Investigation on Estimation and Prediction of Resistivity of Limestone Rocks based on Physico-Mechanical Properties of Rocks

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Abstract
Prediction of rock resistivity indirectly is of paramount importance in several geophysical and civil engineering applications. Physico-mechanical properties such as p-wave velocity, porosity and dry density tend to have a good correlation with electrical resistivity of rocks. Conventional approaches for measuring resistivity produce results which may consume more time and efforts and are not accessible every location. To overcome this, an Artificial Neural Network (ANN) model was evolved in this study, using Python and TensorFlow. The model was trained using known values to predict electrical resistivity of unknown and similar materials. Actual results of resistivity were compared with resistivity values obtained from ANN model. The obtained values were evaluated for reliability using non-linear regression models.

It was observed that predicted resistivity values generated using p-wave velocity were more reliable. Also, validations made based on the ANN model, using mean absolute error (MAE) and average residuals indicate that P-wave velocity is the most reliable predictor, achieving the lowest MAE (4.638) and near-zero residuals (-0.005), while porosity and dry density showed higher errors and weaker correlations. This study revealed that the ANN model developed results in reliable predictions of rock resistivity based on p-wave values.

Keywords: Resistivity prediction, Artificial neural networks, P-wave velocity, Porosity, Dry density.

Introduction

Prediction of resistivity of rocks is quite essential in applications in geophysics, petrophysics and civil engineering, especially in inaccessible locations[2]. Resistivity is a basic property of rocks that reflects its ability to conduct electrical current and is influenced by various physical and mechanical properties, as well as its mineral composition. These properties play a vital role in determining movement of fluids and electricity through rock formations. Thus prediction of resistivity from mechanical properties is highly valuable in both theoretical and practical aspects[20]. However, the relationship between physico-mechanical properties and resistivity is complex and therefore conventional predictive models are inadequate in predicting with reliable values[21].

Conventional predictivity models tend to give errors when applied to rocks with heterogeneous structures or varying mineral compositions[6]. Limestone, which has minerals such as quartz and pyrite, shows resistivity that cannot be sufficiently understood by simple models[9]. These errors tend to make predictions which are unreliable in practical applications[16]. The use of artificial neural networks (ANN) in this context provides a lucrative alternative to conventional linear models in prediction of resistivity. Non-linear fit of data can give predictivity of regression compared with linear fit of data[14].

Thus, ANNs have a good scope in effectively predicting complex geological properties. However, it is application in rock resistivity prediction, using physico-mechanical properties, is yet to be explored[17]. Much of the present literature has been around prediction using properties such as porosity and fluid saturation. Investigation on physico-mechanical properties including P-wave velocity, porosity and dry density in prediction of resistivity is still not fully explored[1,9]. Limestone, has a diverse microstructure and its mineralogy is unique and conventional methods of prediction have low predictivity of resistivity[10,13]. This warrants a thorough investigation on models that could reliably evaluate the predictivity potential for limestone, especially using ANN models[7].

This study is aimed to fulfil this requirement, by developing an ANN-based model to predict rock resistivity based on P-wave velocity, porosity and dry density. Unlike conventional models, this proposed ANN model is designed to use non-linear relationships between these physico-mechanical properties, to yield a more reliable approach in predicting resistivity in limestone. The performances of different models developed would be evaluated using key metrics such as Mean Absolute Error (MAE) and Average Residuals[6]. So, this study would provide a new approach to resistivity prediction and would also contribute to the existing State-of-the-Art on the application of machine learning in prediction of resistivity of limestone rocks and would aim to overcome the limitations of existing models.

Material and Methods

Limestones of 20 numbers were collected from Yerraguntla, Andhra Pradesh, India. The samples were used for further laboratory investigations such as porosity, dry density, P-

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wave velocity and resistivity. The location map is illustrated in figure 1.

Resistivity measurement: Resistance measurement is carried out for limestone rocks using a resistivity digital multimeter. The exact setup of resistivity measurement is shown in figure 2. Rock samples were cut into cylindrical shape, extracted at specific orientations to maintain consistency in measurements. The prepared samples are illustrated in figure 3. Electrodes were connected to both sides of the rock samples and a direct current (DC) was applied to it. Samples were tested under dry conditions to eliminate the influence of moisture on resistivity. The obtained dataset acts as actual resistivity data.

