sand protection, and safe reservoir management. The main objectives in this paper are a) to assess the suitability of machine learning-based connectionist model using geophysical log data and b) effects of predictor variable on rock strength estimation. The machine learning technique of least square support vector machine (LSSVM) is utilized to construct the data-driven connectionist model while predicting of UCS. The predictor variables are obtained gas reservoir log data of subsurface sandstone formation in the Bengal basin which utilized to obtain the output. For the evaluation of predictive model, statistical parameters such as correlation of determination (CC), and average absolute percentage relative error are applied in the study. According to the simulation study, it is found that the LSSVM-based model is performed excellent with the least error and high CC to predict UCS. The predictor variable of gamma-ray has major effects on UCS estimation rather than other input variables of formation bulk density, modules of elasticity and acoustic waves. These systematic research steps can be applied for connectionist model development and feature ranking to the petroleum industry such as predicting of reservoir rock and fluid properties, production optimization, and sanding potentiality of gas wells.

Keywords: Machine learning; Variable effects; Rock strength, Gas reservoir, Wellbore stability.

1. INTRODUCTION

An accurate estimation of uniaxial compressive rock strength (UCS) is crucial for wellbore failure analysis to protect a gas well blowout during drilling operation, sand protection, and safe reservoir management. The rock strength parameter of UCS can be measured through experimental measurements using standard core specimen. In general, an accurate rock (core sample) specimen preparation is very costly and time-consuming with keeping stress unloading and loading into the sample [1,2]. When the direct testing is not possible with capturing the subsurface gas reservoir environment to obtain sample collections for precise core specimens, the geophysical log data are the alternative option to obtain continuous profile of dynamic rock strength parameter of UCS. Accurate rock modeling and reliable rock strength parameters are important for evaluating of sanding potentiality and wellbore failure analysis during safe drilling operations. Several studies by different scholars have been done with a focus on the corresponding their research methods, limitations and scopes while obtaining rock geomechanically parameters and rock strength of which can be found available literature [3-6]. Based on the literature survey, it is revealed that a systematic comprehensive investigation is required to investigate the applicability of connectionist model with machine learning approach while obtaining rock strength, and effects of predictor log variables on UCS estimation for clastic sedimentary rock of gas reservoir in the Bengal basin.

The major objectives in this paper are a) to assess the suitability of machine learning-based connectionist model and b) effects of predictor variable to obtain rock strength of UCS using geophysical log data of a gas reservoir.

2. MATERIALS AND METHODS

The available field well logs data of formation gamma-ray (GR), bulk density (RB), compressional wave velocity (Vp), shear wave velocity (Vs) and modulus of elasticity (E) are adopted as predictor variables, while the target variable is the rock strength parameter of dynamic UCS, respectively. The process of geophysical log data quality is led to ensure the reliability of each log dataset variables. Furthermore, the machine learning technique is applied to develop the connectionist models using Mathlab and Python programming environment. In the project, hybrid connectionist tool of least square support vector machine (LSSVM) with coupled simulated annealing (CSA) is utilized to develop predictive model because of it is capable to handle high-dimensional complex relationships among real field core and log data variables [4,7,8]. In the study, the coupled-simulated annealing (CSA) optimization process applied which is proven to be more effective than multi-start gradient descent technique [9]. A typical methodological flowchart is shown in Figure 1, which will be adopted to assess the rock strength parameter using hybrid connectionist models using dynamic log data.

