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Accurate prediction of drill bit penetration rate in rock using supervised machine learning techniques base on laboratory test data

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Abstract

Knowing the rate of penetration of a drill bit in rocks is among the most important parameters in their behaviour measurement. However, the direct measurement of ROP in rocks is a high-cost and time-intensive process. Therefore, obtaining the ROP parameter through a method other than direct measurement can be very useful and effective. Predictive machine learning methods are among the strong and precise techniques for the indirect measurement of ROP. To this end, 492 samples were tested under different UCS, μ, WOB, and ω conditions to obtain the corresponding ROP. To achieve an accurate model, three methods of linear regression analysis, lasso regression, and ridge regression were compared in terms of prediction accuracy. These models were compared through performance criteria of the prediction process and error-based charts. The performance criteria were measured using three measures: mean absolute percentage error, D-squared pinball score, and mean Poisson deviance error. For the MAPE index, the Lasso and Ridge models performed the best with values of 0.2557. Concerning the D^2PS index, the linear regression model and Ridge performed better with values of 0.4083 and 0.4025, respectively. Finally, for the MPDE index, the Ridge model provided a more accurate performance with a value of 0.0105. For a better comparison, an objective function was created and calculated by combining these three indicators. The results showed the best rank for the Ridge model with an estimated value of 659.475. Finally, it was concluded that the Ridge model is a reliable and accurate model for predicting the ROP.

Keywords:

rate of penetration; cooling/lubricating fluid; simple linear regression; lasso regression; ridge regression

1. Introduction

Drilling implies penetrating rocks by strongly affecting their assorted types of strength. This process is also the central part of rock structures in mining and civil constructions, whose quantity and quality significantly shapes the efficiency and progress of projects (**Hassan et al., 2020**). In view of the value of drilling, devoting much more attention to the qualitative and quantitative characteristics of this process can substantiate successful projects. Numerous studies have been fulfilled up to now to provide a better understanding of drilling and its associated parameters, revealing that two factors, namely, the rate of penetration (ROP) and the specific energy consumption rate (SECR), control the efficiency of this process (**Sobhi et al., 2022**). Optimal drilling is accordingly illustrated by high ROP and acceptable SECR. In point of fact, the former denotes the physical progress of projects and the latter represents an integral part of the costs incurred in this line (**Etesami, 2020**).

As a key factor in overall project progress, the ROP by itself is a function of countless factors, such as those related to the rock mass and the technical ones connected with drill machines and the drilling process. In concrete terms, it means the ROP is typically influenced by rock resistance characteristics, such as compressive strength, wear resistance, and other geomechanical features. From a different parallel dimension, the drill machine technical parameters, e.g. the type of cutting tools and their array as well as their movement, the forces on them and the working conditions are among the

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other factors affecting the ROP (**Bani Mustafa et al., 2021**).

Predicting the ROP has been thus acknowledged as a major part of drilling operation optimization (**Amadi and Iyalla, 2012**). In this respect, the correct estimation and forecast of this parameter significantly helps increase efficiency and improve the drilling performance quality, in such a way that it seems to be useful in choosing the most suitable type of drill bit and drill machine, as it provides the right information about rocks and the desired structures, thereby reducing the drilling process (**Kolapo, 2021; Kahraman, 1997**). The rock uniaxial compressive strength (UCS) has also been the most widely used parameter for predicting the performance of drill bits in drilling operations (**Yarali and Soyer, 2013**) as well as the uppermost mechanical property of rocks in geological and geotechnical engineering works (**Nazir et al. 2013**). In this line, **Bieniawski (1974)** calculating rock resistance parameters in several studies, stated that determining the rock UCS was much more required in mining than other properties. As well, **Tiryaki (2008)** found that rock drilling projects needed to measure and predict UCS by some statistical methods in order to minimize drilling costs. Therefore, forecasting UCS as the critical parameter in augmenting ROP; in other words, increasing drilling performance, has been of interest in previous research (**Palchik, 1999; Lashkaripour, 2002; Gokceoglu and Zorlu, 2004; Karakus and Tutmez, 2006; Moradian and Behnia, 2009; Yagiz, 2011; Mishra and Basu, 2013; Kahraman, 2014; Kahraman et al., 2017**). Boosting drilling performance in this way can adjust overall mining economics, and contain lowering energy consumption rate, extending drill bit lifetime, diminishing drill machine vibration, reducing drill bit wear rate, increasing the ROP, and generally cut drilling costs. One of the main strategies to achieve such improvements is the use of cooling/lubricating fluids in drilling processes (**Zhao et al., 2011**) that are now commonly applied following their development in drilling technology (**Long, 1996**).

To this point, many researchers have investigated different ways to increase drilling performance, including the use of chemicals added to water as a drilling fluid, in which the ROP has significantly expanded during drilling operations in the presence of this fluid and its contact with the rock surface (**El-Shall et al., 2000; Mills and Westwood, 1978; Engelmann, 1987; Tuzinski et al., 1989; Staroselsky and Kim, 1997**). For example, **Messaoud (2009)** examined the effect of cooling/lubricating fluids on drilling performance, and concluded that the ROP could increase upon the utilization of such fluids, as compared to plain water. In 2010 and 2011, Bhatnagar et al. established that the ROP increased during drilling with fluids containing non-ionic polymer additives, as compared to that with plain water **(Bhatnagar et al., 2010; Bhatnagar et al., 2011)**. Moreover, **Zhao et al. (2011)** showed that the ROP amplified in sandstone undergoing drilling with fluids having mineral additives. **Aalizad (2012)** utilizing neural network (NN) models, predicted the ROP, and developed several models in which UCS was correlated with the ROP, and there was even a high correlation between the ROP and the operating parameters. **Gupta et al. (2013)** reflecting on drilling performance, correspondingly reiterated that simultaneous balancing between the wear rate and the ROP was vital for optimizing the drilling process. **Basarir et al. (2014)** presented that the ROP could be calculated via multivariate regression models, with an acceptable correlation coefficient. Using the techniques of nonlinear multiple regression analysis (RA), **Saeidi et al. (2014)** developed a model to predict the ROP in rotary drilling operations and confirmed its high accuracy. **Kivade et al. (2015)** forecasting the ROP in drilling via multivariate RA then detected significant relationships between the ROP and rock properties and operating parameters. As well, **Li et al. (2015)** investigating the impact of fluids on drilling performance found that the ROP increased in diamond rotary drilling when there were fluids containing surfactants. **Taheri et al. (2016)** also settled a measure to predict the ROP, so that the rock ROP could drop following a rise in it.

In light of this, **Rohit et al. (2016)** shed light on the effect of polymer additives in water on drilling performance, and suggested that the performance value could improve due to a certain concentration of these additives, thereby augmenting the ROP. Comparably, **Kahraman (2016)** explored the predictability of the ROP using multiple RA and artificial NNs (ANNs), and demonstrated that the ANN models were much more reliable than the techniques of regression. Recruiting the ANN models and linear multivariate analysis, **Fathipour et al. (2017)** further disclosed that these measures could have high accuracy in calculating the ROP, and then reduce drilling cost and time. Besides, **Vorobyov and Kulynych (2017)** investigated the impact of surfactants as cooling/lubricating fluids on drilling performance and revealed that the time spent on drilling operations diminished by 40-55% while applying fluids with surfactant additives, due to the decline in rock resistance. As well, **Shad et al. (2018)** declared that rock properties, operating parameters of drill machines, and ferric oxide percentage could significantly contribute to forecasting the drilling ROP of iron ore. **Rudolf et al. (2019)** also concluded that drilling fluids were the essential parameters in rock drilling, which could significantly affect the acceptable ROP. **Zhao et al. (2020)**, practicing optimization paradigms, presented an ANN model and assumed that the model proposed for this purpose was accurate enough for predicting and optimizing the ROP. Similarly, **Elkatatny et al. (2020)** developed a novel model based on ANN, which could estimate the ROP with a high correlation coefficient.

