AGAM GOSWAMI
M. K. MISHRA
DIPTI PATRA
and
S. CHOUDHURY

Incorporating spatial variability of lithological units into ore grade estimation of an Indian limestone deposit

The ore grade estimation requires accurate prediction of the grade at location from limited borehole information. It plays the dominant role in the decision-making process for investment and development of various mining projects and hence become an important and crucial stage.This paper evaluates the application of multi-layer perceptron neural network (MLP NN) architecture to improve the predictability in grade estimation from west coast limestone deposit, Chandrapur district, Maharashtra. The spatial variability of lithological information is incorporated as secondary information in the model for grade estimation. In this investigation the three dimensional spatial coordinates along with four underlying lithological units are taken as input variables and, the four grade attribute of limestone deposit such as CaO, Al_2O_3, Fe_2O_3, and SiO_2 are taken as the output variable. The comparative analysis of these models have been carried out and the results obtained, are validated with geostatistical method ordinary Kriging (OK). The observed value of various performance criteria viz. regression coefficient and mean square error revealed that the MLP NN performed well as compared to OK in terms of generalization and predictability of ore grades.

Keywords: *Grade estimation, multi-layer perceptron neural network (MLP NN), ordinary Kriging (OK), spatial uncertainty.*

1. Introduction

Accurate ore grade estimation is vital to sustainable mine economics. It plays a significant role in the decision-making process for the investment in mining, pit designing, production scheduling, and grade control (David, 1977; Wu and Zhou, 1993; Mahmoudabadi et al., 2009; Tahmasebi and Hezarkhani, 2010-2012). Typically, the mineral grade are assessed from limited borehole information (Li et al., 2013; Goswami et al., 2017). The various neural network (NN) architectures such as multi-layer perceptron neural network (MLP NN), radial basis function (RBF) and general regression neural network (GRNN), hybrid ensemble and optimized network are widely employed to improve the predictability of grade estimation of various ore deposits (Koike et a., 2002; Kapageridis, 2005; Chatterjee et al., 2006-2010; Dutta et al., 2010; Samanta and Bandopadhyay, 2009; Samanta, 2010; Hyun and Saro, 2010). These models vary for uncertainty assessment of the geological and geophysical variables realistically. The detail on several approaches for grade estimation is discussed elsewhere (Goswami et al., 2017). This paper discuss the application of MLP NN for improvement in ore grade estimation for limestone deposit in Chandrapur region, Maharashtra, India. A comparative evolution of the MLP NN against OK has been investigated.

Messrs. Agam Goswami, M. K. Mishra, Department of Mining Engineering, NIT Rourkela-769008, Dipti Patra, Department of Electrical Engineering, NIT Rourkela-769008 and S Choudhury, Sr Manager, Corporate Mineral Resource Dept., ACL, Mumbai

2. Geological Location

The investigation considered borehole log data that belong to a major limestone ore belt of Chardrapur district, Maharashtra. The area is situated between 19.7775°N and 79.3663°E. The exploratory borehole data represent the lithology, geology, assay and surveying of 60 boreholes logs of varying depths from 6 to 160m, with an average depth of 68 m. The boreholes are drilled at regular intervals of about 80 m in a grid pattern. The borehole data comprises three spatial coordinates: easting (X), northing (Y) and depth (Z) along with assay values of CaO, Al_2O_3, Fe_2O_3, and SiO_2 and lithological information. The assay value for each borehole is collected at interval of 1 m depth. A total of 1686 samples are collected at each depth interval. The geological map of the study area is presented in Fig.1.