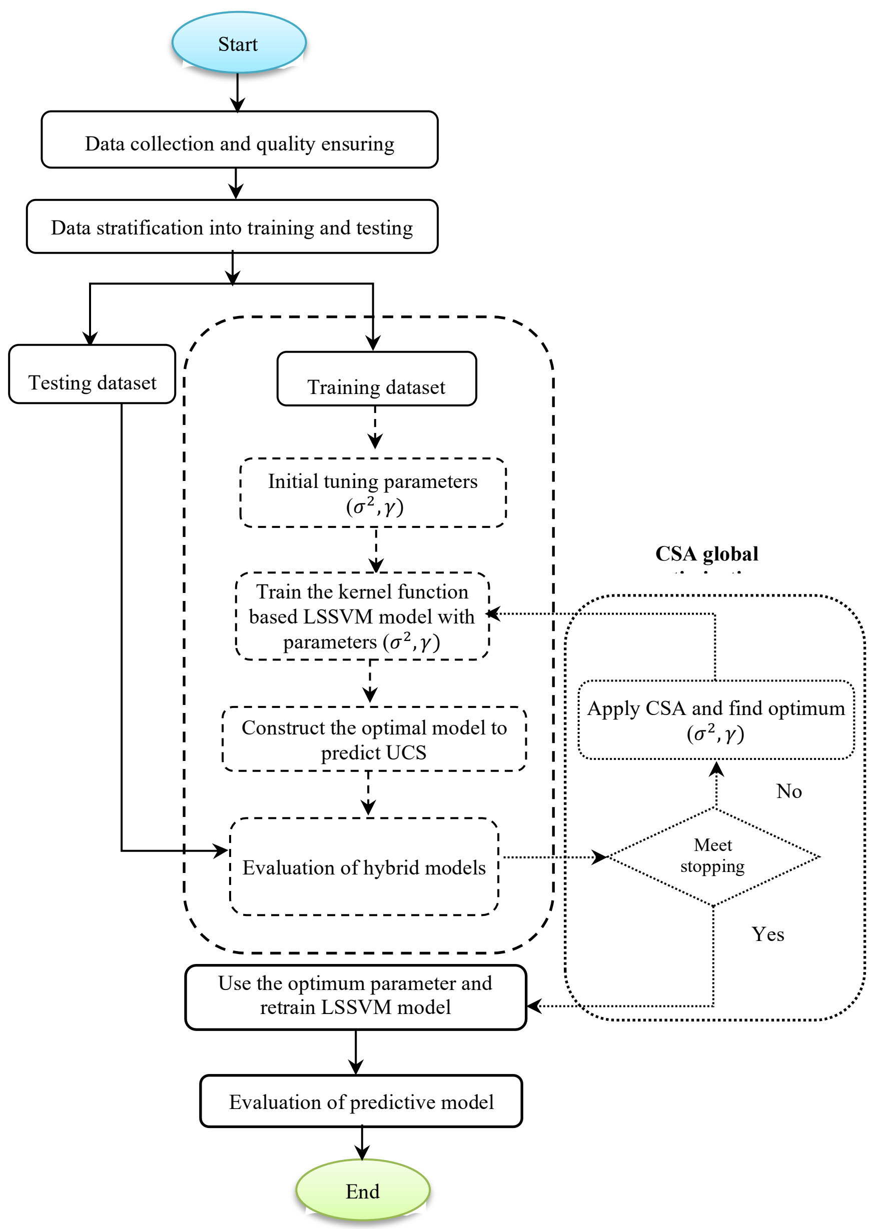

Figure 1: An illustration of hybrid connectionist model with LSSVM-CSA with major steps (Modified from [3]).

In the Gaussian radial basis kernel function (RBF)-based LSSVM model, the kernel and hyper-parameters of γ and σ^2 are tuned through a global optimization technique of CSA [10]:

$$K(x, x_i) = \exp\left(-\frac{\left(\left\|x_i - x\right\|\right)^2}{2\sigma^2}\right) \tag{1}$$

Additionally, the following mathematical model of LSSVM is applied to obtain output of rock strength parameter when b is the bias term and α is a weight factor, x is the training sample; and x_i refers to the support vector:

$$\mathrm{y}(\mathrm{x_i}) = \sum_{\mathrm{i}}^{\mathrm{n}} \alpha_{\mathrm{i}} \mathrm{K}(\mathrm{x}, \mathrm{x_i}) + \mathrm{b} \tag{2}$$

In the study, the total samples will be categorized into two groups (such as, 65 % for training, and 35% for testing phases) in the LSSVM connectionist model with the CSA optimization approach. Additionally, the statistical performance indicators (SPIs) are used in this study to analyze the predictive model performance. In the study, the model is best for the higher value of CC and minimal error of AAPE using single-input and single-output strategy', approach and vice-versa. The mathematical equations for the SPIs to evaluate the model performance are mentioned below:

$$AAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{(UCS_{t,i} - UCS_{p,i})}{RSP_{t,i}} \tag{3}$$

$$CC = 1 - \frac{\sum_{i=1}^{n}\left(UCS_{t,i} - UCS_{p,i}\right)^2}{\sum_{i=1}^{n}\left(UCS_{t,i} - UCS_{t,mean}\right)^2} \tag{4}$$

Where, n denotes the total number of data points, UCS_t denotes the target value of rock strength parameter UCS), $UCS_{t,\ mean}$ is the mean value of UCS_t, and UCS_p indicates the predicted output variable.