Hongsheng et al. (2020) then conducted laboratory tests with regard to the effect of the drill machine operat-

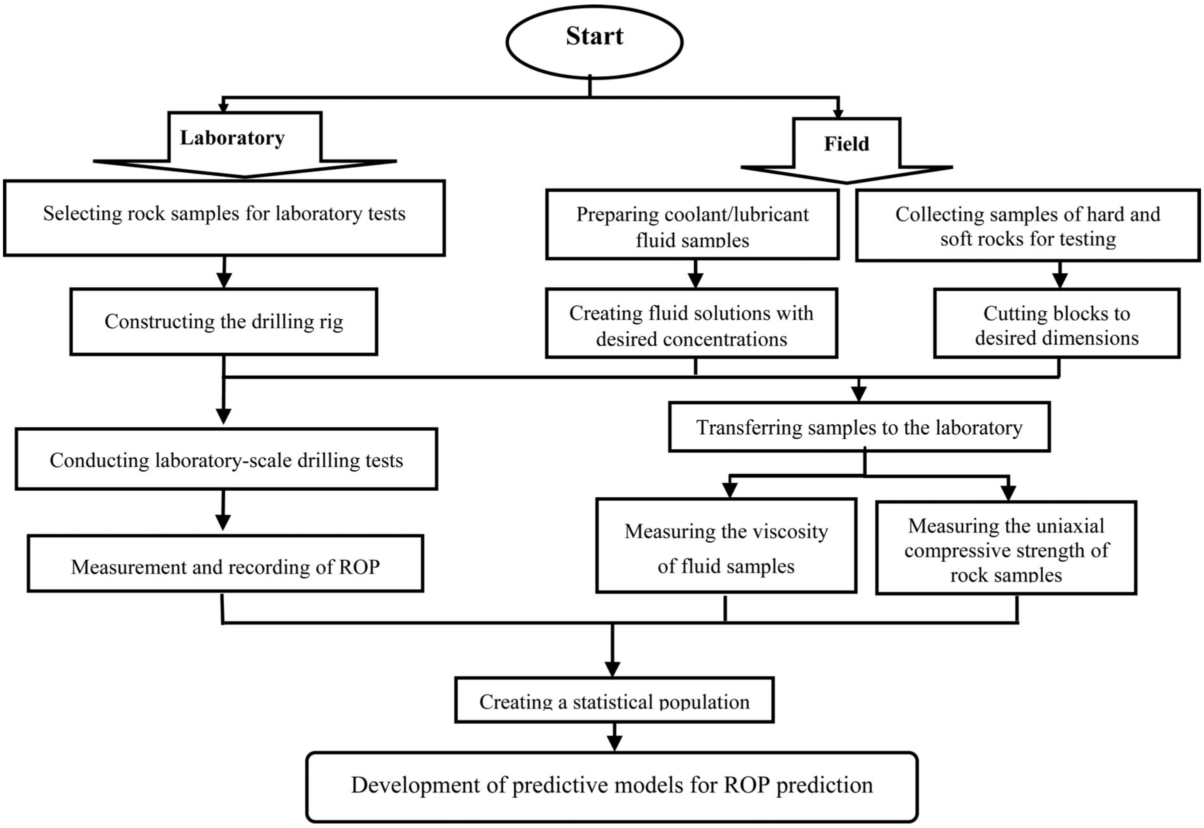


Figure 1: Flowchart of the research process

ing parameters and rock properties on the ROP, and presented a model to predict the ROP with a high correlation coefficient. As well, **Rezaei and Asadizadeh (2020)** attempted to forecast the intact rock UCS, using hybrid intelligent systems, including adaptive neural-fuzzy inference system (ANFIS), genetic algorithm (GA), and particle swarm optimization (PSO). They then concluded that the presented models had good performance. **Al-Rubaii et al. (2020)** also analyzed the ROP optimization and established that drilling performance elevated by 40% through the proposed method. Recruiting statistical methods and artificial ANN models, **Lawal et al. (2021)** correspondingly calculated the ROP. In addition, **Khosravimanesh et al. (2021)** investigated the effect of cooling/lubricating fluids on the ROP, and reported a rising trend in this parameter upon using such fluids, as compared to water. In this vein, **Khosravimanesh et al. (2021)**, presented models with reference to linear and non-linear multivariate RA for predicting drilling ROP with the help of cooling/lubricating fluids, and inferred that the ROP could be accurately evaluated in drilling environments based on rock mechanical properties, fluid characteristics, and drill machine operating features. Besides, **Bilim and Karakaya (2021)** proposed high-accuracy models for forecasting the ROP according to the physicomechanical properties of rocks. As well, **Kamran (2021)** employed three statistical methods, namely, decision tree (DT) algorithm, adaptive boosting (AdaBoost), and random forest (RF) to predict the drilling rate index (DRI), and stated that the model performance could help accurately calculate it. **Rawal et al. (2022)** also conducted studies on the application of polymer-based drilling fluids to reduce drill bit wear rate, and showed that the drill bit wear while using fluids containing polymer additives significantly decreased, which led to an upsurge in drilling performance. Furthermore, **Rezaei and Nyazyan (2023)** suggested new optimal empirical equations for predicting the DRI based on statistical modeling, and finally affirmed that the presented models had acceptable accuracy as validated by the analysis results. **Kazemi et al. (2023)** proposed hybrid models of extreme gradient boosting (XGB), optimized by particle swarm optimization (PSO) and gray wolf optimization (GWO) to predict time-to-failure (TTF) in mining machinery. The obtained results showed that the PSO-XGB method has high accuracy in predicting the TTF of mining machinery. **Kazemi et al. (2023)** conducted research on the prediction of blast-induced air overpressure (AOp) using a hybrid machine learning model and gene expression programming (GEP). The research presents a hybrid model which combines an extreme gradient boosting algorithm (XGB) with grey wolf optimization (GWO) for accurately predicting AOp. The results showed that the proposed model was robust and applicable for predicting AOp driven by blasting operations. **Nabavi et al. (2023)** developed a hybrid model for Back-Break prediction using XGBoost machine learning and meta-heuristic algorithms in the

Chadormello iron mine. According to the obtained results, the performance and accuracy level of the presented models is high. **Kazemi et al. (2023)** presented a novel hybrid XGBoost Methodology in predicting rotary penetration rate based on rock mass and material properties. According to the obtained results, they stated that the presented models are strong models for predicting the penetration rate of similar rock formations. **Khosravimanesh et al. (2024)** according to the research they conducted, stated that the use of cooling and lubricating fluids reduces the specific energy and increases the penetration rate of drilling, which, as a result, leads to an increase in drilling performance.

Given the importance of ROP prediction for improving drilling cost, rate, and efficiency, this study investigated the simultaneous effect of the mechanical properties of rock (uniaxial compressive strength), properties of the cooling-lubricating fluid (viscosity) and operating parameters of the drilling rig (weight on bit and bit rota-

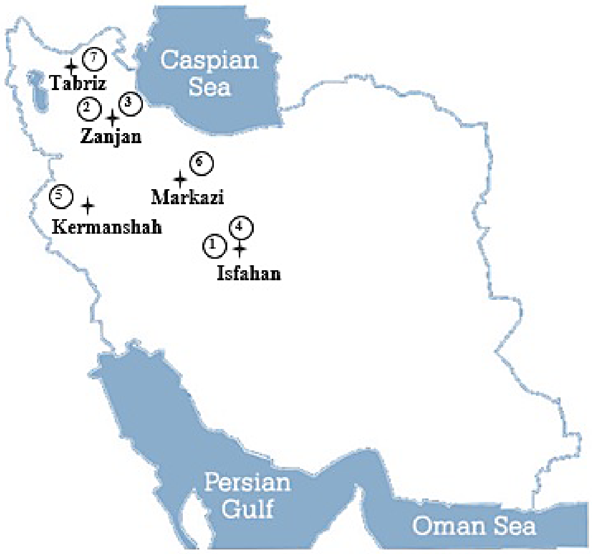
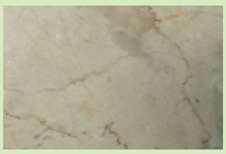


