A Hybrid Random Forest optimized with the Dolphin Swarm Algorithm for predicting P-Wave Velocity of Sedimentary Rocks using Ball Mill Grinding Characteristics

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Abstract
Rock properties play a crucial role in mining, geotechnical engineering and various engineering projects. P-wave velocity helps in determining the quality and stability of rock masses, essential for tunnel excavation, slope stability and mining operations. P-wave velocity also provides critical input for designing foundations for dams, bridges and other rock structures. Accurate determination of P-wave velocity relies on high-quality samples. However, challenges such as preparation, cost and time constraints have prompted a growing reliance on computational methods for its prediction. Previous investigations predominantly leaned on laboratory-based tests and indirect methodologies for predicting rock properties including P-wave velocity.

In contrast, this study introduces an innovative technique for predicting wave velocity (V_p) of sedimentary rocks, particularly limestone using ball mill grinding characteristics throughout the grinding procedure, an unconventional yet effective approach. A hybrid random forest model optimized with dolphin swarm algorithm was developed to predict V_p from grinding characteristics. The performance of the model in training and testing phases was assessed based on determination coefficients (R^2), root mean-squared error (RMSE) and variance account for (VAF) which are 0.984, 96.204 m/s and 98.25% in training and 0.973, 102.32 m/s and 97.63% in testing phase respectively.

Keywords: Ball mill, Grinding characteristics, P-wave velocity, Prediction models

Introduction

Rock engineers traditionally estimate the physico-mechanical properties of rocks through labor-intensive and time-consuming processes involving coring and laboratory tests. However, these methods have limitations in terms of efficiency and cost-effectiveness. The P-wave velocity of rocks plays a significant role in rock mechanics. This velocity is influenced by various factors including the physico-mechanical properties of rocks[25].

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The P-wave velocity can provide insights into the anisotropic behavior of rocks, which is the variation in properties along different directions[24]. Furthermore, the P-wave velocity has practical applications in various fields. In geotechnical engineering, it can be used to assess the quality of rock masses and to predict subsurface rock quality[22].

In seismic exploration, the P-wave velocity is used to perform amplitude variation with offset analysis and search for oil reservoirs[7]. In acoustic logging, the P-wave velocity is utilized to calculate rock porosity, mechanical parameters (such as Young's modulus and Poisson ratio) and to calibrate seismic data[4]. However, obtaining accurate samples from weak, weathered and highly fractured rocks for laboratory testing can be challenging[18]. This may lead to evaluations based on limited high-grade samples, potentially affecting the accuracy of results. To address these constraints, researchers are exploring experimental predictive models to enhance rock characterization.

Many studies have utilized index-based tests to predict rock properties, establishing correlations between specific indices and rock properties to predict UCS from point load values[10], slake durability index[27], block punch index[12] , basic rock index properties[19] and using P-wave velocity to predict different rock properties[13]. Several researchers have investigated the use of indirect approaches for predicting seismic wave velocities. Hadi and Nygaard[8] developed a reliable prediction tool for estimating shear wave velocity from P-wave velocity measurable from well logs using both regression and artificial neural network (ANN).

The ANN model demonstrated superior performance with $R^2 = 0.96$ and lower mean square error of 0.0011. The study also highlights that the P-wave velocity outperforms bulk density in predicting shear wave velocity and combining these parameters enhances the prediction. Karakul and Ulusay[14] established relationship between V_p and strength properties such as uniaxial compressive strength and tensile strength of different rock types under varying saturation levels. Multivariate models were developed to predict the rock properties by incorporating saturation degree and effective clay content. Kasab and Weller[15] investigated the behavior of P-wave and S-wave velocities in porous sandstone. The results of the study showed that P-wave velocity was higher in saturated samples, averaging to 2950 m/s compared to 2766 m/s in dry samples.

https://doi.org/10.25303/185da0109

The study established equations to predict P-wave and S-wave based on their corresponding dry sample velocities. Kim et al[17] explored the use of machine learning models such as Gradient Boosting, Random Forest and Artificial Neural Network to predict compression (V_p) and shear (V_s) velocities using borehole data from seismograph networks with input parameters such as density, N-value, slope angle, elevation, geology, soil/rock type and site coordinates. The results of the study showed that gradient boosting outperformed other methods for both V_p and V_s predictions across both the networks. Basarir and Dincer[5] developed predictive models utilizing linear and non-linear regression techniques alongside Adaptive Neuro Fuzzy Inference System (ANFIS) for estimating P-wave velocity of rock masses.