3. RESULTS AND DISCUSSION

3.1 Data Analysis

In this study, the geophysical log data samples are collected from a gas field of sandstone reservoir in the Bengal basin. In total, 183 samples of petrophysical log data adopted as the predicting variables, named gamma-ray (GR), bulk density (RB), sonic acoustic compressional velocity (Vp), shear wave velocity (Vs), modulus of elasticity (E) and the target variable of uniaxial compressive strength (UCS), respectively. The magnitudes of the geophysical log data samples under consideration differ significantly from one sample to the next as a result of formation depth, reservoir rocks' composition, and their diagenesis. The maximum and minimum values of UCS (MPa) over the entire lithology with sandstone formation are 42.60 and 26.57, respectively while the average value of UCS is 31.13. The following Table 1 depicts a summary of the statistical values of the predictor variables and target variable of dynamic rock strength, UCS.

Table 1: Summarized statistical values of studied variables in the study.

Statistical Values	GR (API)	RHOB (g/cm^3)	Vp (Km/sec)	Vs (Km/sec)	E (GPa)	UCS (Mpa)
Maximum	157.82	2.53	3.5506	1.9903	24.17	42.60
Minimum	76.28	2.30	3.1294	1.6498	17.02	26.57
Average	100.19	2.37	3.2893	1.7927	19.61	31.13
Standard deviation	13.84	0.04	0.0862	0.0702	1.47	2.76

The matrix of correlation between petrophysical log variables and uniaxial compressive strength and modulus of elasticity is shown in Figure 3 in order to represent the variable features.

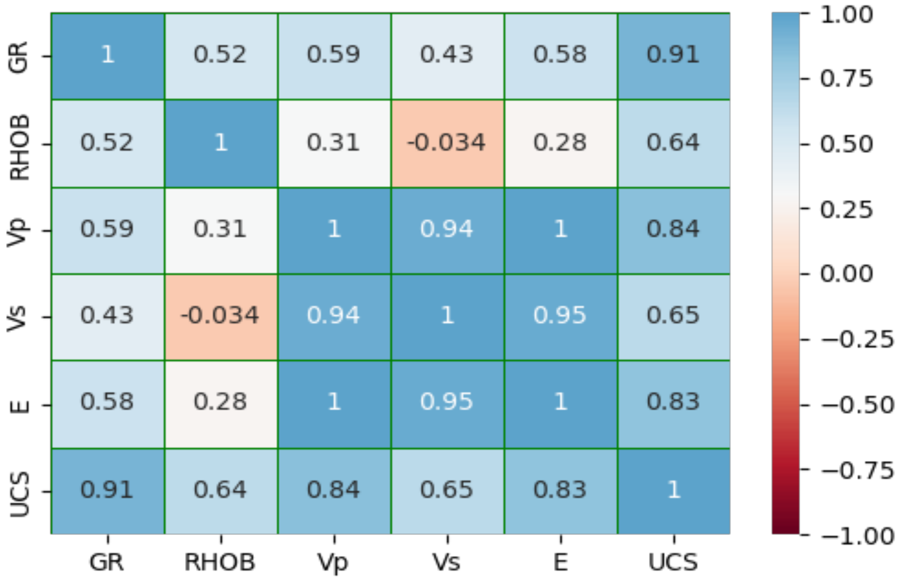

Figure 3: Heatmap of relationship between predictor and target variable of UCS.

3.2 Assessment of LSSVM-CSA based Predictive Model

In the predictive model development of UCS, the 'single variable elimination' strategy is applied to find the relative importance of predictor variable using statistical parameters for each training and testing data phases. In the study, the training dataset contains 65 % data while testing dataset covers 35 % data. To ensure the model's performance with data stratification, trial and error approach is conducted to avoid the overfitting of the training dataset. In the predictive models with an input of single variable, the gamma-ray and compressional wave velocity variables have more impacts with high precision and minimal error which shown in Figures 4 and 5 respectively on the UCS prediction than the other variables of shear wave velocity, modulus of elasticity and formation bulk density using LSSVM-CSA approach.