P-wave velocity measurement: Ultrasonic pulse velocity method was used to measure the P-wave velocity of limestone rock samples and the setup of the same is shown in figure 4. This is a non-destructive method which uses calculation of travel time of waves through the rock samples. The arrangement consists of a generator and receiver. They are placed on the opposite ends of the rock core sample. An ultrasonic pulse is passed through the rock and the time taken for the pulse to travel between the transducers is noted.

$$V = \frac{L}{t} \tag{1}$$

where 'V' is the P-wave velocity (m/s), 'L' is the distance (m) between the transducers and 't' is the transit time (s). The velocity of P-waves is calculated using eq. 1:

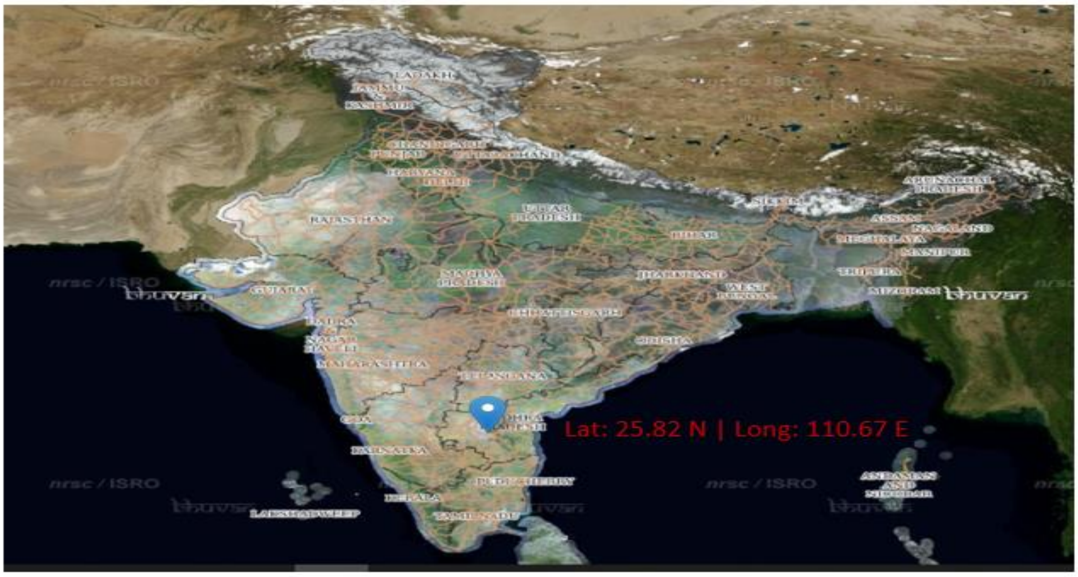

Figure 1: Location Map with Latitude and Longitude of Yerrguntla, Andhra Pradesh, India. (Source: Bhuvan app, NRSC)[10]

Figure 2: Resistance measurement setup for rocks

Figure 3: Core samples of limestone rocks

Figure 4: Measurement of P-wave velocity of limestone rock.

Porosity and dry density: Porosity of limestone rocks is measured using Archimedes principle. The volume of rock sample was measured by measuring displaced water. Initially, the samples are dried and the weight is calculated. The displaced water is measured by submerging the rock sample in a graduated jar and by measuring the difference in water level, before and after submerging the sample. Porosity is obtained by calculating the difference in the dimensional volume of the rock to the volume obtained by displacement of water.

Artificial Neural Network (ANN): Artificial Neural Network (ANN) model is developed using Python software and the Tensor Flow library to predict rock resistivity based on physico-mechanical properties such as porosity, dry density and P-wave velocity. The ANN model is designed with an input layer for porosity, dry density and P-wave velocity. Several hidden layers are designated to establish non-linear relationships. Similarly, an output layer is designated to predict resistivity. The dataset is divided into training and testing subsets. The training data is utilized to adjust the network's weights effectively, employing the backpropagation algorithm for optimization.

Library of Tensor Flow consists of tools which enable real-time monitoring of the model's performance. Suitable adjustments were made to the learning phase and network architecture to maximise accuracy. After the training phase, the ANN model was validated with test data and the predicted resistivity values were compared with actual data of resistivity to assess the model's accuracy.