Figure 2: The location of the studied quarries

Table 1: Name and geology characteristics of the studied quarries

Dimension stone sample		Commercial name	Name of quarry	Geological age	Major mineral	Rock mass quality
A_1		Granite	Sefid Natanz	Cretaceous	Feldspar Quartz	Good
A_2		Granite	Khoramdare	Cretaceous	Feldspar Quartz	Good
A_3		Granite	Khoshtinat	Post-Eocene	Feldspar Quartz	Fair-Good
A_4		Marble	Salsali	Oligo-Miocene	Calcite	Good
A_5		Marble	Harsin	Oligo-Miocene	Calcite	Fair-Good
A_6		Travertine	Hajiabad	Quaternary	Calcite	Fair-Good
A_7		Travertine	Azarshahr	Quaternary	Calcite	Good

 pp. 115-130, DOI: 10.17794/rgn.2024.1.10

tion speed) on ROP prediction. Given the utmost importance of the ROP, it was inspected in two different phases in this study. At first, the data related to the determination of the rock strength characteristics, such as UCS, as well as the properties of the cooling/lubricating fluids of the drill machine, i.e. viscosity (μ), were obtained and measured as independent variables. Then, laboratory tests were conducted and the ROP data, as the dependent variable, were recorded by designing and building a laboratory-scale machine under operating conditions. At the next step, there was an attempt to develop a model for predicting the ROP. Upon access to this predictive model, an approximate estimate with certain accuracy could thus be provided for the dependent variable by importing the independent ones, which could be the primary data for planning and subsequent steps, and even save time and money. Considering the benefits of predictive models, compared to laboratory works, they are currently being practiced to improve the overall operating efficiency of projects. Against this background, the relationship between the independent variables and the dependent one was delineated through the simple linear, lasso, and ridge techniques of RA.

Table 2: UCS values of rock samples in this study

NO.	Stone samples	UCS(MPa)
A_1	Sefid Natanz Granite	154
A_2	Khoramdare Granite	141
A_3	Khoshtinat Granite	132
A_4	Salsali Marble	68.03
A_5	Harsin Marble	71.53
A_6	Hajiabad Travertine	61.48
A_7	Azarshahr Travertine	52.96

Table 3: Viscosity values of fluid samples in this study

Fluid sample	Commercial name	Concentration of the additive in the water	Viscosity (mPa.s)
B_1	water	-	1.012
B_2	Soap water	1/60	1.312
B_3	Soap water	1/120	1.295
B_4	Syncool	1/100	1.381
B_5	Syncool	1/120	1.196
B_6	Boron nitride powder	5/20	1.155

2. Methodology

This study was to develop a statistical population for predicting drilling ROP with the aid of the RA techniques. **Figure 1** illustrates the flowchart of the research steps.

2.1. Geology and Quarries studied

Iran is one of the countries with high potential and capabilities to produce dimension stones. The country has extensive resources for metamorphic, sedimentary, and igneous dimension stones. The amount of dimension stone deposits in Iran is 59 million tons of travertine, 500 million tons of marble, and 60 million tons of granite. The present research examines 7 dimension stone samples from different mines in Iran (**Ghorbani, 2013**). These were two travertine samples, three granite samples, and two marble samples. **Figure 2** and **Table 1** illustrate the studied quarries' location and geological setting, respectively. The studied stone samples were collected from these mines and transferred to the laboratory.

2.2. Laboratory Studies

After examining and selecting the rock samples to conduct the laboratory studies, they were collected from seven mines. Then, they were transferred to the rock mechanics laboratory to determine their mechanical properties.

At first, the key parameter of the rock, UCS, was measured, like that considered in most engineering studies. The rock UCS test was also carried out in accordance with the International Standard for Results Management (ISRM) (**Brown, 1981**). For this purpose, five samples with a diameter of 54 mm and a length-to-diameter ratio (LDR) of 2.5:3 were prepared. During this process, cylindrical samples were first taken from the rocks, and then, the top and bottom of the samples were cut and sanded to achieve a smooth surface and load the UCS device uniformly. These tests were performed with a loading rate of 0.5 to 1 MPa/s. Finally, the mean UCS

Table 4: Statistical descriptive features of the collected data.

	UCS (MPa)	Weight on Bit (kg)	Viscosity (mPa.s)	Bit rotation speed (rpm)
count	492	492	492	492
mean	80.804	90.688	1.226	839.121
std	33.525	22.904	0.130	167.098
min	52.96	58.087	1.012	610
25%	61.48	76.784	1.155	720
50%	68.03	95.135	1.295	845
75%	71.53	116.225	1.312	933
max	154	133.384	1.381	1190

was calculated for each rock sample. **Table 2** depicts the results of measuring UCS for the rock samples.

Investigating cooling/lubricating fluids, six fluids were utilized for drilling on the blocks prepared from seven rock samples, and then transferred to the laboratory to determine their physical characteristics, including the fluid viscosity, as the most important one. **Table 3** shows the results of the laboratory studies to determine the viscosity of the fluids. **Table 4** illustrates some descriptive statistics features of obtained data.

2.2.1. Rock Drill Machine Construction

To reach homogeneous data and investigate the effect of cooling/lubricating fluids on the drilling of the rock samples, a laboratory-scale rock drill machine was designed and manufactured in order to advance the research goals. Afterward, it was operated and successfully tested. This machine comprised of two main parts, namely, the drilling part to perform the drilling operation, and the electrical panel to control it and meet commands during the drilling operation. The electrical panel contained a processor with a touch screen for recording the drilling data. **Figure 3** depicts a view of the drill machine and the rock sample of the rocks used in the rock mechanic laboratory.

Figure 3: A view of drill machine and rock samples used

2.2.2. Drilling Tests

To do the drilling tests, the rock samples with the approximate dimensions of 15×10×10 cm^3, 20×10×10 cm^3, and 30×10×10 cm^3 and a tungsten carbide drill bit with a diameter of 10 mm were used. To determine the rotation speed (ω) of the drill bit and the weight on bit (WOB), several tests were performed as trial and error on the hard and soft rock samples, then the ω values of 1190, 1057, and 933 rpm and the WOB scores of 133, 116, 95, and 77 kg were selected for the hard rocks, and 933, 845, 720, and 610 rpm and 116, 95, 77, and 58 kg were chosen for the soft ones, respectively. To find the fluid with the right concentration for drilling, drilling tests were fulfilled under different operating conditions using the water fluid and five types of cooling/lubricating fluids, including B_1, B_2, B_3, B_4, and B_5 in the medium and soft rock samples of A_4, A_5, A_6, and A_7. After examining the results, among the five fluid samples, two with the most changes recorded, compared to water, were selected for drilling in the hard rock samples. Then, the drilling tests, under different operating conditions, using water fluid and two samples of cooling/lubricating fluid, including B_3 and B_4, in the hard rock samples of A_1, A_2, and A_3 were performed. In total, 492 tests were carried out to investigate the relationship between the rock mechanical properties, the fluid physical characteristics, and the drill machine operating parameters in order to predict the ROP in seven rock samples, that is, the hard and soft rocks, employing three fluids in the hard rock samples and six fluids in the soft ones.

3. Statistical Analysis

In this research, RA techniques have been used in order to provide a model for predicting the ROP of drilling. For this purpose, three regression methods, simple linear, lasso and ridge, were used.

3.1. RA Techniques

3.1.1. Ridge Regression

The ridge technique of RA as a model fitting method is typically employed to analyze data with no collinearity, via the L_2 regularization. Once collinearity occurs, the least square is unbiased and the variance tends to larger values, thereby leading to the deviation of the predicted values from the actual ones. In fact, ridge RA is a linear method to correct its own coefficients through a penalty term, the L_2-norm, and then manages data collinearity effects. To deal with the negative influence of collinearity, ridge regression introduces a penalty term for the error calculation function of the predicted and actual data, called the L_2 regularization. This makes the coefficients inclined toward 0 and reduces their values. The ridge technique of RA also controls the value of coefficients, and essentially simplifies the final model, which prevents the abnormal fitting of the model to the data. Moreover, the ridge mechanism even minimizes the negative effects of outliers. The ridge regression steps are presented in **Figure 4** in a flowchart (**Hoerl, 2020**).