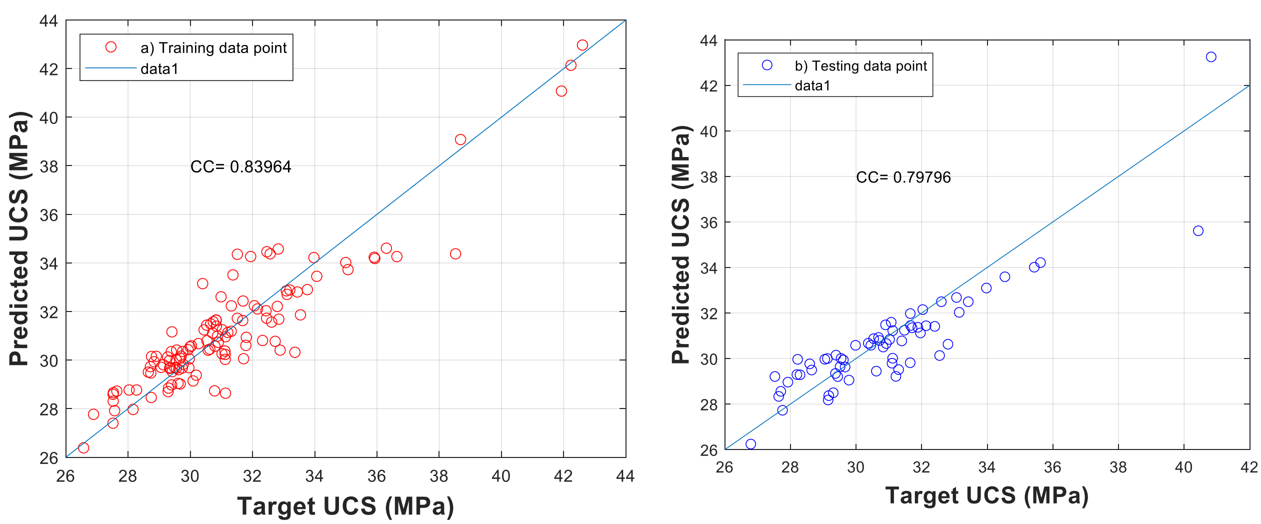

Figure 4: A representation between target and predicted results of UCS with GR for a) training and b) testing data sets.

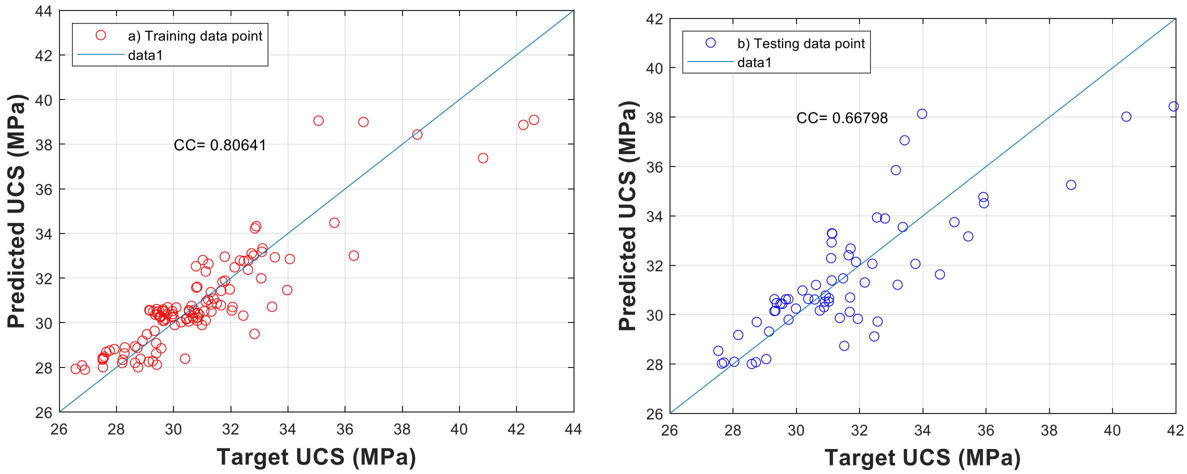

Figure 5: A representation between target and predicted results of UCS with Vp for a) training and b) testing data sets.