Validation of predictions: Mean Absolute Error (MAE) and Average Residuals are used to validate data and to find the best fit for limestone rock resistivity[6]. The MAE measures the average magnitude of the errors in predictions and is calculated using eq. 2:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (2)$$

where'y_i' is the actual resistivity value for the 'y_i^{th}' sample, $\hat{y}_i$'is predicted resistivity value for the 'y_i^{th}-' sample and n is the total number of samples. Lower is the MAE value, better is the fit.

Similarly, Average Residuals, is calculated using eq. 3:

$$Average\ Residuals = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i) \quad (3)$$

A near-zero value for average residuals implies the best fit.

Results and Discussion

The estimation and prediction of rock resistivity were performed using ANN based on various physico-mechanical properties of limestone materials such as porosity, dry density and P-wave velocity. Relationships between these properties and resistivity are analysed and the performance of the predictive models was evaluated through MAE and average residuals analysis to assess the reliability of the predictions.

Characterization Studies of Limestone Rocks: Scanning Electron Microscopy (SEM) analysis was carried out to analyse the microstructural characteristics of limestone samples. The SEM image of sample 1 is shown in figure 5a. It can be observed that it has minimal visible cracks, indicative of a stable and compact structure. Mineral constituents such as FeO, quartz and $CaCO_3$ contribute to the mechanical strength of the sample. This kind of structure has less porosity and more resistivity due to reduced water ingress. This ensures durability and stability of limestone rocks[8,17]. Similarly, figure 5b analysis reveals a slightly rougher texture with minor cracks. The mineral composition of both the limestone rock samples is almost the same, consisting of calcite (72%), quartz (18%) and pyrite (6%).

The EDAX (Energy Dispersive X-ray Analysis) images, corresponding to the sample 1 and sample 2 images in figure 5a and figure 5b, are presented in figure 6a and figure 6b respectively. Results of these investigations offer insights into the elemental composition of the rock samples from the Yerraguntla region. Figure 5a reveals presence of iron (Fe), silicon (Si) and calcium (Ca), indicating the existence of FeO, quartz (SiO_2) and $CaCO_3$. Similarly, figure 5b too exhibits a similar elemental composition, with significant presence of Fe (2.33%), Si (7.01%) and Ca (32%), with a few dominating the previous sample. These variations may explain the presence of minor cracks and slightly higher porosity observed in the corresponding SEM image.

Physico-mechanical properties of Limestone materials: The experimental results of physico-mechanical properties such as P-Wave Velocity (m/s), porosity (%), dry density (g/cm³) and Resistivity (Ohm-m) for 20 limestone rocks are presented in table 1.

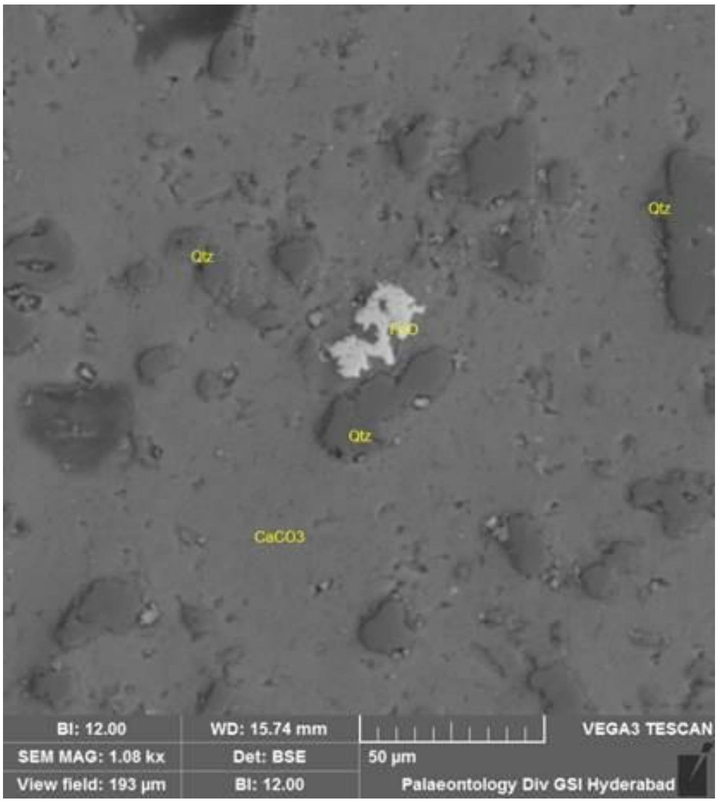

Figure 5a: SEM Image of limestone Rock Sample 1 from Yerraguntla Region, Andhra Pradesh State, India.