3.1.2. Lasso Regression

Also known as the L_1 regularization, the lasso technique of RA as a predictive model is commonly recruited in statistical modeling and machine learning to find the relationship between variables. Lasso, standing for the least absolute shrinkage and selection operator, is to find a balance point between a simple model and an accurate one. This technique aims to achieve its goal using a penalty term entered into the simple linear regression

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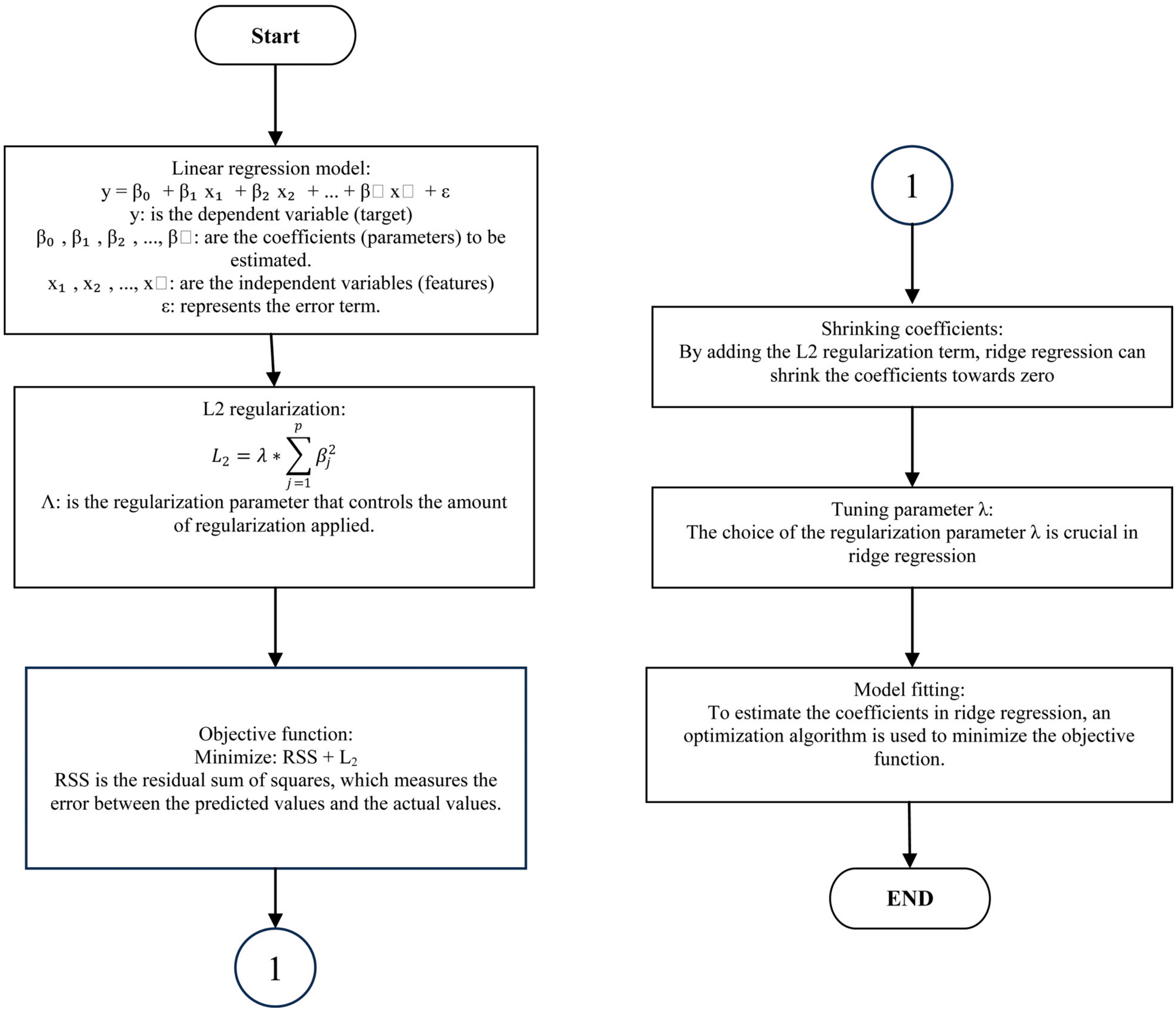

Figure 4: A flowchart of ridge regression steps

model. In its operating process, lasso strengthens sparse solutions resulting in 0 coefficients in predictive equations by the proposed term. Accordingly, the L_1 regularization provides high-accuracy predictions. The steps of the lasso technique of RA are given in **Figure 5** as a flowchart (**Yazdi et al., 2021**).

3.2. Evaluation Measures for Regression Performance Quality

To evaluate the performance quality of the regression models, three measures of mean absolute percentage error (MAPE), D-squared pinball score (D^2PS), and mean Poisson deviance error (MPDE) were then utilized.

3.2.1. Mean Absolute Percentage Error (MAPE)

The MAPE was the most common measure to evaluate the predictive accuracy and quality of the presented model. **Equation 1** is typically used to calculate this measure (**Utpat and Kulkarni, 2023**).

$$MAPE = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right| \quad (1)$$

Where:

y_i - True value,

$\hat{y}_i$ - Predicted value,

n - Number of Observation.

3.2.2. Mean Poisson Deviance Error (MPDE)

The MPDE was in fact a special form of Tweedie's deviance estimator, wherein the exponential value was 1. **Equation 2** was thus utilized for computation purposes (**Jakšić et al., 2023**).

$$D(y,\hat{y}) = \frac{1}{n} \sum_{i=0}^{n-1} \begin{cases} (y_i - \hat{y}_i)^2 & for\ p = 0\,(Normal) \\ 2(y_i \log(y_i / \hat{y}_i) + \hat{y}_i - y_i) & for\ p = 1\,(Poisson) \\ 2(\log(y_i / \hat{y}_i) + (y_i / \hat{y}_i) - 1) & for\ p = 2\,(Gamma) \\ 2\left(\frac{\max(y_i, 0)^{2-p}}{(1-p)(2-p)} - \frac{y_i \hat{y}_i^{1-p}}{1-p} + \frac{\hat{y}_i^{2-p}}{2-p} \right) & otherwise \end{cases} \quad (2)$$