The predictors dataset included the drilling parameters compiled from field investigations conducted at 13 open pit lignite mines. The ANFIS model demonstrated superior predictive performance, indicating its potential for reliable estimation of V_p in rock masses. Najibi and Asef[20] investigated on prediction of V_p and V_s velocities using rock density, elastic modulus measured at unconfined atmospheric pressure. The analysis included 285 points from various locations. The predicted wave velocities showed an accuracy of 2-3% compared to the measured values. This approach is crucial for understanding the rock behavior under deep-well conditions, with applications in geophysical property prediction, wellbore stability and in-situ stress analysis. Altindag[1] correlated several physico-mechanical properties with P-wave velocity of sedimentary rocks. A total of 97 samples were analyzed statistically.

The multiple regression analysis based on P-wave velocity resulted in empirical equations with high correlation coefficients tailored for rock engineering applications. The derived equations were compared to those reported in earlier studies for validation and performance assessment. Bery and Saad[6] demonstrated the potential of P-wave seismic velocities for cost effective subsurface material characterization, reducing investigation costs while improving the understanding of soil and rock properties in tropical regions. The study findings include empirical correlations for tropical environments such as V_p = 23.605(N) – 160.43 (with R^2 = 93.15%) and V_p = 21.951(RQD) + 0.1368 (with R^2 = 83.77%). Additionally, the squared ratio of field to laboratory P-wave velocities approximates to RQD, providing a practical method for estimating rock quality.

There are some studies which used grinding parameters to correlate with the dimensional properties of material being ground in grind mills. Avinash et al[4] and Petrakis and Komnitsas[21] investigated the use of grinding parameters of rocks to correlate and predict the rock properties. Aras et al[2] successfully used ANNs to predict Bond's work index from rock properties, demonstrating the potential of machine learning approaches to capture the complex behavior during ball mill grinding. Umucu et al[26] used neural networks to evaluate the grinding process illustrating the importance of material properties.

Asghari et al[3] investigated the relationship among ore features, operating variables and other product shape properties in an industrial semi-autogenous grinding (SAG) mill, further illustrating the interdependence of various factors affecting the grinding process and the potential for using this data to infer rock properties. An investigation was carried out by Kekec et al[16] to study the effect of textural properties of rocks on their crushing and grinding characteristics, highlighting the importance of considering rock properties beyond just strength and hardness when analyzing the grinding behavior.

In the domain of rock properties prediction, there is a notable gap in the literature regarding the utilization of grinding characteristics of mills as an indirect approach to correlate with rock properties including P-wave velocity. Recently, advanced algorithms such as metaheuristic algorithms, stacking algorithms, hybrid algorithms etc. have gained a momentum in the recent past in rock engineering for predictive modelling.

Consequently, a study is proposed which uses the grinding characteristics of ball mill such as feed input, grinding media (number of balls), grinding media weight, grind duration, mill volume occupied by rock charge, mill volume occupied by ball charge, interstitial filling ratio, grinding duration, charge ratio, extent of mill filling and the representative particle sizes at which 10%, 50% and 90% of the particles by weight are finer as predictor variables to predict P-wave velocity of sedimentary rocks such as limestone, using a hybridized random forest optimized with bio-inspired metaheuristic dolphin-swarm algorithm.

Model Establishment

Rocks often display non-linear behavior under various stress and their properties can vary due to anisotropic nature. Predictive models capture these complexities and provide more accurate estimation of rock properties. A brief overview of model development of hybrid random forest model optimized with dolphin swarm algorithm for regression is discussed as follows:

Random Forest (RF) model: Random forests, also known as random decision forests, represent ensemble learning techniques used for a variety of tasks such as classification and regression. These methods function by creating a collection of decision trees randomly and subsequently estimate the dominant class in classification or the average value in regression based on the outputs from individual trees.

These methods are generally considered improvements over traditional bootstrap regression techniques. In Random Forest algorithm, the feature space undergoes segmentation through various partitioning criteria. Initially, the algorithm identifies the corresponding region of an observed data point.

Subsequently, predictions are made based on either the mean or mode of all the data within that region. Regression trees offer the advantage of being able to capture complex relationships within the data and accommodate non-linear associations between predictors and targets due to their adaptive decision rules. However, when grown to maximum depth, they run the risk of overfitting the data, as the tree becomes overly complex[11].

Dolphin swarm optimization (DSO): The Dolphin swarm algorithm is a nature-inspired optimizing technique. It mimics the intelligent behavior of dolphins in their hunting and social interactions. This algorithm is used to solve complex optimization problems by simulating the cooperative hunting strategy of dolphins. The key steps involved in the Dolphin Swarm Optimization Algorithm are:

a) **Initialization:** Generate an initial population of dolphins randomly within the search space. Each dolphin represents a possible solution to the optimization problem.
b) **Evaluation:** Evaluate the fitness of each dolphin based on the objective function. The objective function measures the best solution.
c) **Update Positions:** Dolphins update their positions based on their own experiences and the best positions of their neighbors. This involves both exploitation (local search) and exploration (global search).
d) **Breaching and Echolocation:** Dolphins use a breaching mechanism to jump out of the water and search for prey. Echolocation helps dolphins to detect the location of prey and navigate towards it.
e) **Swarm Communication:** Dolphins communicate with each other to share information about the best positions. This helps in finding the optimal solution collectively.
f) **Convergence:** The algorithm iterates through the above steps until a stopping criterion is met (e.g. a maximum number of iterations or a satisfactory fitness level).