3. Statistical analysis of the data

The detailed statistical analysis of the exploratory borehole data is carried out, before performing the grade estimation (Table 1). CaO and SiO_2 are major constituents in the ore material. The histogram plots of CaO, Al_2O3, Fe_2O_3, and SiO_2 are presented in the Fig.2. The frequency distribution of various ore constituents Al_2O_3, Fe_2O_3 and SiO_2 are right-skewed whereas CaO is left-skewed distribution (Fig.2). The nonlinear complex relation between grade and their underlying lithologies causes skewed nature in the spatial distribution

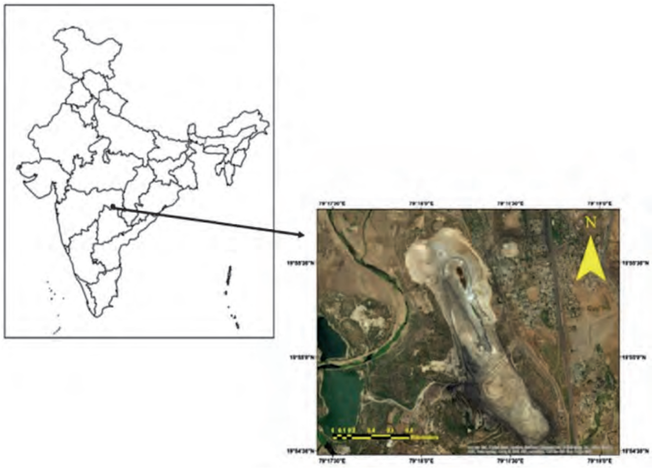

Fig.1 Geological map of the study area for limestone deposit

TABLE 1: DESCRIPTIVE STATISTICS OF SEVERAL ATTRIBUTES OF LIMESTONE DEPOSIT

Statistics	CaO	Al_2O_3	Fe_2O_3	SiO_2
Minimum	12.0700	0.0300	0.0900	1.0100
Maximum	54.4200	17.3100	12.9900	45.0800
Mean	41.8814	3.2568	1.9734	14.5103
Standard deviation	8.8492	3.4095	1.7010	9.3023
Variance	78.3081	11.6247	2.8934	86.5326
Skewness	-1.1827	1.6574	2.6816	1.1941
Kurtosis	3.4425	5.1135	12.7666	3.4220

of ore constituents of limestone deposit. The histogram plots of the individual variables along with bivariate scatter plots of the variables are presented in Fig.2. It is observed that all of the variables deviate from the normal distribution.

4. Ordinary kriging for grade estimation

Ordinary kriging (OK) by geostatistical software SgeMs is used for grade estimation of several attributes of limestone deposit. Spherical variogram model is fitted over experimental variogram to capture the spatial variability of the several constituents of limestone deposit. Directional variogram modelling is carried out to study the anisotropic behaviour of various constituents of limestone deposit. It is found that majority of the total 30 variograms had same range and sill that exhibits anisotropic behaviour of the deposit. Therefore, the spatial continuity of the grade attributes of limestone deposit is analyzed using omnidirectional variogram (Fig.3). The typical variogram (γ) is represented as,

$$\gamma = \frac{1}{2n}\sum_{i=1}^{N}\left(Z(x+h)-Z(x)\right)^2$$

Where N is the number of samples, Z(x) and Z(x+h) represent the assay value of several constituents of limestone deposit at location x, (x+h) respectively.

5. Multi-layer perceptron neural network for ore grade estimation

The ore grade estimation for limestone deposit using MLP NN architecture has three layers: input layer, hidden layer and output layer. The network composed of three spatial coordinates (X, Y, and Z), and four lithological units as input variables and the four limestone constituents as for CaO, Al_2O_3, Fe_2O_3, and SiO_2 grade as the output variable. The MLP NN network architecture for grade estimation of