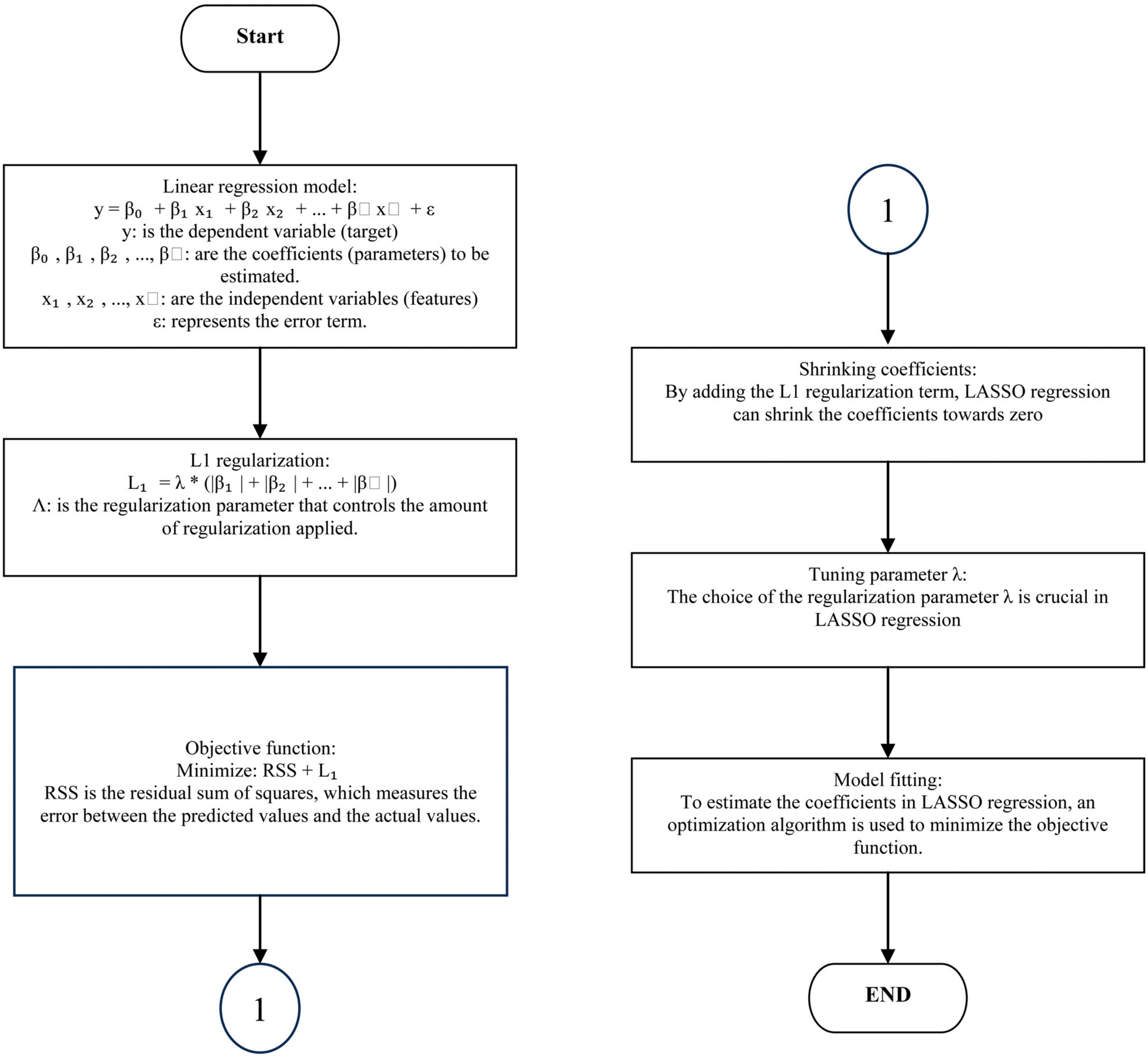

Figure 5: A flowchart of lasso regression steps

3.2.3. D-Squared Pinball Score (D^2PS)

The D^2PS was a measure to evaluate the quality of the predictive model by examining the quartiles of the predicted and actual values. In this measure, unlike others, the data were not checked separately but as a set. Therefore, this measure was somehow different from other measures. **Equation 3** was used to calculate this measure (**Koenker and Machado, 1999**).

$$D2PS = \begin{cases} (y_i - z)\tau & \text{if } y_i \geq z \\ (y_i - z)(1-\tau) & \text{if } y_i < z \end{cases} \quad (3)$$

Where:

z - Predicted quantile,

τ - True quantile.

Following a general introduction to the techniques of RA implemented in this study, the data from the laboratory studies undergone regression with the mentioned methods, simple linear, lasso, and ridge. After examining the results, there was an attempt to select the best predictive model. As well, prediction quality measures, viz., MAPE, MPDE, and D2PS, were exploited to identify the best model. **Figure 6** exhibits an overview of the best model selection process.

As there were several parameters to describe a rock mass in terms of resistance, hydraulic behaviour, thermal behaviour, and time function, UCS, WOB and ω, and cooling/lubricating fluid viscosity were selected as the input or independent variables of the model with regard to the target or dependent variable and the effect of the selected parameter on it. **Table 5** shows the independent variables.

Before commencing the RA process, investigating the relationship between the independent variables could significantly help reach an efficient predictive model. For this purpose, the degree of correlation of the independent variables was mapped in **Figure 7**.

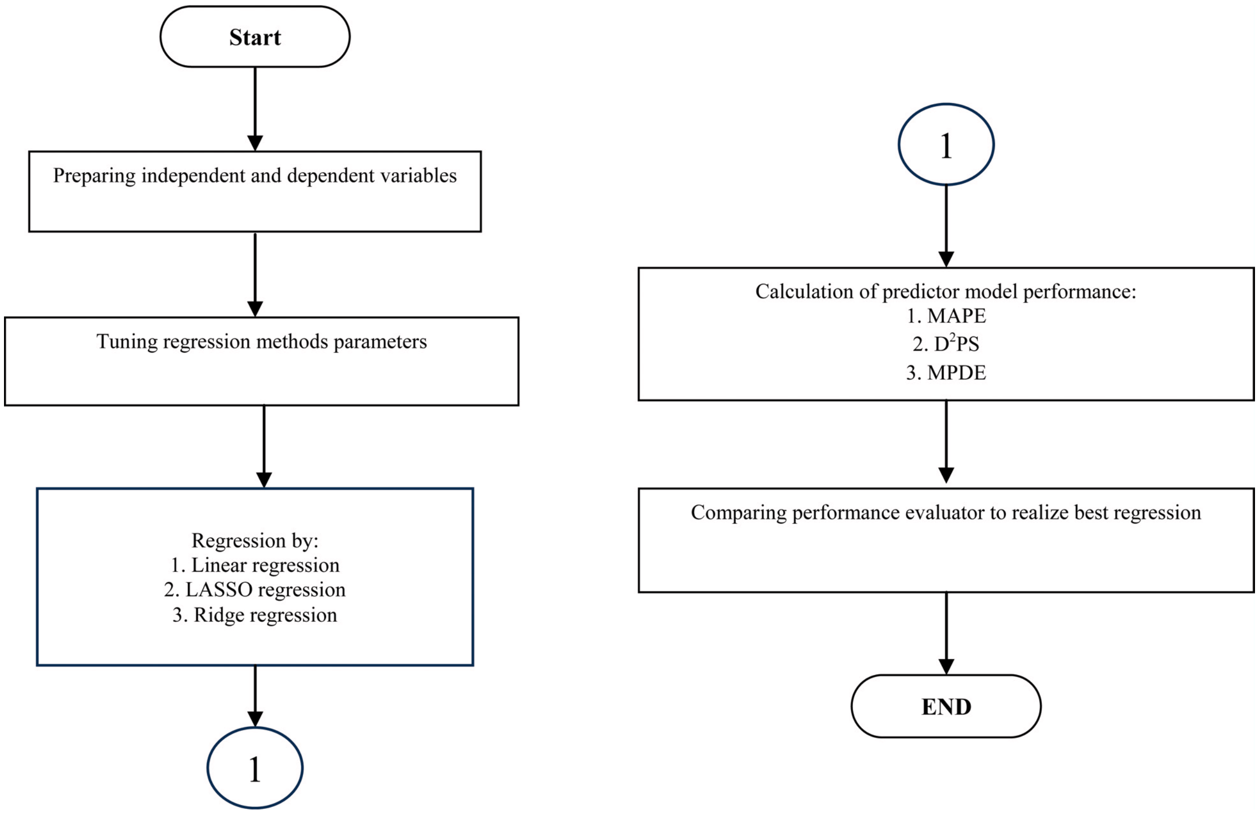

Figure 6: An overview of the best model selection process

Table 5: Independent variables of the predictive model

parameters	Uniaxial compressive strength	weight On Bit	Bit rotation speed	Viscosity
Unit	UCS(MPa)	WOB(Kg)	ω (rpm)	μ (mPa.s)

In this map, the highest degree of correlation is observed between the rock UCS and ω, valued 0.68, which does not provide a high correlation; therefore, the data are not significantly correlated. As well, the lowest correlation is between the rock UCS and the cooling-working fluid viscosity, equal to 0.0013. According to the correlation between the independent variables, the conditions for regression were evaluated as favourable.