According to the simulation studies, the detailed performance of each model scheme such as models 1-5 with single input variable in the predictive model of UCS for LSSVM is shown in Table 2. The graphical representation of relative performance of the predictive models using LSSVM method is shown in Figures 6-7.

Table 2: Relative significance of the predictor variables to obtain UCS with LSSVM-CSA approach.

Model Scheme No.	Input variable	CC (%) Training (Testing)	AAPE (%) Training (Testing)	Hyper parameters: b; γ; σ^2
1	GR	83.96 (79.80)	2.72 (2.69)	-0.44; 1120; 2.07
2	Vp	80.64 (66.80)	2.75 3.10	0.62; 3.72; 1.66
3	E	79.03 (55.19)	2.62 (4.10)	0.63; 4.36; 0.17
4	RB	61.50 (61.96)	4.05 (4.58)	4.27; 480.54; 1.80
5	Vs	48.76 (19.86)	4.40 (4.23)	0.65; 3.23; 10.15

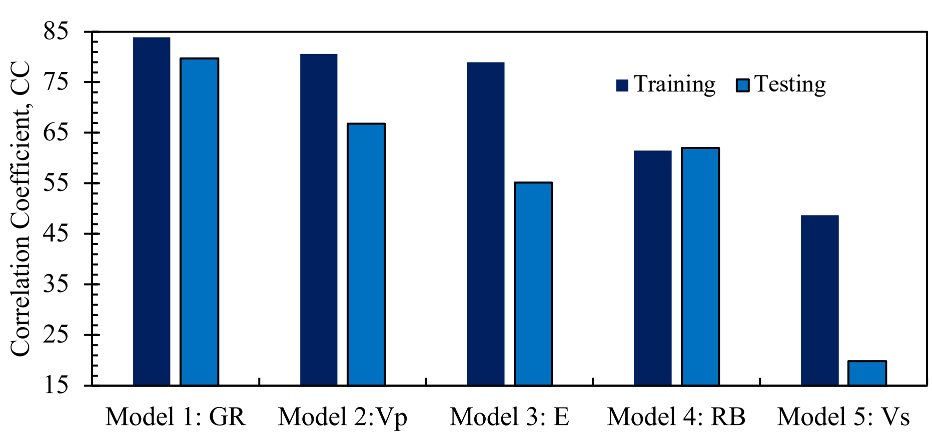

Figure 5: A comparison of CC performance for LSSVM-based model schemes using predictor variable.

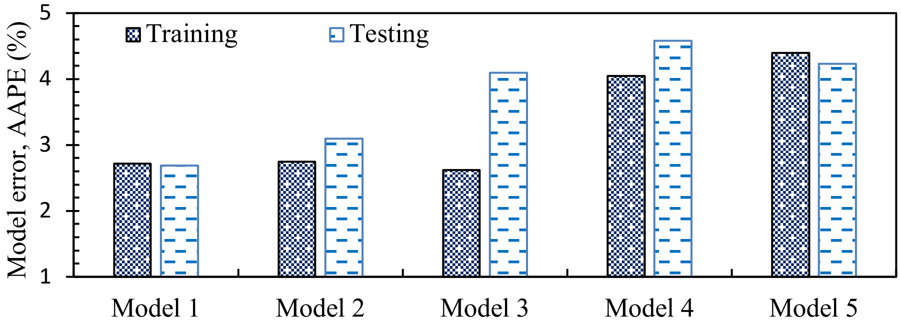

Figure 6: A comparison of AAPE performance for LSSVM-based model schemes using predictor variable.

Moreover, the effects of modulus of elasticity, formation bulk density and shear sonic travel waves have minimal impacts on the UCS prediction because of model schemes 3 through 5 performed with less CC and high error using LSSVM-CSA based predictive model in the study for clastic sedimentary rocks of the Bengal basin.

3.3 Effects of Geophysical Log Data for UCS Estimation

To investigate the effects of geophysical log data with rock strength of UCS, the regression-based polynomial curve fitting also studied and illustrated in Figures 7- 11 using real filed log data of a gas well, Bengal basin.