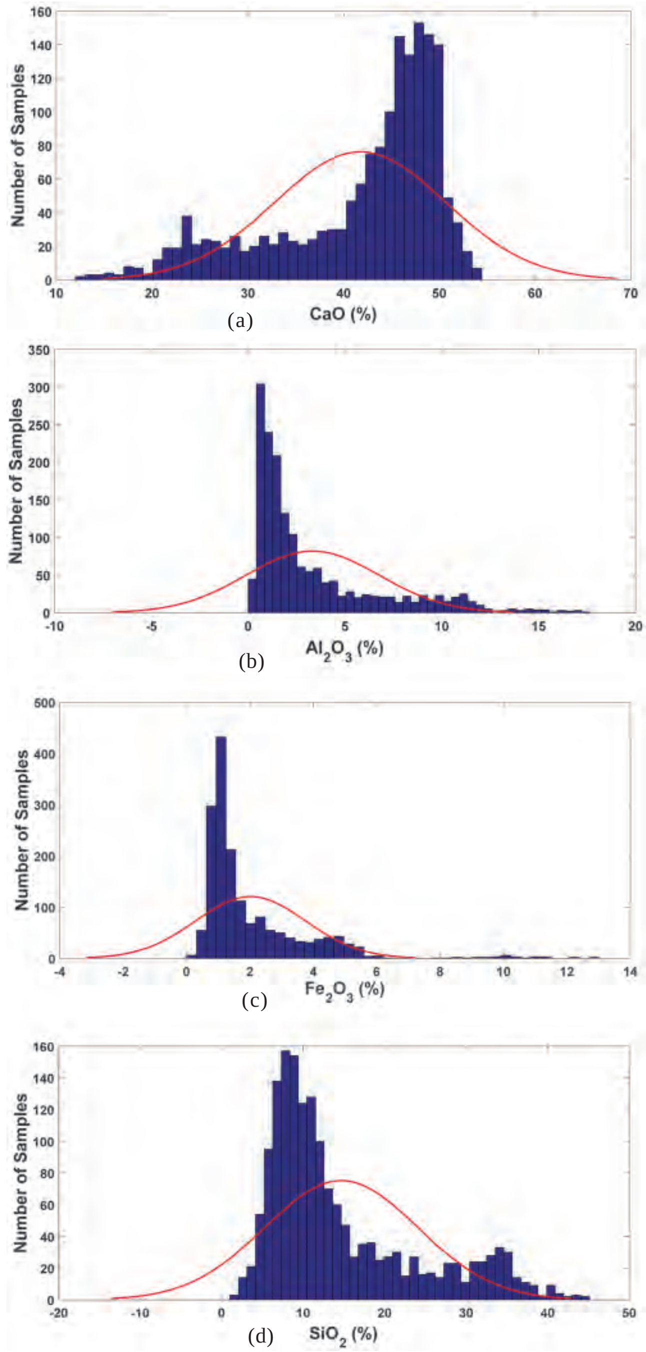

Fig.2 Histogram plot of limestone constituents (a) CaO, (b) Al_2O_3, (c) Fe_2O_3, and (d) SiO_2