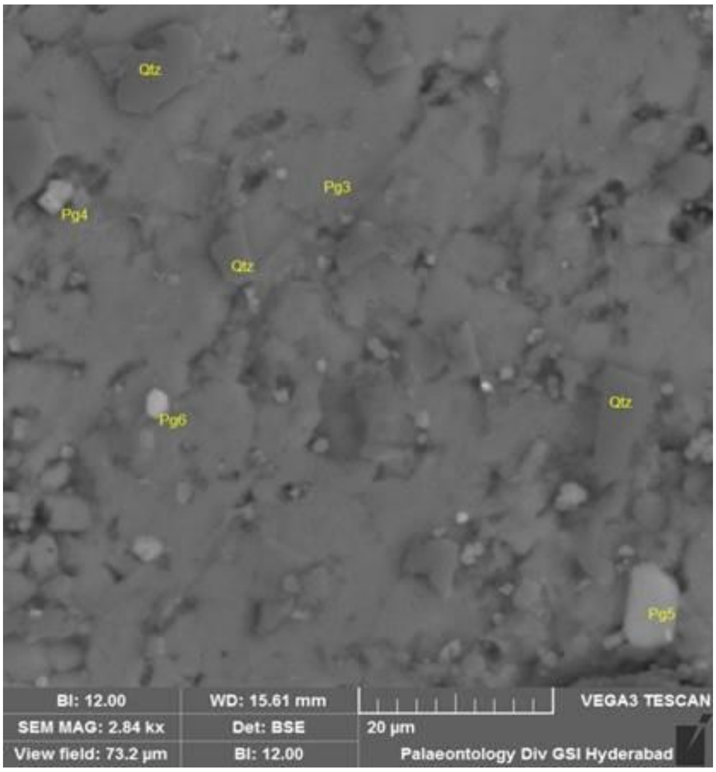

Figure 5b: SEM Image of Limestone Rock Sample 2 from Yerraguntla Region, Andhra Pradesh State, India.

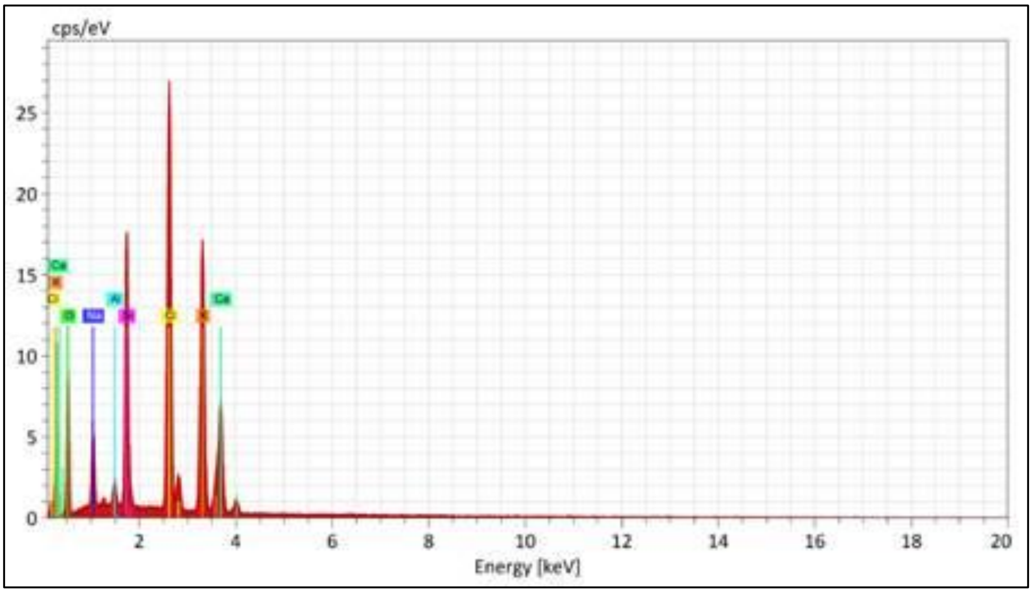

Figure 6a: Energy Dispersive X-ray Analysis graph of Limestone rock sample 1 from Yerraguntla Region, Andhra Pradesh State, India.