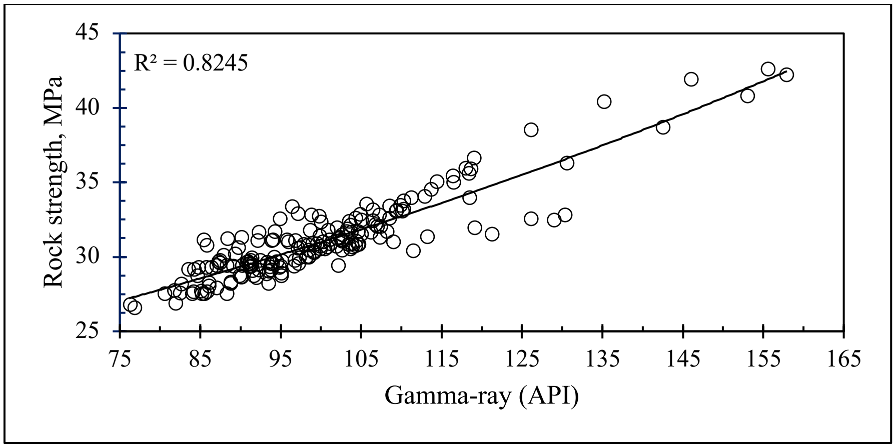

Figure 7: A relationship between gamma-ray and rock strength with CC of 81.44 %.

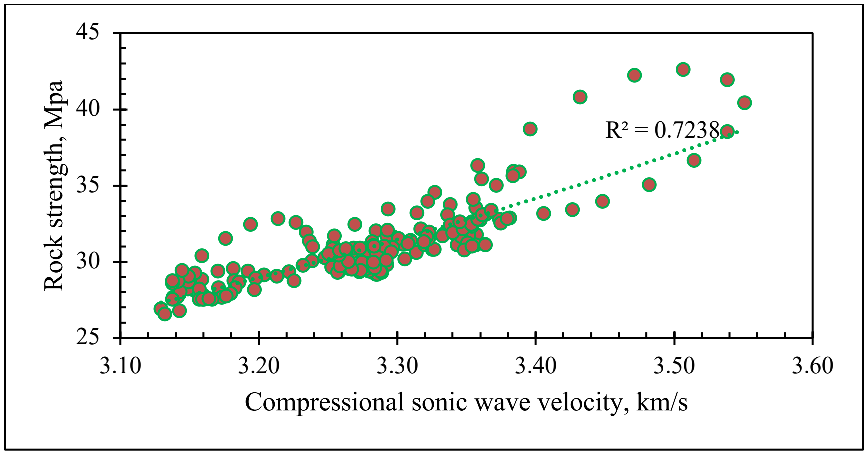

Figure 8: A relationship between compressional sonic velocity and rock strength with CC of 72.71 %.

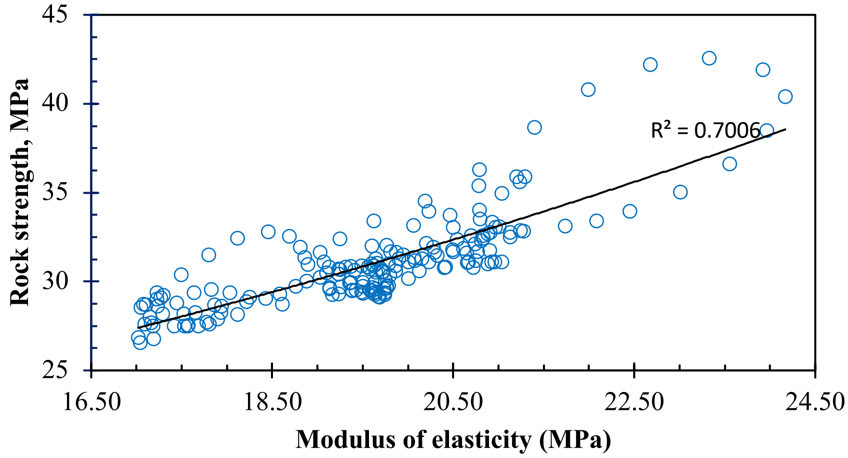

Figure 9: A relationship between modulus of elasticity and rock strength with CC of 70.49 %.