The general flow diagram for the implementation of hybrid random forest algorithm optimized with dolphin swarm algorithm is illustrated in Figure 1.

Material and Methods

Field visits were conducted to collect limestone samples from various mines located in different geographical regions in India. These samples were then transported to the laboratory. Limestone primarily comprises of calcium carbonate ($CaCO_3$) in the form of the mineral calcite. Additionally, it may contain minerals like quartz, feldspar, clay minerals, pyrite, siderite etc. Texture-wise, limestone exhibits a fine-grained or crystalline structure. Rock samples collected during field visits were prepared and tested in the laboratory for their properties as per ISRM suggested methods.

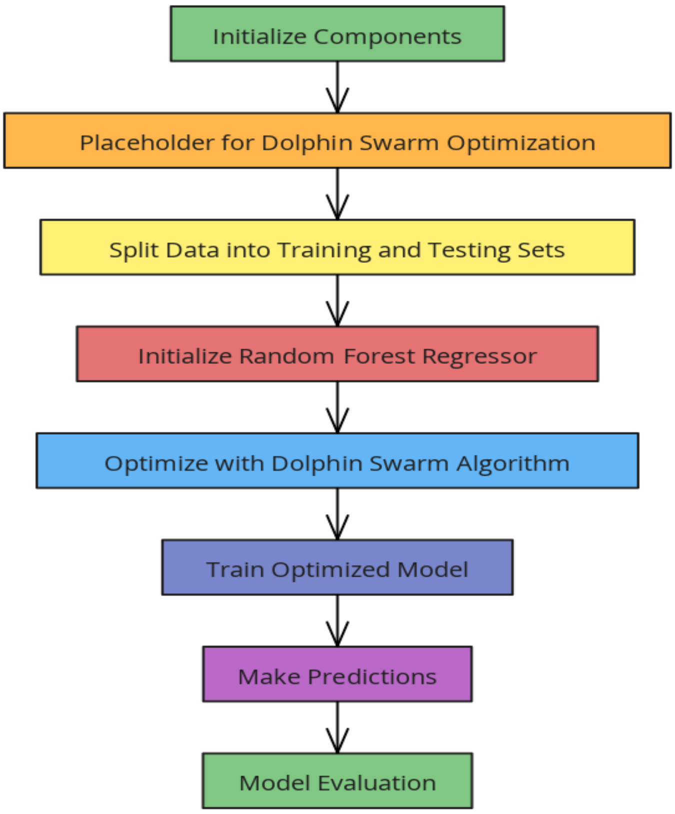

Figure 1: Proposed hybrid random forest regressor optimized with dolphin swarm algorithm for prediction of P-wave velocity

https://doi.org/10.25303/185da0109

In this study a total of 298 limestone core samples with standard NX size were tested to determine the P-wave velocity (V_p). These samples have a diameter of 54 mm, with a length-to-diameter ratio of 2.5 for rock properties determination. V_p is determined through direct transmission using a portable Cronosonic ultrasonic pulse testing device. This device accurately measures the time taken for ultrasound pulses to propagate, with a precision of 0.1 µs. The transducers used were operating at 47.2 kHz. The V_p tests were conducted perpendicular to the observed layers and the set-up is shown in figure 1. The P-wave velocities of the examined rocks vary within the range of 2043.71-6697.54 m/s. The laboratory test results for limestone samples are summarized in table 1. The mean P-wave velocity was found to be 4386.365 m/s with a standard deviation of 1054.7 m/s.

Ball mill grinding tests: In this investigation, rock specimens were initially fractured to an approximate size of 50-60 mm. Subsequently, the fragmented material underwent sieving to achieve a size range of –10+6.3 mm. The sieved rock charge obtained serves as the input feed for the ball mill. Grinding experiments were carried out using a traditional laboratory-scale ball mill with a total volume of 0.0865 m^3, as illustrated in figure 2. The mill operates at a speed of 55 rpm, which is 70% of its critical speed. To facilitate the grinding process, an adequate amount of grinding medium (high carbon high chrome steel balls having density = 7.35 g/cc) is added to the ball mill drum. For the dry grinding experiments, the test sample's volume is selected such that the combined volume of the sample and grinding media is less than 40% of the total mill volume. The grinding characteristics of the ball mill for limestone samples are shown in table 2.