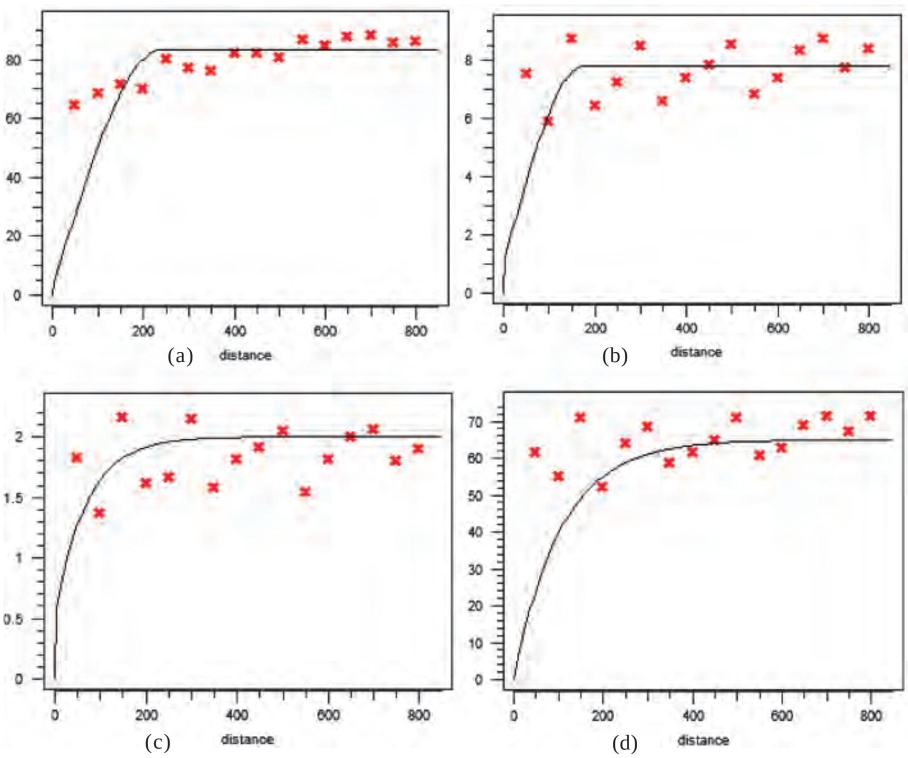

Fig.3 Omnidirectional plot for (a) CaO, (b) Al_2O_3, (c) Fe_2O_3, (d) SiO_2

limestone deposit is presented in Fig.4.

The entire data is normalized in the range [0, 1] to ensure that all the input and output variables lie in the same specified range. All the input and output variables are transformed using Eq.1

$$N_i = \frac{(R_{id} - R_{d,\min})}{(R_{d,\max} - R_{d,\min})} \quad \text{... (1)}$$

Where N_i indicates the normalized value of x_{id}, R_{id} is the observed value of the ith sample of dth feature variable. $R_{d,\ min}$ is minimimum and $R_{d,\ max}$ is maximum observed value of dth feature space respectively. Then entire data set is divided into training and testing data set. The MLP NN captures the nonlinear characteristics of deposit with training data set whereas its performance is validated with test data set. Cross validation to measure the model performance is an accepted practice from limited borehole data leads to over fitting with actual data analysis (Dutta et al., 2006; Samanta and Bandopadhyay 2009). In this analysis, 60% (1013) of the data from each lithological unit are randomly considered as training data set and rest (671) are used as testing data set. This approach conforming to similar exercise reported elsewhere (Chatterjee et al., 2006).

The Levenberg-Marquardt (LM) back propagation learning algorithm is used for training the network because of its robustness and capability to perform nonlinear regression (Chatterjee et al., 2006). The details on MLP NN architecture is discussed elsewhere (Haykins, 1999). Various learning parameters are selected iteratively to get the optimized network. The number of neurons in hidden layers varied from

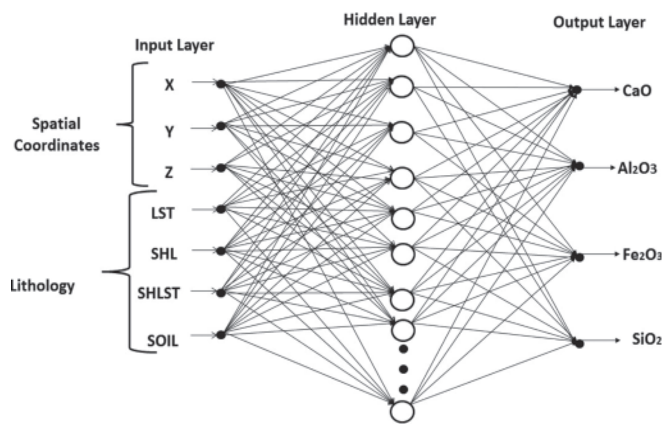

Fig.4 MLP NN architecture for limestone deposit

TABLE 2: STATISTICAL DESCRIPTION OF TRAINING AND TESTING DATA SET FOR GRNN AND SVR

Attributes	Mean			Standard Deviation		
	Entire	Training	Testing	Entire	Training	Testing
No. of samples	1686	1013	671	1686	1013	671
X	365494.98	365487.93	365504.24	366.1962	362.3889	371.587
Y	2234930.44	2234938.39	2234920.14	396.4613	385.5935	411.682
Z	289.795	290.49	288.86	23.2712	23.3808	23.0197
CaO	41.8814	41.8510	42.0007	8.8492	8.8863	8.7043
Al_2O_3	3.2568	3.2495	3.2323	3.4095	3.4335	3.3156
Fe_2O_3	1.9734	1.9727	1.9494	1.7010	1.7232	1.6011
SiO_2	14.5103	14.4809	14.4812	9.3023	9.2789	9.2577