As per the table 1, it can be observed that the limestone samples exhibit a generally high P-wave speed ranges 4318.2 - 7090.9 m/s, with lower porosity values mostly below 0.5%, except sample 19 at 1.85%, indicating a dense and compact structure. Dry density remains relatively consistent, mostly between 2.63 and 2.80 g/cm³, suggesting uniformity in composition across samples. Resistivity varies significantly from 32.50 to 50.86 Ohm-m, showing higher values in samples with slightly higher porosity, potentially reflecting changes in mineral composition or microstructural differences.

Resistivity of limestone samples using Artificial Neural Networks:

Predictions on resistivity, generated by ANN, based on dependencies on P-wave velocity, porosity and dry density are presented. The reliability of these findings and the metrics to evaluate the best fit are demonstrated using ANN.

Porosity based Resistivity predictions: Findings from ANN model predictions on resistivity are graphically presented in figure 7. It shows a plot between actual resistivity and predicted resistivity derived from porosity using artificial neural networks (ANN). Non-linear regression graphs are plotted and presented in this plot. An upward trend of the graph suggests a positive correlation between actual and predicted resistivity. However, the wide scatter of points around the curve, at lower resistivity values, indicates a lower correlation between porosity and resistivity predictions, using ANN. This kind of discrepancy was also observed in earlier studies between porosity and resistivity[11].

Results of the ANN model shows a positive trend in predicting resistivity from porosity, with actual and predicted resistivity values aligning well at higher resistivity levels. However, a wider scatter at lower resistivity values indicates inconsistencies in predictions, suggesting weaker correlations between porosity and resistivity in those ranges.

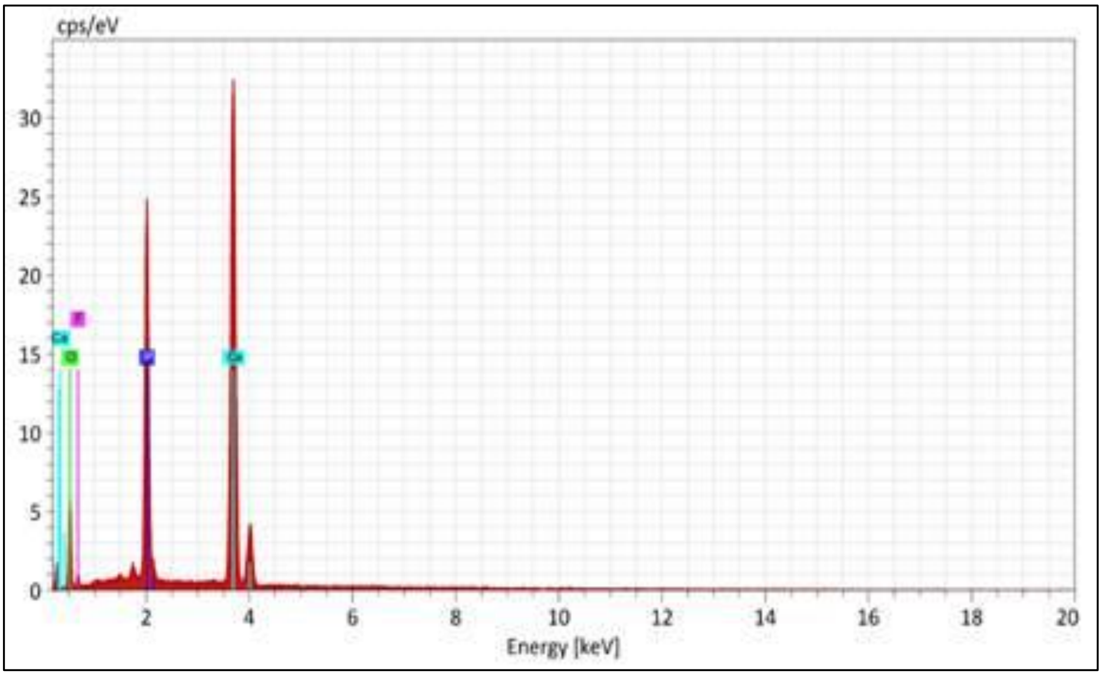

Figure 6b: Energy Dispersive X-ray Analysis graph of Limestone rock sample 2 from Yerraguntla Region, Andhra Pradesh State, India