Figure 2: Laboratory determination of P-wave velocity

Table 1
Descriptive statistical test results of P-wave velocity of limestone samples

Variable	N	Mean	Minimum	Maximum	StDev	Median	Range	Skewness	Kurtosis
P-wave velocity, m/s	298	4386.4	2043.7	6697.5	1054.7	4333.1	4653.8	-0.07	-0.80

Figure 3: A view of laboratory ball mill

Table 2
Grinding characteristics of ball mill with variations

Operating Parameters of Ball Mill	Parametric Variations
Feed Input (FI), g	1000, 1250,1500,1750,2000
Number of balls	125,135,140,145,155
Grinding Media Weight (GMW), g	15924, 18789, 20222, 23097, 25972
Grind time (τ), min	5, 7.5,10, 12.5,15
Mill volume occupied by sample charge (J_r), %	0.62 – 1.26
Mill volume occupied by ball charge (J_b), %	3.913, 4.617, 4.969, 5.676, 6.382
Interstitial filling ratio (U)	0.25 – 0.67
Charge ratio (υ)	15.924, 15.031, 13.481, 13.198, 12.986
Mill filling (ψ), %	4.71 – 10.88
Representative Particle sizes	**Size Ranges**
D_{10} (µm)	36.34 – 85.04
D_{50} (µm)	125.71 – 325.48
D_{90} (µm)	3790.7 – 5434.3

Certain parameters of the ball mill are estimated using the following expressions shown in eqs. 1 to 5:

$$J_r = \frac{\frac{m_r}{\rho_r}}{V_{mill}} * \frac{100}{1-\varepsilon} \quad (1)$$

$$J_b = \frac{\frac{m_b}{\rho_b}}{V_{mill}} * \frac{100}{1-\varepsilon} \quad (2)$$

$$\omega = \frac{J_r}{J_b} * \frac{1}{\varepsilon} \quad (3)$$

$$\upsilon = \frac{m_b}{m_r} \quad (4)$$

$$\psi = \frac{\left(\frac{m_r}{\rho_r}+\frac{m_b}{\rho_b}\right)}{V_{mill}} * \frac{100}{1-\varepsilon} \quad (5)$$

where m_r is the mass of rock charge, mb is the mass of balls charge, ρ_r, is density of rock charge, ρ_b is density of ball charge (ρ_b = 7.65 g/cc), V_{mill} is the mill volume and ε is bed porosity for ball mill (30-40%).

Results and Discussion

Correlation between P-wave velocity with grinding characteristics of ball mill is discussed. Sensitivity analysis is performed to identify significant predictors influencing the target variable P-wave velocity.

Prediction model for P-wave velocity: The performance of a ball mill in various industrial processes relies on a combination of its strength properties and operating parameters. Understanding the correlation between these factors is crucial for optimizing the performance of the mills, enhancing production output and achieving desired product quality[23]. In predictive modelling, especially regression task, the accuracy and robustness of the models are paramount. Traditional Random Forest (RF) models, while powerful, mostly rely on default or heuristic hyperparameter settings that may not yield optimal performance for complex datasets. To address this limitation, optimization techniques such as dolphin swarm optimizer (DSO) are increasingly integrated with machine learning models to fine-tune the hyperparameters, forming a hybrid approach.

The Hybrid Random Forest Dolphin Swarm-Optimizer (RF-DSO) method leverages the strength of both RF and DSO to improve the predictive accuracy and model generalization. The input data with which the RF-DSO model is trained, consists of grinding characteristics of ball mill as predictors. The hyperparameters were tuned for the optimal conditions that yield in higher accuracy of random forest regression models to predict P-wave velocity. For model development, the dataset was split into two parts: 238 samples (80% of the data) for training, 60 samples (20% of the data) for testing. The comparison between the predicted and actual p-wave velocity in both training and testing phase is shown in figure 4.

Performance evaluation of prediction models: One of the crucial steps in the development of a prediction model is the assessment of model based on performance indices reporting its validity for prediction. A few commonly used metrics for evaluating the performance of RF-DSO models include coefficient of determination (R^2), root mean square error (RMSE) and variance accounted for (VAF) and they are shown in eq. (6) to eq. (8). R^2 quantifies the strength and direction of linear relationship between the two variables. RMSE reflects the standard deviation of residuals. VAF measures the proportion of error variance relative to the variance in the observed data.