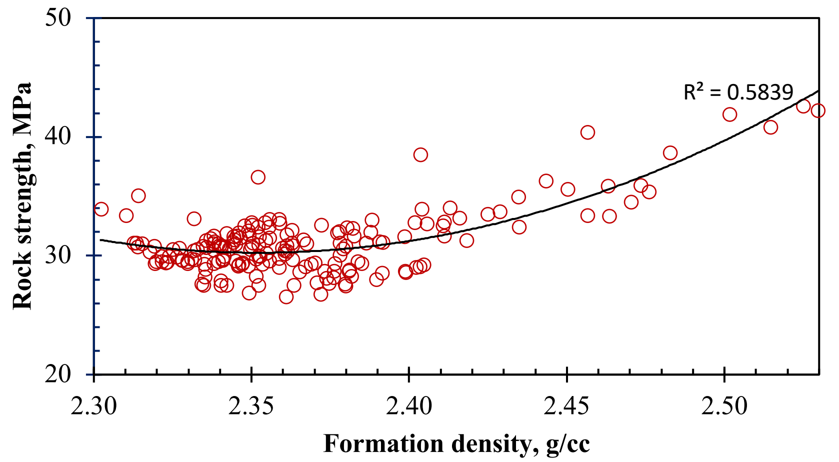

Figure 10: A relationship between formation bulk density and rock strength with CC of 58.39 %.

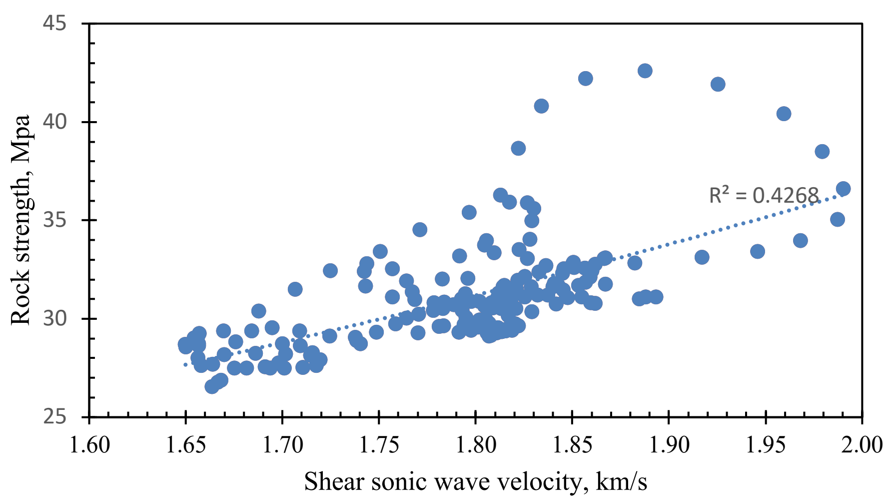

Figure 11: A relationship between shear sonic velocity and rock strength with CC of 45.33 %.

Based on the simulated results with LSSVM-CSA based predictive models and the exponential regression-based correlations, it is found that the gamma-ray radioactive property has major effects on formation UCS estimation while shear sonic velocity minor effects in the studied gas field of the Bengal formation. The geophysical log data of a gas well in the Bengal basin can be ranked, higher to lower order: GR> Vp >E >RB >Vs.

4. CONCLUSIONS

The machine learning techniques of least square support vector machine (LSSVM) is utilized to predict the dynamic rock strength of unconfined compressive strength (UCS) of clastic sedimentary rocks using geophysical log data such as gamma-ray, formation bulk density, modulus of elasticity, compressional and shear wave velocities. The key findings of this work are mentioned as follows:

- The connectionist models based on the LSSVM with CSA optimization strategy is capable of accurately estimating the dynamic rock strength parameter of UCS using geophysical log data.
- The formation gamma-ray property and compressional sonic velocity are two crucial parameters and have major impacts on dynamic rock strength estimation of clastic sedimentary formation.

For the scope of future study for the scholars, the studied similar methodological steps with deep learning and ensemble machine learning tools such as convolution neural network (CNN), long-short term memory (LSTM), and random forest (RF) can be applied for data-driven model developments and feature ranking in the discipline of petroleum and chemical engineering using big datasets.

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