A machine learning model to estimate in-situ rock strength from borehole geophysical logs

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ABSTRACT: This paper proposes an artificial neural network (ANN) model, which aims to improve the estimation accuracy of in-situ rock uniaxial compressive strength (UCS) for the Australian mining industry. The model utilises borehole geophysical logs (i.e., sonic, neutron, gamma and porosity logs) and rock density as inputs. A dataset of 274 samples from two mine sites in Australia is applied for the training, testing and validation of the model. Compared with the conventional sonic velocity model, the mean absolute percentage error of the predictions improves from 34.3% to 19.8% and the root mean squared error is reduced by over 4.6 MPa. In addition, it is also obtained that the accuracy of the model varies depending on the lithologies and mine locations. The proposed model is expected to provide more accurate rock strength estimations and be beneficial for further geotechnical analysis, such as estimating in-situ stresses based on borehole breakout.

Keywords: Uniaxial compression strength, In-situ rock strength estimation, Borehole geophysical logs, Artificial neural network.

1 INTRODUCTION

In-situ rock strength is a crucial parameter for design and safety in underground operations. In the current Australian mining industry, the sonic velocity models are widely adopted to estimate rock uniaxial compressive strength (UCS) to represent the in-situ rock strength (McNally, 1987; Oyler et al., 2010). The models are constructed based on the empirical relationship between laboratory-measured UCS and sonic logs in the form of Eq. (1) (McNally, 1990). Despite the simplicity and practical aspect of the approach, the estimation accuracy could vary significantly between mine sites (Hatherly et al., 2002; Butel et al., 2014), and the effectiveness of such models was questioned by Medhurst et al. (2010).

$$UCS = a \times e^{b \times v} \tag{1}$$

where a and b are fitting coefficients, and v is the sonic velocity obtained from sonic logs.

Machine learning techniques have been employed to estimate the in-situ rock strength from borehole logs, and these models generally produce more accurate predictions compared to the conventional empirical methods (Yilmaz & Yuksek, 2009; Sharma et al., 2010; Majdi & Rezaei, 2013; Miah et al., 2020). Among the machine learning approaches, artificial neural network (ANN) is one of the most widely adopted methods for this purpose due to its capability and flexibility in complex regression analysis. However, current models are primarily developed based on petroleum data and have not yet been widely tested in mining applications due to the difference between mining and petroleum logging systems (Butel et al., 2014; Gan et al., 2016).

To address the abovementioned challenges, a new ANN model based on Australian mineral logging data is proposed in this study to estimate intact rock UCS. The impacts of lithology and mine locations on the model performance were also evaluated.

2 DATA COLLECTION

The borehole geophysical logging data used in this study were collected from 35 boreholes in two longwall coal mines (Mine A and Mine B) in Australia. In total, 274 UCS were obtained at depths around 300 m to 600 m, with the values mostly ranging from 15 to 75 MPa. Four types of geophysical logs were extracted at the same locations as the UCS samples were cored: sonic, gamma, neutron, and porosity logs. In addition to the logging data, the density of the core samples measured in the laboratory was also utilised as one of the inputs. The sizes of tested samples are around 60 mm (diameter) × 150 mm (height), and one sample was tested over each logging interval. The empirical sonic velocity models used in Mine A and Mine B are given in Eqs. (2) and (3), respectively.

$$UCS = 6.313 \times e^{0.0005664 \times v} \; (Mine\ A) \tag{2}$$

$$UCS = 1352 \times e^{-\frac{12500}{v}} \; (Mine\ B) \tag{3}$$

3 MODEL DEVELOPMENT AND RESULTS

The correlation between each input and the UCS values is illustrated in Figure 1. In general, the rock UCS exhibits positive correlations with the sonic velocity, density and neutron logs, and a negative relationship can be observed between the porosity of the rock and the UCS values. The gammy log does not seem to be linearly correlated with the UCS. Nonetheless, a nonlinear correlation may exist, and thus, it is still included in the analysis.