According to Hair et al[9], a VAF > 80% indicates full mediation, between 20% and 80% suggests partial mediation and < 20% implies no mediation. The proposed model is evaluated based on few statistical performance metrics such as Coefficient of Determination (R^2), Root Mean-Squared Error (RMSE) and Variance Account For (VAF) in both training and testing segments.

$$R^2 = 1 - \frac{\sum_i (y_a - y_p)^2}{\sum_i (y_a - y_m)^2} \quad (6)$$

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_p - y_a)^2} \quad (7)$$

$$\text{VAF} = \left(1 - \frac{Var(y_a - y_p)}{Var(y_a)}\right) * 100 \quad (8)$$

where N represents the number of samples, y_a represents the true value or actual value, y_p represents the predicted values and y_m represents mean value.

In figures 5, 6 and 7, training data an R^2 of 0.991, RMSE of 96.209 m/s and VAF of 99.16% are observed. Similarly, for testing phase, an R^2 of 0.973, RMSE of 112.209 m/s and VAF of 97.32% is noted.

Influence of critical grinding characteristics of ball mill on P-wave velocity: The impact of different grinding characteristics variables is assessed based on sensitivity analysis. This method is crucial for understanding how the model results are affected by different factors, enabling the identification of important factors that affect the output variables.

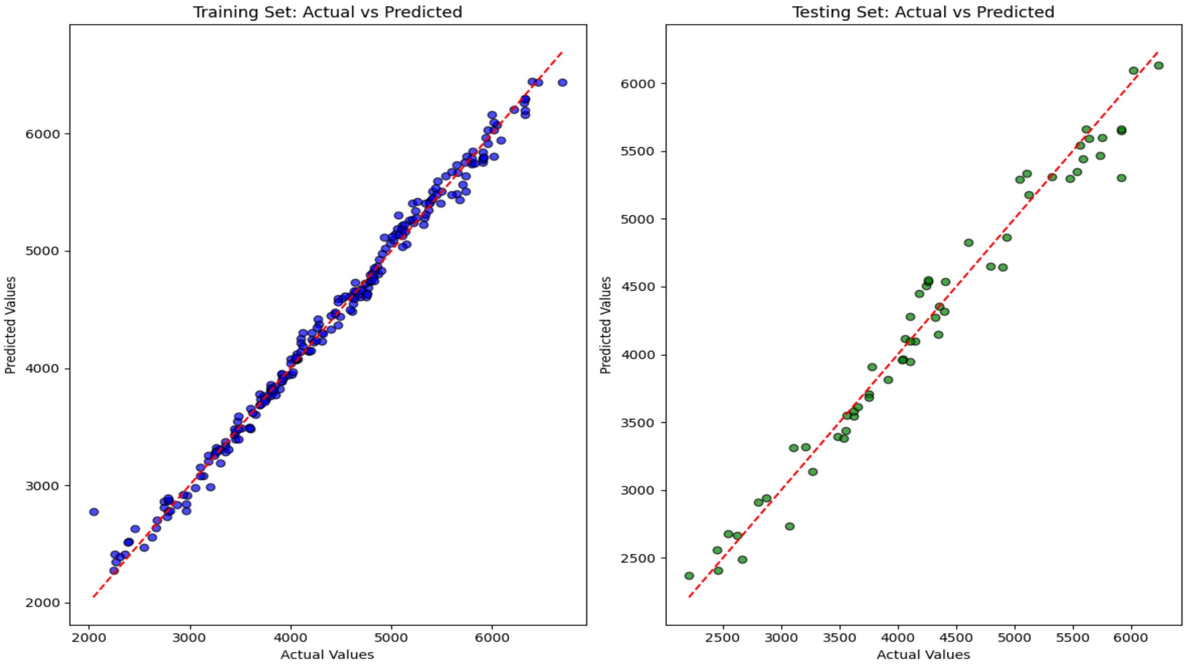

Figure 4: Predicted and actual P-wave velocity in both training and testing phase