Table 1
Physico-mechanical properties of limestoneRock Samples

Sample No.	P-Wave Velocity (m/s)	Porosity (%)	Dry Density (g/cm³)	Resistivity (Ohm-m)
1	6253.4	0.14	2.K3	39.46
2	4318.2	0.07	2.69	40.15
3	6132.1	0.06	2.70	32.50
4	6256.2	0.33	2.71	36.04
5	6552.7	0.11	2.71	36.74
6	5971.6	0.06	2.64	33.53
7	6308.1	0.32	2.72	35.48
8	6050.8	0.09	2.71	34.94
9	6265.1	0.23	2.80	32.50
10	6545.5	0.49	2.66	50.86
11	6318.4	0.19	2.72	33.27
12	7090.9	0.10	2.41	36.12
13	6548.7	0.30	2.71	41.24
14	6222.2	0.16	2.68	36.33
15	6489.7	0.07	2.52	41.61
16	6709.3	0	2.71	43.60
17	5570.3	0.32	2.73	43.6
18	6139.2	0.09	2.72	43.56
19	6598.6	1.85	2.67	43.56
20	6543.2	0.76	2.63	43.56

P-Wave velocity-based Resistivity predictions: Relationship between actual resistivity and predicted resistivity based on P-wave velocity using ANN is presented in figure 8. Nonlinear regression analysis is carried out for the obtained results from ANN model. It can be observed from the plot that the scatter of points in this case with p-wave velocity prediction is lesser wide compared to other plots. Also it may be noticed that the predicted values of resistivity, derived from P-wave velocity are closer to actual values of resistivity, compared with other parameters. The mechanism involved in better prediction of resistivity by p-wave velocity could be the combined to effect of P-wave velocity and mineral heterogeneity on resistivity, which could be captured well by p-wave velocity[22].

Dry Density based Resistivity predictions: The results of laboratory investigations and predictions made on resistivity derived from dry density using ANN are presented in figure 9. Non-linear regression analysis was also carried out to evaluate the relationship between actual resistivity values and predicted resistivity based on dry density. The scatter of the points is wider compared with other parameters. Also the non-linear curve did not fit perfectly with the data points. This shows that dry density is a poor parameter to fit for prediction of resistivity.