The target or dependent variable in this study was the drill bit ROP, as one of the key parameters employed in rock mass measurement, rock cutting and tunnelling tool design, which was time-consuming and demanded high costs. Accordingly, proposing a model to predict the drill bit ROP could be really attractive as it could save time and funds. Upon defining the dependent variable and the independent ones, as well as evaluating the independent variables in terms of their correlation, the conditions to develop regression models were met. To start RA, the parameters of the associated technique needed to be specified. For the simple linear type, the parameter was not considered for regularization, but the alpha parameter, the maximum value of repetition and tolerance, and the type of solution algorithm were respected for the ridge and lasso ones. Of note, the optimal values for each parameter in the regressions were selected after many repetitions, and once the sensitivity of the models to change them was checked. **Table 6** illustrates the regularization values of the mentioned methods. For deter-

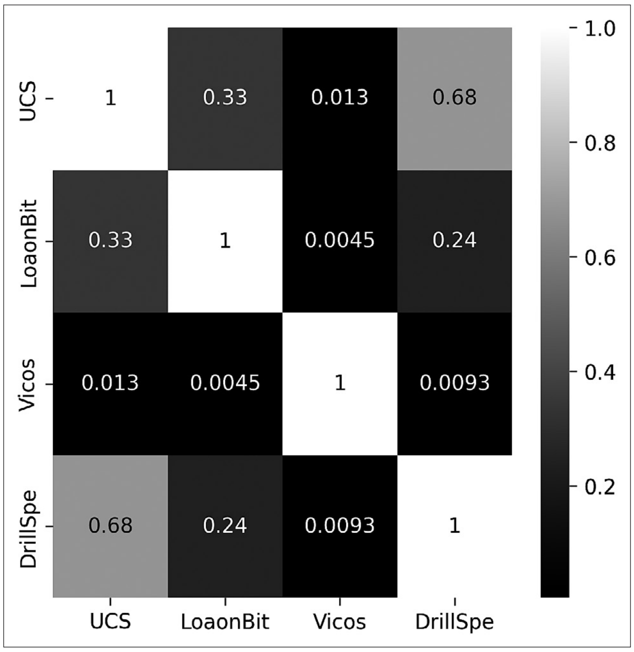

Figure 7: Independent Variables Correlation map

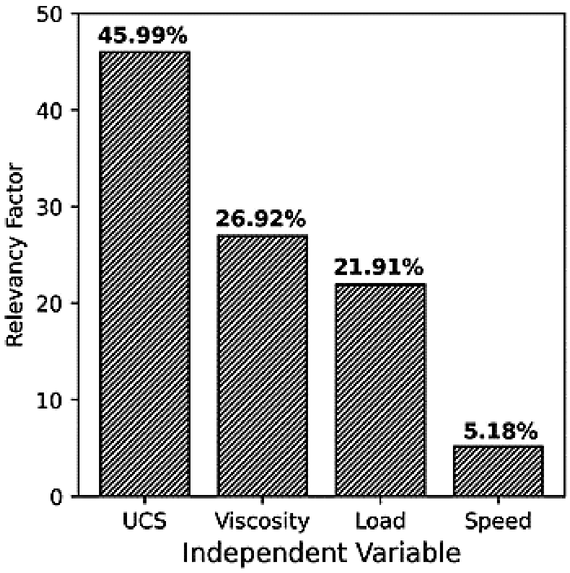

Figure 8: Relevancy factor of independent variable

Table 6: Values of regularization parameters for regression techniques

Method	Parameters				
Base LR	No Parameters Exist.				
Ridge LR	alpha	Max iteration	Tolerance	Solver	
	1.1	1000	0.0001	auto	
LASSO LR	alpha	Max iteration	Tolerance	selection	Pre compute
	0.001	1000	0.0001	cyclic	Non

mination of the weight of each variable that affect the ROP, sensitivity analysis is needed. In order to do sensitivity analysis, the relevancy factor is used. **Figure 8** shows the calculated relevancy factor of each independent parameter of the model. As shown in **Figure 8**, the USC factor with a value of 45.99% has the highest effect on ROP behaviour.

4. Results and Discussion

Considering rock UCS, WOB and ω, and cooling/lubricating fluid viscosity as the independent variables and the ROP as a dependent one, undergoing RA, a linear equation was developed, characterized by the coefficients of the independent variables and the y-intercept. The main objective was to reach a linear function with an acceptable fit on the input data of the regression process. The results of the regression outputs are listed in **Table 7**.

In this table, based on the type of regression, the coefficients of the independent variables are outlined in their own rows. The y-intercept of each regression model is also presented in the last column. Examining this table

Table 7: Regression outputs

Method	Coefficients		Intercept
Base LR	UCS	-0.0017	-0.2104
	Weight on Bit	0.0017	
	Viscosity	0.1612	
	Bit Rotation Speed	0.0002	
Ridge LR	UCS	-0.001738844986	-0.19472217
	Weight on Bit	0.001706277706	
	Viscosity	0.148155504	
	Bit Rotation Speed	0.0001968079889	
Lasso LR	UCS	-0.0014	0.0112
	Weight on Bit	0.0015	
	Viscosity	0	
	Bit Rotation Speed	0.0002	

Table 8: Evaluators Value

Metrics	Base LR	Ridge LR	LASSO LR
Mean Absolute Percentage Error	0.2565	0.2557	0.2557
D_2_p_s	0.4088	0.4083	0.4025
Mean Poisson Deviance Error	0.0106	0.0105	0.0107
Target Value	622.1174	629.475	611.7128

more closely shows that the rock UCS had the least effect in the lasso model and the most effect in the simple linear one. In addition, the inverse effect of the rock UCS was evident in all models, so there was a logical correlation between this measure and the ROP, implying the accuracy of the model performance. Among the regression models, the drill bit WOB in the lasso model once again had the lowest coefficient, but the ridge model reflected its highest influence. A direct relationship was observed between the drill bit WOB and the ROP in all models, denoting their logical behaviour. In relation to the drill bit ω, the lasso model had given the highest weight to this measure, compared to the other methods, but the simple linear regression model, included the lowest coefficient. The direct relationship between this parameter and the ROP accordingly showed the logic of the proposed model. The cooling/lubricating fluid viscosity, as one of the significant factors affecting the ROP was thus neutral in the lasso regression model, but it brought a good effect in the simple linear regression model. Comparing the outcomes of different methods, the lasso model provided the most contraction coefficients, due to the utilization of the L2 regularization.

To check the performance quality of the regression models, it was not possible to reach accurate and reliable results merely by the visual study of the coefficients. Therefore, there was a need to use quantitative methods

 pp. 115-130, DOI: 10.17794/rgn.2024.1.10

to compare the predictive models. For this purpose, several evaluation parameters were provided and calculated to find the quality and efficiency of the predictive model. These parameters could help examine the performance of the predictive model with different calculation structures and score them. Knowing the scores and ranks could thus determine the performance accuracy and quality of the models. As mentioned earlier, there were many quality measures, including MAPE, D2PS, and MPDE, which were considered in this study to compare the performance of the regression models. The results are outlined in **Table 8**.

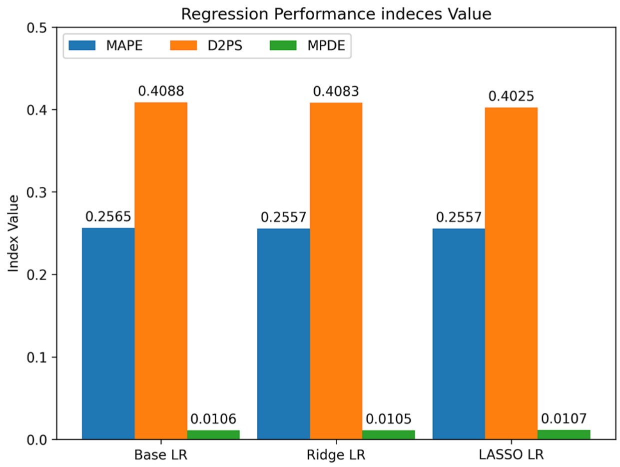

Figure 9: Column chart of values of evaluation parameters of different regression models

The above table contains the values of the evaluation parameters. Of note, the MAPE values tend to be low and even 0 under the best conditions following the improvement in the quality of the predictive model. In connection with D2PS, it moves toward 1 as the predictive model shows a better performance, thereby increasing the prediction quality. In the best case, the value of this parameter is equal to 1. MPDE also has the same behaviour as that of MAPE. This measure has a tendency to be 0 when faced with predictive models. Under the best conditions, this parameter shows a value of 0. According to the behaviour of the parameters and performance evaluation measures of the predictive models, it was possible to check the performance of the models by considering the values of these parameters for each regression model. For a detailed investigation and more reflections on the effect of these three parameters in keeping with their behaviour, the function in **Equation 4**, as the combination of the above three parameters, was used to rank the models.