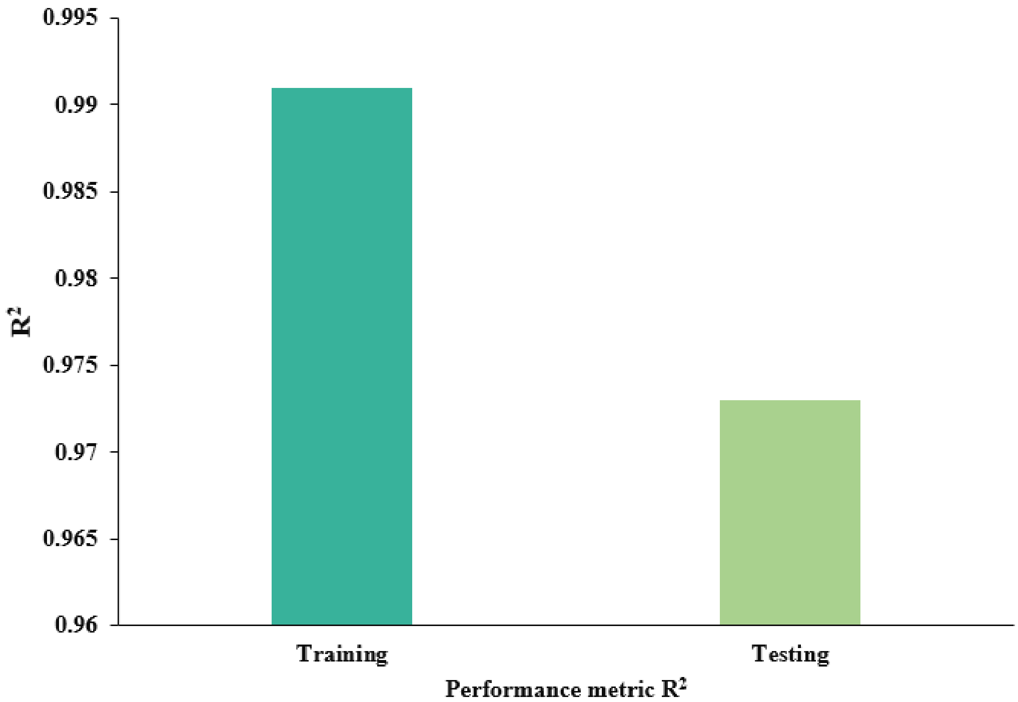

Figure 5: Performance comparison of RF-DSO model based on R^2

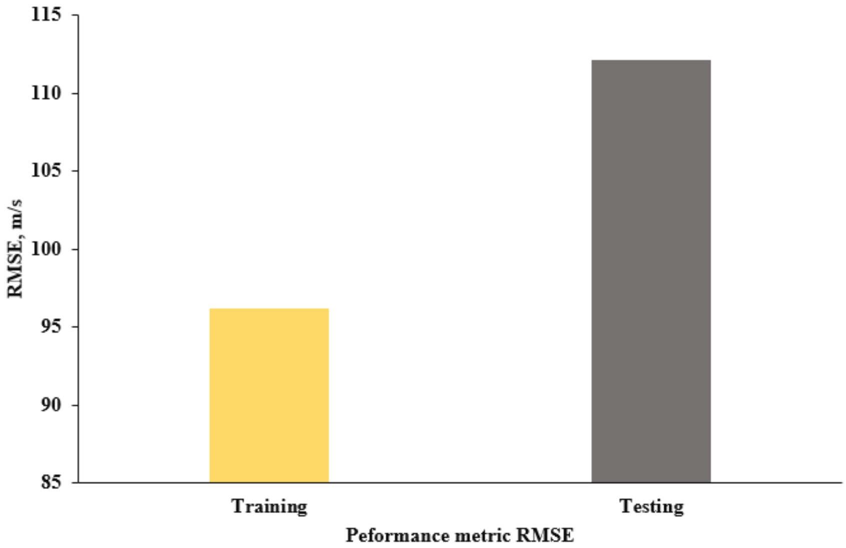

Figure 6: Performance comparison of RF-DSO model based on RMSE

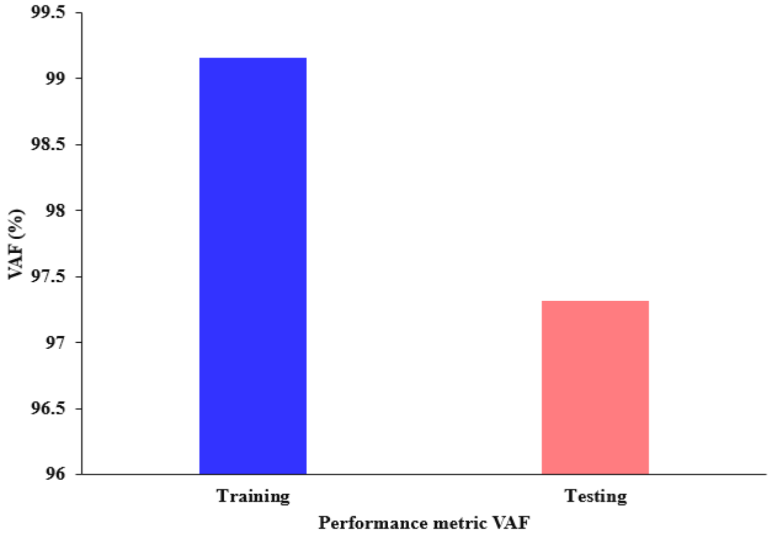

Figure 7: Performance comparison of RF-DSO model based on VAF

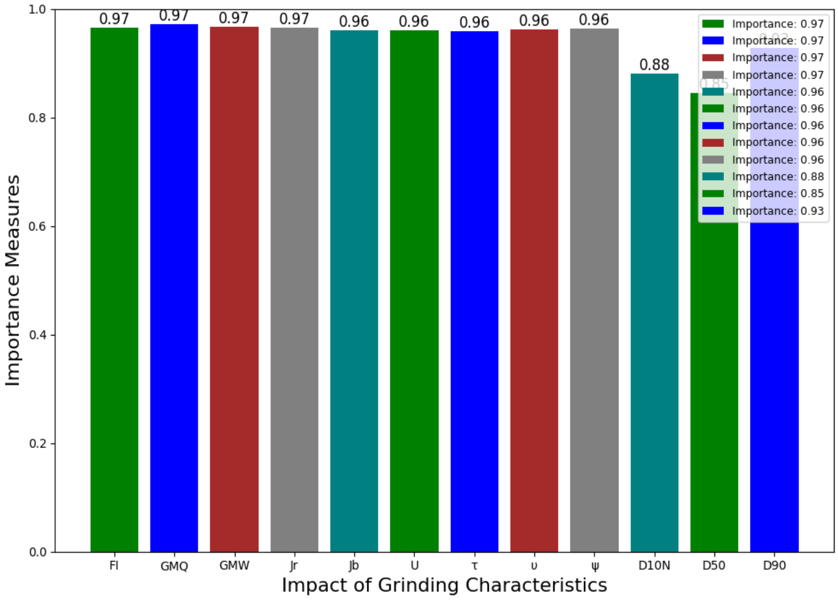

Figure 8: Impact of grinding characteristics of ball mill on P-wave velocity

By methodically altering the input parameters within a specified range and analyzing the resulting changes in the outputs, sensitivity analysis quantifies the effect of each input variable. In this study, the sensitivity analysis is performed using the cosine amplitude method, which quantifies the sensitivity by measuring the angular similarity between the input and output vectors. This allows for an efficient evaluation of the relationships between the input parameters and model output.

As depicted in figure 8, apart from D_{10} and D_{50} variables, most of the grinding characteristics have shown to influence the P-wave velocity as the importance measure is more than 0.9. This analysis provides valuable insights into the relative importance of each parameter and highlights the critical factors that affect the compressive strength of rocks.

Conclusion

Numerous researchers have investigated into various indirect methodologies for the estimation of rock properties, particularly when the direct assessment of these properties in rock engineering projects proves to be intricate and time-consuming. This study introduces an innovative approach that utilizes the grinding characteristics of a ball mill to predict P-wave velocity. The distinctive advantage of this method over other indirect techniques lies in its capacity to offer precise and direct insights into the behavior of rocks under diverse conditions. This study introduces a hybrid random forest model enhanced with the dolphin swarm algorithm to predict P-wave velocity from grinding characteristics.