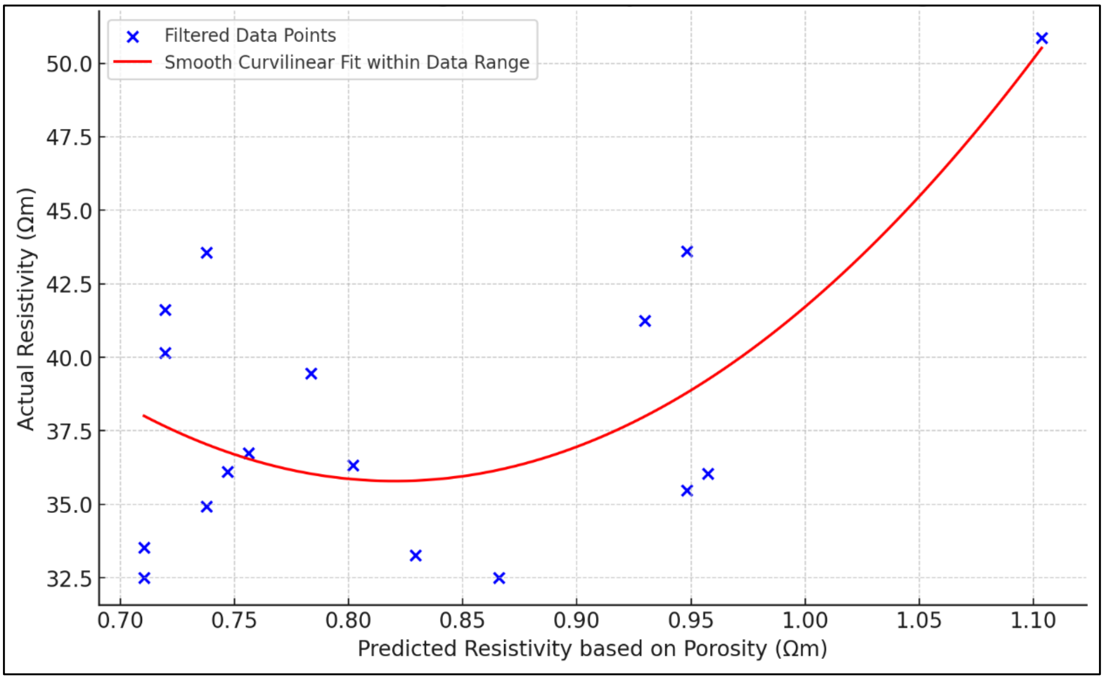

Figure 7: Non-Linear regression analysis curve for actual resistivity Vs predicted resistivity based on porosity.

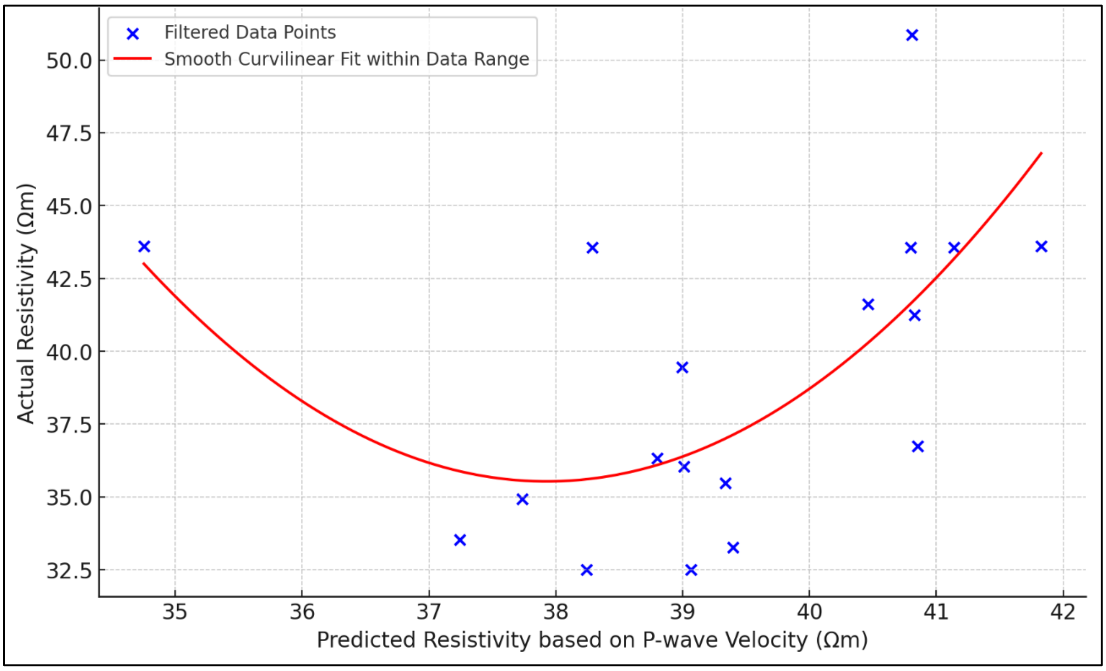

Figure 8: Non-Linear regression analysis curve for actual resistivity Vs predicted resistivity based on P-Wave velocity.