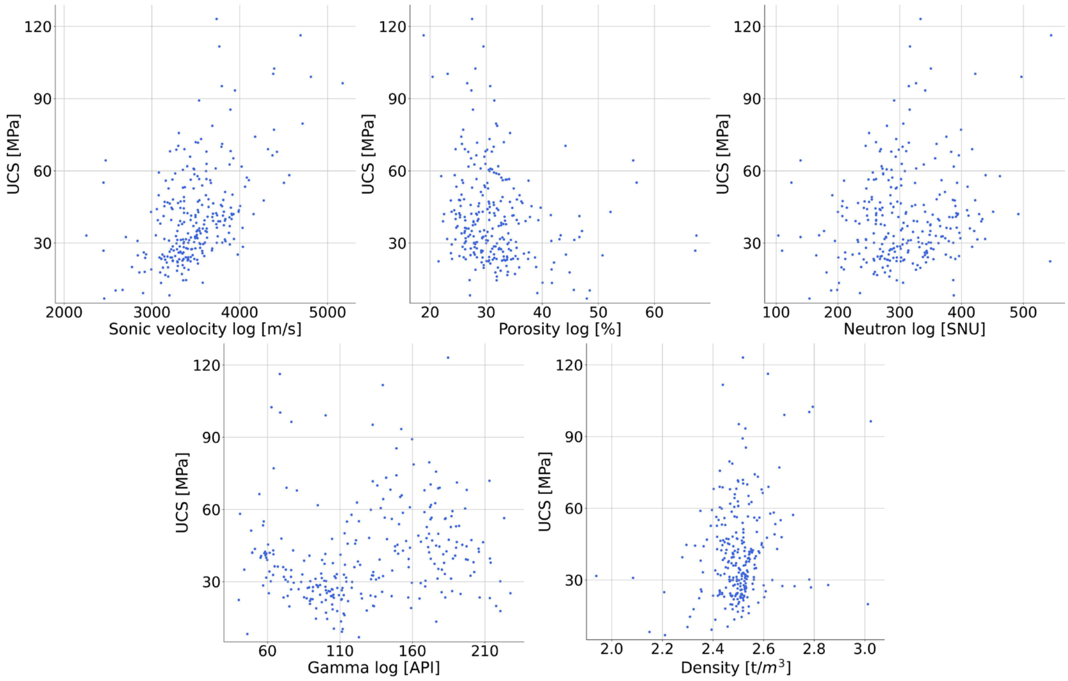


Figure 1. Correlations of the rock UCS with borehole logs and rock density.

The ANN model used in this study consists of one input layer, two hidden layers, and one output layer, with the mean squared error (MSE) as the loss function. The input data were divided into training (75%), validation (15%), and test (10%) subsets. The training was carried out through the Levenberg–Marquardt (LM) algorithm as it outperformed other algorithms for this purpose (Ceryan et al., 2013). Three performance measures were used to evaluate the prediction accuracy of the models: mean absolute percentage error (MAPE), root mean squared error (RMSE), and maximum absolute error (MAE). These performance measures could reflect the mean discrepancy and maximum error of the model compared to the target values. The number of neurons for each layer was tested from 1-15 per hidden layer and was determined to optimise the model performance while avoiding overfitting by checking if the performance measure values are consistent across training, validation and test datasets. The model with the lowest MAPE, RMSE and MAE across all three subsets was selected as the final model.

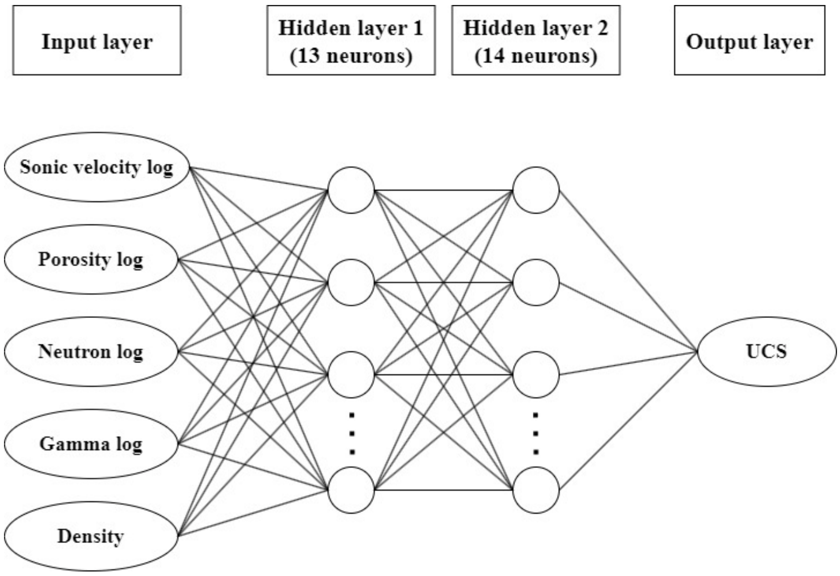
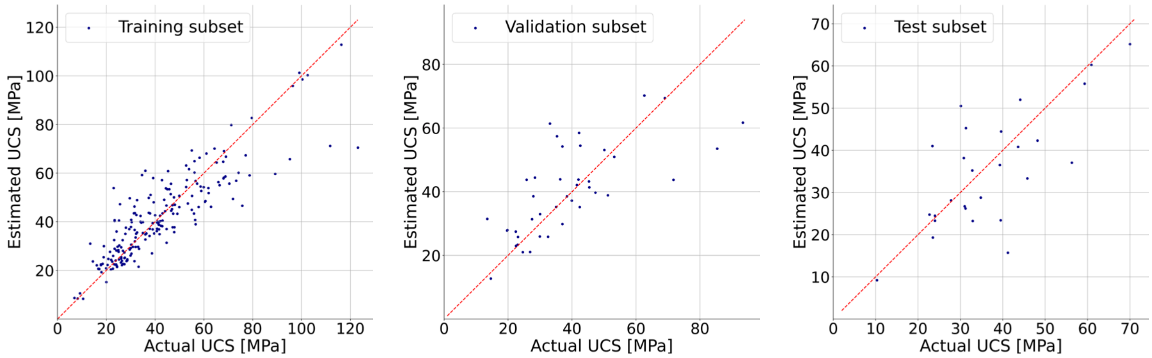