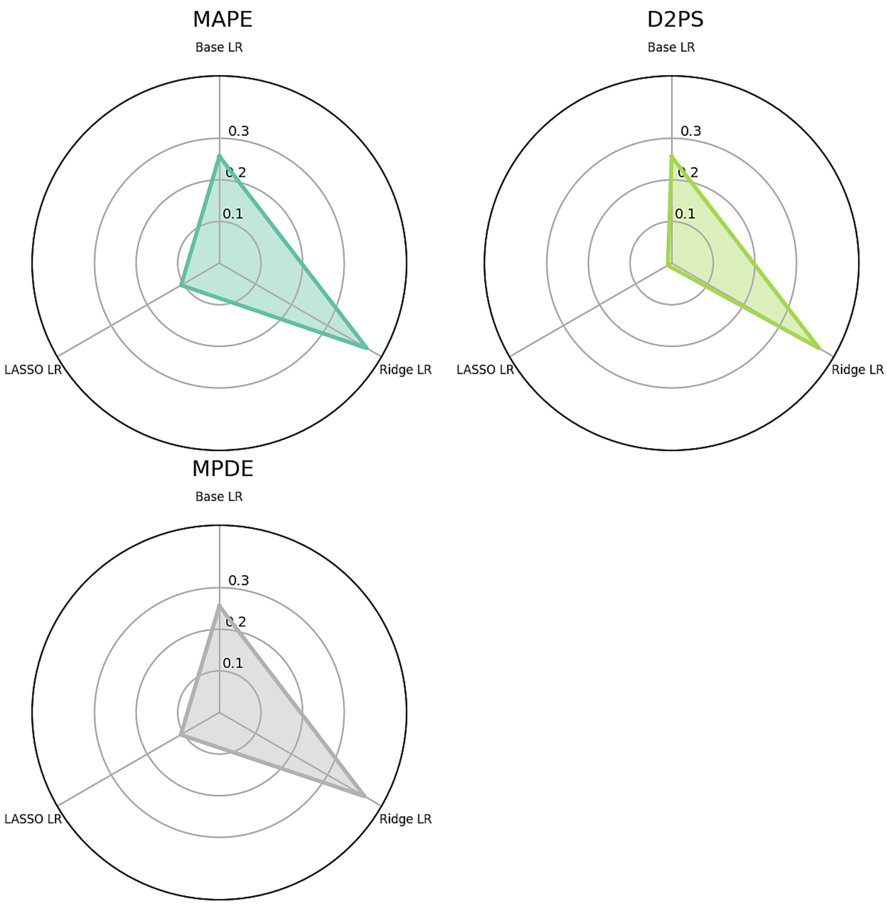

Figure 10: Radar chart of values of evaluation parameters of different regression models

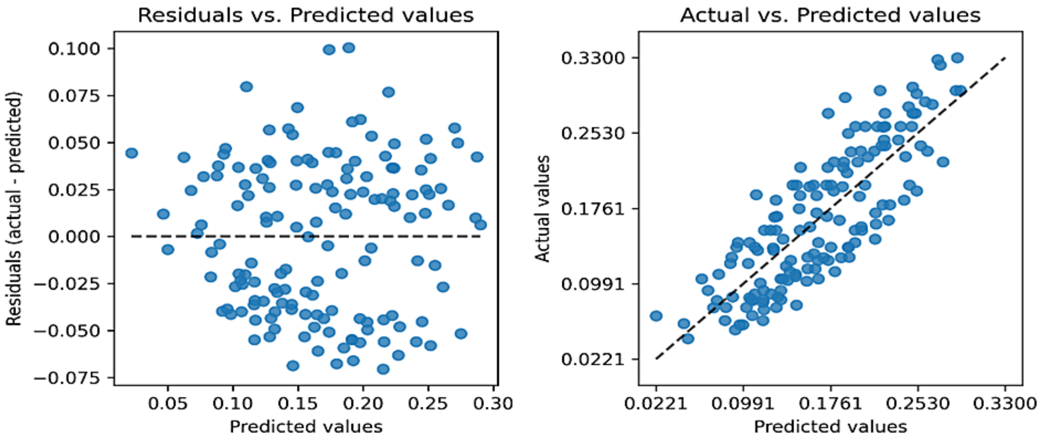

Figure 11: Efficiency diagram of Base LR regression model

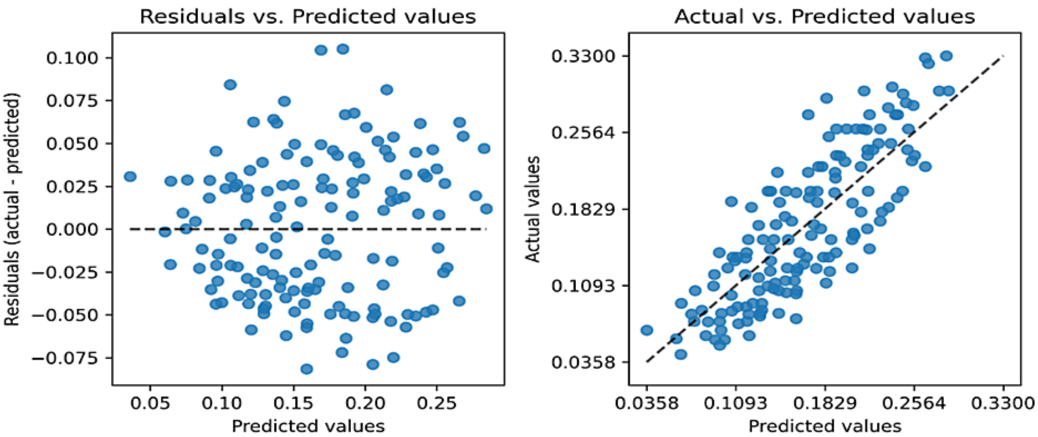

Figure 12: Efficiency diagram of LASSO LR regression model

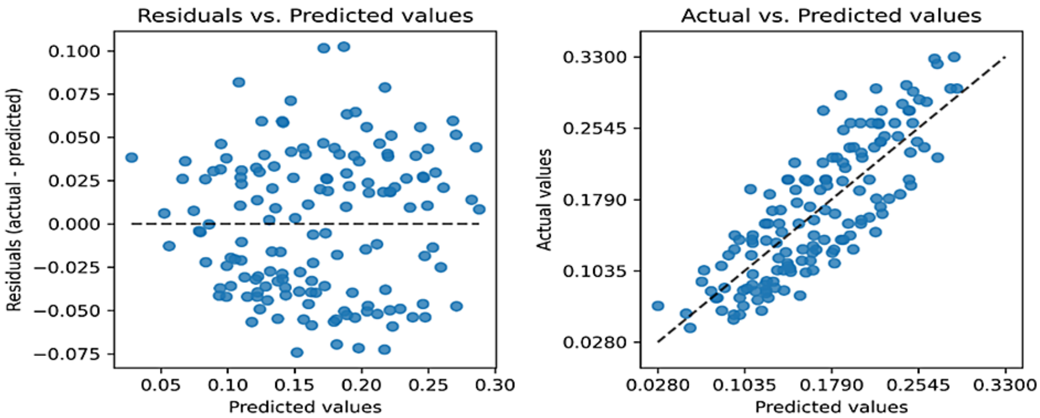

Figure 13: Efficiency diagram of Ridge LR regression model

With regard to the defined objective function (OF), larger OF values could represent a more accurate performance and quality of the predictive model.