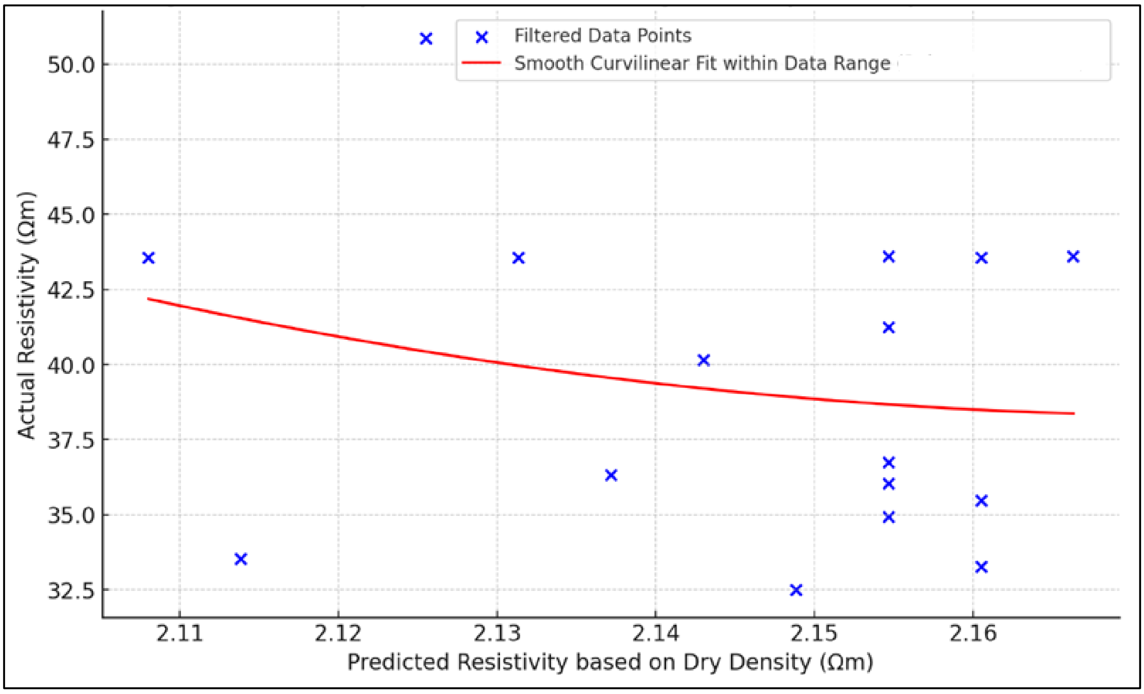

Figure 9: Non-Linear regression analysis curve for actual resistivity Vs predicted resistivity based on Dry density.

Table 2
Mean Absolute Error (MAE) and Average Residuals for Predicting Resistivity

Metric	P-Wave Velocity	Porosity	Dry Density
Mean Absolute Error (MAE)	4.638	38.015	36.796
Average Residuals	-0.005	38.015	36.796

Dry density can only moderately correlate with rock resistivity because several other factors such as matrix of material and nature of void spaces influence resistivity and dry density is not an independent factor[9].

Evaluation of Best Fit: The values of MAE and average residuals calculated using relevant formulae for P-wave velocity, porosity and dry density are presented in table 2. It can be observed that MAE value of 4.638 was the least for P-Wave velocity, compared to other parameters. This suggests that prediction of resistivity from values generated from P-wave velocity offer the best results. Similarly, the average residuals value was near zero (-0.005) for p-zero velocity generated resistivity. Thus, p-wave velocity is a better parameter to be used to train a ANN model and get predictions for resistivity. The possible mechanism of better predictability with p-wave velocity could be because rocks transmit elastic waves more efficiently thus reflecting higher resistivity values[4]. The results suggest that P-wave velocity is the most reliable predictor for resistivity, with porosity and dry density contributing to less accurate models.

Conclusion

Artificial neural networks models were developed using Python and Tensor Flow, to predict rock resistivity. Known laboratory experimental results on physico-mechanical properties such as P-wave velocity, porosity, dry density and resistivity were used to train the model to predict resistivity. The predicted resistivity values have shown that P-wave velocity is the most reliable predictor. The results indicated that models based on P-wave velocity achieved the lowest MAE (4.638) and nearly zero average residuals (-0.005), suggesting a strong correlation between P-wave velocity and resistivity.

Porosity and dry density, on the other hand, exhibited higher errors and greater scatter, indicating weaker correlations with resistivity. Also, the predicted values from those parameters were far away from actual resistivity values. The results emphasise the importance of considering P-wave velocity as a key parameter in predicting resistivity, while also demonstrating the limitations in relying on porosity and dry density alone. ANN models offer a more accurate and reliable predictivity. Non-linear regression models fit better and are more reliable compared to conventional linear regression fit.

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