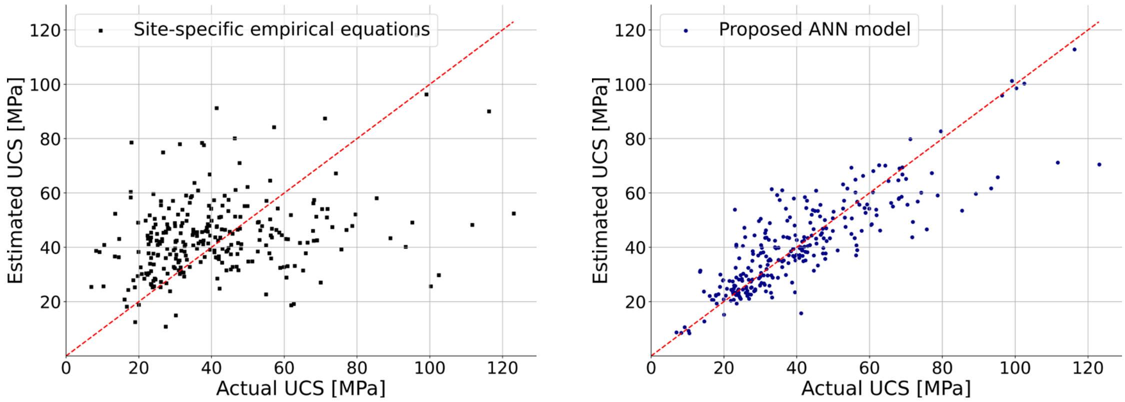
Figure 2. Schematic diagram of the architecture of the ANN model developed in this study.

Based on a series of trials, the model with 13 neurons in the first hidden layer and 14 neurons in the second hidden layer was selected as the optimised model (Figure 2). The predicted performance of the model on each subset is shown in Figure 3 and compared with the empirical models used in the studied mine sites (Eqs. (2) and (3)) in Figure 4. The red dotted lines represent the perfect linear fit. Relatively accurate predictions can be seen when the UCS is under 60 MPa, while slight underestimation is observed when the UCS is greater than 70 MPa, which is believed to be caused by the small number of data exceeding such value in the dataset (18 data). Nonetheless, the new model still significantly improved the accuracy of UCS estimation compared to empirical models, and the MAPE, RMSE and MAE are reduced from 34.3%, 15.2 MPa and 70.66 MPa to 19.8%, 10.6 MPa and 52.6 MPa, respectively.



(a) (b) (c)

Figure 3. Model performance on (a) training, (b) validation, and (c) test subsets.



(a) (b)

Figure 4. Performance comparison between (a) the site-specific equations used in the studied mine sites and (b) the proposed ANN model.

4 DISCUSSION

Further analysis was carried out by splitting the dataset based on the lithology and mine locations. Among the collected data, there are mainly three lithologies: sandstone (88 data), siltstone (79 data) and interbedded sandstone and siltstone (84 data). The prediction accuracies for these three lithologies are listed in Table 1. The model exhibits similar accuracy for sandstone and siltstone datasets, with MAPE and RMSE at around 18.3-18.4% and 8.1-8.9 MPa, respectively. On the other hand, the predictive performance for interbedded sandstone and siltstone is considerably worse than that of sandstone and siltstone. This is believed to be attributed to the rock heterogeneity and anisotropy caused by the different grain sizes of sandstone and siltstone, which may affect the mechanical properties of the core samples.

Moreover, the dataset was also split based on the mine locations to investigate the impact of local geological conditions on the estimation accuracy (Table 1). The results show that the model performed better on Mine A data compared to Mine B data. Specifically, the MAPE, RMSE and MAE of Mine A data are 5.3%, 6.4 MPa and 27.6 MPa lower compared to those of Mine B, respectively. This suggests that the performance of the model is also affected by the mining horizon.

Table 1. Model performance on each subset.

Subset	Number of data	MAPE (%)	RMSE (MPa)	MAE (MPa)
Sandstone	88	18.3	8.1	21.6
Siltstone	79	18.4	8.9	40.5
Interbedded sandstone and siltstone	84	22.7	13.1	31.9
Mine A	143	22.4	13.9	52.6
Mine B	131	17.1	7.5	25.0

5 CONCLUSION

In this study, an ANN model was proposed based on borehole geophysical logs (sonic, gamma, neutron and porosity logs) and rock density to estimate in-situ rock UCS. The model was developed using 274 data collected from 35 boreholes in two Australian coal mines. The structure of the model was determined based on trials, and the LM algorithm was used for model training. Compared to the empirical equations used in the studied mine sites, the MAPE, RMSE, and MAE of the proposed model were improved from 34.3%, 15.2 MPa and 70.66 MPa to 19.8%, 10.6 MPa and 52.6 MPa, respectively. The improved accuracy indicated the proposed machine learning approach based on four borehole logs and rock density could more effectively capture the variation of rock strength under different geological conditions and provide more reliable in-situ rock strength predictions. Furthermore, it was found that the model predictive performance varies depending on the lithologies and mine locations, and thus, further model improvement is suggested to take the impacts of these two factors into account.

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