$$Target\ value = \frac{D2PS}{MPAE \times Poisson} \quad (4)$$

Considering the values calculated for the OF in the above table, this value for the ridge regression model was the largest, 629.447; therefore, it could provide the most accurate predictions. Given no correlation of the independent variables imported into the model, their number led to the best outputs in the ridge regression model. Considering the L1 regularization, the ridge technique of RA indicated a better performance than the simple linear regression model in the face of the multiplicity of the independent variables entered into the model. On the other

 pp. 115-130, DOI: 10.17794/rgn.2024.1.10

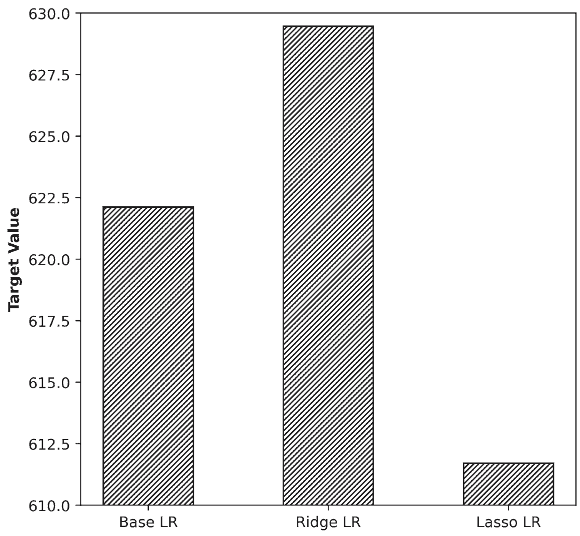

Figure 14: A diagram of target values calculated for different regression models

hand, the lasso technique with the L2 regularization could detect the real independent variables well and greatly reduce the effects of the correlated independent variables in the face of multiple independent ones with a high correlation, having a remarkable performance, as compared to the other models. Nevertheless, in the case where the correlation between the independent variables was low, the manoeuvring power was not so strong, and the ridge regression model showed a better performance**. Figures 9** and **10** show the values of the evaluation parameters of different regression models in the form of column and radar charts, respectively.

Figures 11 to **13** depict the diagrams of regression model efficiency, in two parts. The figure on the left illustrates the residual values of the predictive models. In this diagram, the smaller the scatter of the points around the horizontal line passing from 0 and the denser the data accumulating around the 0 line, the more accurate the model performance in predictions. In the figure on the right, the actual values of the dependent variable, i.e. the ROP, are plotted against the predicted ones. In this figure, the greater the convergence of the points toward the bisector of the first area, the higher the accuracy and quality of the regression model in predicting the dependent variable.

Figure 14 displays the diagram of the OF values calculated for different regression models. Here, the peak value that actually represents the best performance occurred for the ridge regression model.

5. Conclusions

Practicing tests and statistical studies, the relationships and the simultaneous effects of the UCS parameter as one of the most important mechanical properties of rocks, viscosity as the main feature of cooling/lubricating fluids, as well as the drill machine operating characteristics (i.e. drill bit WOB and ω) were investigated in this study to predict the drilling ROP. To this end, laboratory studies on seven rock samples from different parts of Iran, including three hard rock samples and four soft cases while using three fluids (water fluid and two cooling/lubricating fluid samples) for the hard rock samples and six fluids (water fluid and five cooling/lubricating fluid samples) for the soft rock samples were performed. Recruiting a laboratory-scale drill machine built and considering the above-mentioned variables, the ROP in the samples was then analysed and recorded. With respect to the rock UCS, drill bit WOB and ω, and the cooling/lubricating fluid viscosity as the independent variables and the ROP in the rock as the dependent one, there was an attempt to find a predictive model using regression techniques. For this purpose, three regression methods, namely, simple linear, lasso, and ridge, were employed. To evaluate the performance quality of the regression models, three measures of MAPE, D^2PS, and MPDE were also operated. According to the scattering state of points in figures of actual and predicted data and predicted data and their correspondent residual errors figure, the ridge method has the best performance. The best regression model was then obtained by defining the OF, as a combination of the evaluation parameters, and calculating their values. The ridge regression method with an OF value of 629.475 was ultimately selected as the best, and the simple linear and lasso models were placed in the next ranks with the OF values of 622.1174 and 611.7128, respectively.

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SAŽETAK

Točna procjena brzine bušenja stijene bušaćim dlijetom pomoću nadziranih tehnika strojnoga učenja koje se temelje na laboratorijski određenim podatcima

Poznavanje brzine bušenja (ROP eng. *rate of penetration*) dlijeta jedan je od najvažnijih parametara u njihovu vrednovanju. Međutim, izravno mjerenje ROP-a u stijenama skup je i vremenski zahtjevan postupak. Zbog toga može biti vrlo korisno i učinkovito određivanje ROP parametra metodom koja nije izravno mjerenje. Prediktivne metode strojnoga učenja moćne su i precizne tehnike za neizravno mjerenje ROP-a. Ispitana su 492 uzorka pod različitim uvjetima jednoosne tlačne čvrstoće, viskoznosti, mase dlijeta i brzine rotacije dlijeta kako bi se odredila odgovarajuća brzina bušenja. Točniji model za procjenu nastojao se pronaći usporedbom triju metoda: linearna regresija, LASSO regresija i hrbatna regresija. Njihovi modeli uspoređeni su pomoću kriterija izvedbe procesa procjene i grafikona temeljenih na greškama. U kriteriju izvedbe uspoređene su tri mjere uspješnosti: srednja apsolutna postotna pogreška, D2PS indeks i MPDE indeks. Prema srednjoj apsolutnoj postotnoj pogrešci najbolje su se pokazali modeli LASSO i hrbatne regresije s vrijednostima od 0,2557. Prema D2PS indeksu, modeli linearne regresije i hrbatne regresije pokazali su bolje rezultate s vrijednostima od 0,4083 odnosno 0,4025. Prema MPDE indeksu model hrbatne regresije pružio je točniju procjenu s vrijednosti od 0,0105. Radi još bolje usporedbe kreirana je objektivna funkcija koja je izračunana kombinacijom prije spomenutih triju pokazatelja. Rezultati su pokazali najbolji rang za model hrbatne regresije s procijenjenom vrijednošću od 659,475. Zaključeno je da je model hrbatne regresije pouzdan i točan za procjenjivanje brzine bušenja.

Ključne riječi:
brzina bušenja, tekućina za hlađenje i podmazivanje, jednostavna linearna regresija LASSO regresija, hrbatna regresija

Authors' contribution

Shahrokh Khosravimanesh (PhD, Isfahan University of Technology): participated in all work stages such as providing samples, running experimental tests,data analyses, writing and editing of the paper. **Akbar Esmaeilzadeh** (Assistant Professor, Urmia University of Technology): shared contributions throughout the whole process and data analyses. **Masopud Akhyani** (Assistant Professor, Islamic Azad University of shahrood): contributed to reviewing and editing the paper. **Reza Mikaeil** (Associate Professor, Urmia University of Technology): supervised the project and contributed to the writing and editing of the paper. **Mojtaba Mokhtarian Asl** (Assistant Professor, Urmia University of Technology) reviewed and edited the paper.

Nomenclature:

ROP[mm/s]	Rate of Penetration	L_1[-]	Regulator of Lasso method
UCS[MPa]	Uniaxial compressive Strength	z[-]	Predicted quantile
μ[mPa.s]	Viscosity	WOB[Kg]	weight on bit
Y[-]	dependent variable (target)	n[-]	Number of Observation
L_2 [-]	Regulator of Ridge method	$MAPE$[-]	Mean Absolute Percentage Error
RSS[-]	residual sum of squares	ω (rpm)	Bit rotation speed
λ [-]	Controller of the amount of regularization	y_i [-]	True Value
E[-]	error term	$\hat{y}_i$ [-]	Predicted value
τ[-]	True quantile	$\beta_0, \beta_1, \beta_2, ..., \beta_n$[-]	coefficients to be estimated
D^2PS[-]	D-Squared Pinball Score	$x_0, x_1, ..., x_n$[-]	independent variables (features)
MPDE[-]	Mean Poisson Deviance Error		