The metrics of performance of the model indicate a high degree of accuracy, indicating a robustness and reliability of the model. It may be noted that the rock properties are also dependent on the mineralogical and petrographical features of charge involved in grinding. Hence, a detailed investigation may be carried out as a scope for future work to explore the intensive relationship between the grinding characteristics of ball mill and rock properties.

References

1. Altindag R., Correlation between P-wave velocity and some mechanical properties for sedimentary rocks, *J. the Southern African Institute of Mining and Metallurgy*, **112(3)**, 229-37 **(2012)**

2. Aras A., Aras A., Özşen H. and Dursun A.E., Using Artificial Neural Networks for the Prediction of Bond Work Index from Rock Mechanics Properties, *Mineral Processing and Extractive Metallurgy Review*, **41(3)**, 145–52 **(2020)**

3. Asghari M., Vand Ghorbany O. and Nakhaei F., Relationship among operational parameters, ore characteristics and product shape properties in an industrial SAG mill, *Particulate Science and Technology*, **38(4)**, 482–93 **(2020)**

4. Avinash D., Kumar K.P., Umamahesh A. and Chandar K.R., Prediction of rock properties using grinding characteristics of ball mill, *Int. J. Mining and Mineral Engineering*, **11(4)**, 285 **(2020)**

5. Basarir H. and Dincer T., Prediction of rock mass P-wave velocity using blasthole drilling information, *Int. J. Mining, Reclamation and Environment*, **33(1)**, 61–74 **(2019)**

6. Bery A.A. and Saad R., Correlation of Seismic P-Wave Velocities with Engineering Parameters (N Value and Rock Quality) for Tropical Environmental Study, *Int. J. Geosciences*, **3(4)**, 749–57 **(2012)**

7. Fa L., Yang H., Fa Y., Meng S., Bai J., Zhang Y., Fang X., Zou X., Cui X., Wang Y. and Zhao M., Progress in acoustic measurements and geoacoustic applications, *AAPPS Bulletin*, **34(1)**, 23 **(2024)**

8. Hadi F.A. and Nygaard R., Shear Wave Prediction in Carbonate Reservoirs: Can Artificial Neural Network Outperform Regression Analysis?, *One Petro*, **52**, 16-23 **(2018)**

9. Hair J.F., Ringle C.M. and Sarstedt M., PLS-SEM: Indeed, a Silver Bullet, *J. Marketing Theory and Practice*, **19(2)**, 139–52 **(2011)**

10. Heidari M., Khanlari G.R., Kaveh M.T. and Kargarian S., Predicting the uniaxial compressive and tensile strengths of gypsum rock by point load testing, *Rock Mechanics and Rock Engineering*, **45(2)**, 265–73 **(2012)**

11. James G., James G., Witten D., Hastie T., Tibshirani R. and Taylor J., An introduction to statistical learning: With applications in python, Springer Nature **(2023)**

12. Kahraman S., Toraman O.Y. and Cayirli S., Predicting the strength and brittleness of rocks from a crushability index, *Bulletin of Engineering Geology and the Environment*, **77(4)**, 1639–45 **(2018)**

13. Kahraman S. and Yeken T., Determination of physical properties of carbonate rocks from P-wave velocity, *Bulletin of Engineering Geology and the Environment*, **67(2)**, 277–81 **(2024)**

14. Karakul H. and Ulusay R., Empirical correlations for predicting strength properties of rocks from P-wave velocity under different degrees of saturation, *Rock Mechanics and Rock Engineering*, **46(5)**, 981–99 **(2013)**

15. Kassab M.A. and Weller A., Study on P-wave and S-wave velocity in dry and wet sandstones of Tushka region, Egypt, *Egyptian J. Petroleum*, **24(1)**, 1–11 **(2015)**

16. Kekec B., Unal M. and Sensogut C., Effect of the textural properties of rocks on their crushing and grinding features, *J. Univ. Science and Technology Beijing*, **13(5)**, 385–92 **(2006)**

17. Kim J., Kang J. Do and Kim B., Machine-learning models to predict P- and S-wave velocity profiles for Japan as an example, *Frontiers in Earth Science*, **11**, 1267386 **(2023)**

18. Lakshminarayana C.R., Tripathi A.K. and Pal S.K., Prediction of Mechanical Properties of Sedimentary Type Rocks Using Rotary Drilling Parameters, *Geotechnical and Geological Engineering*, **38(5)**, 4863–76 **(2020)**

19. Mishra D.A. and Basu A., Estimation of uniaxial compressive strength of rock materials by index tests using regression analysis

and fuzzy inference system, *Engineering Geology*, **160**, 54–68 **(2013)**

20. Najibi A.R. and Asef M.R., Prediction of seismic-wave velocities in rock at various confining pressures based on unconfined data, *Geophysics*, **79(4)**, D235–42 **(2014)**

21. Petrakis E. and Komnitsas K., Correlation between material properties and breakage rate parameters determined from grinding tests, *Applied Sciences*, **8(2)**, 220 **(2018)**

22. Salaamah A.F., Fathani T.F. and Wilopo W., Correlation of P-wave Velocity with Rock Quality Designation (RQD) in Volcanic Rocks, *J. Applied Geology*, **3(2)**, 11**(2019)**

23. Santosh T., Eswaraiah C., Soni R.K. and Kumar S., Size reduction performance evaluation of HPGR/ball mill and HPGR/stirred mill for PGE bearing chromite ore, *Advanced Powder Technology*, **34(1)**, 103907 **(2023)**

24. Shen W., Liu S., Yang D., Wang W., Xu X. and Yang S., The crustal and uppermost mantle dynamics of the Tengchong–Baoshan region revealed by P-wave velocity and azimuthal anisotropic tomography, *Geophysical J. Int.*, **230(2)**, 1092–105 **(2022)**

25. Singh T.N., Kanchan R., Verma A.K. and Saigal K., A comparative study of ANN and Neuro-fuzzy for the prediction of dynamic constant of rockmass, *J. Earth System Science*, **114(1)**, 75–86 **(2024)**

26. Umucu Y., Deniz V., Bozkurt V. and Fatih Çağlar M., The evaluation of grinding process using artificial neural network, *Int. J. Mineral Processing*, **146**, 46–53 **(2016)**

27. Yagiz S., Sezer E.A. and Gokceoglu C., Artificial neural networks and nonlinear regression techniques to assess the influence of slake durability cycles on the prediction of uniaxial compressive strength and modulus of elasticity for carbonate rocks, *Int. J. for Numerical and Analytical Methods in Geomechanics*, **36(14)**, 1636–50 **(2012)**.

(Received 21st November 2024, accepted 25th December 2024)