TABLE 3: ERROR STATISTICS FOR LIMESTONE ATTRIBUTES ON TEST DATA USING OK AND MLP NN

Error statistics		ME	MAE	MSE	RMSE	R	R^2
CaO	OK	-0.0895	2.6491	24.4418	4.9439	0.8541	0.7295
	MLPNN	-0.0172	2.1083	24.1015	4.9093	0.8721	0.7605
Al_2O_3	OK	0.0752	0.9283	3.2747	1.8096	0.8800	0.7744
	MLPNN	0.0119	0.7049	3.7537	1.9374	0.8722	0.7607
Fe_2O_3	OK	-0.0009	0.6973	1.5587	1.2485	0.7447	0.5546
	MLPNN	-0.0232	0.3567	1.4662	1.2108	0.7855	0.6170
SiO_2	OK	0.1092	2.6112	24.7938	4.9793	0.8696	0.7562
	MLPNN	0.0360	2.1372	23.9653	4.8954	0.8871	0.7869

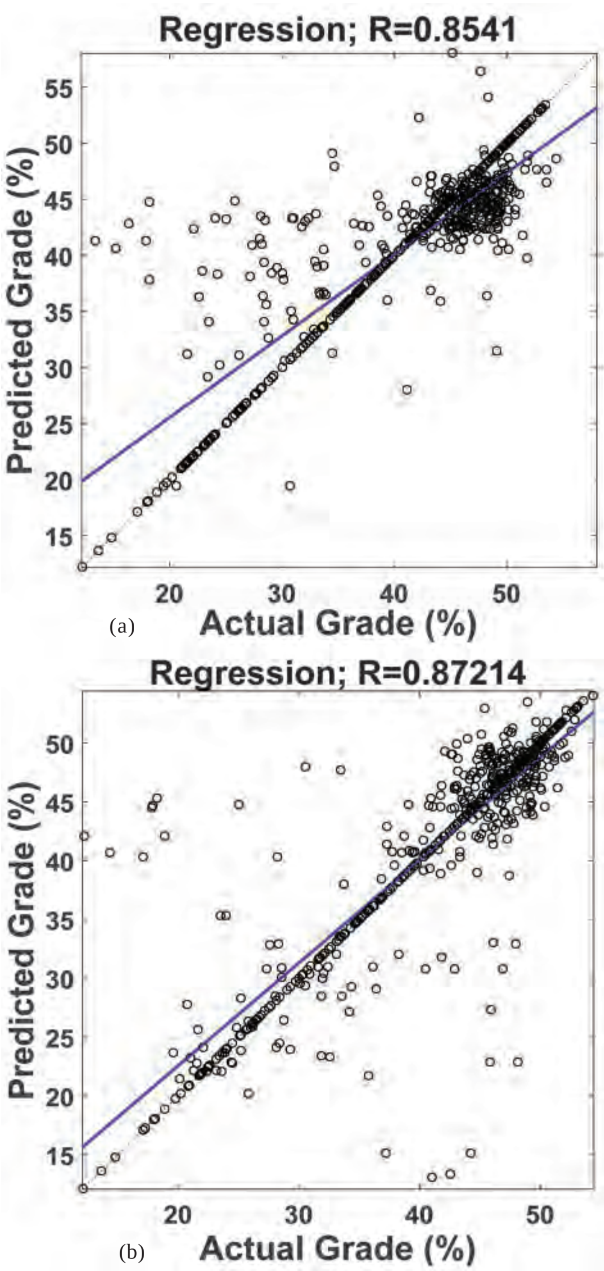

Fig.5 Regression plot for CaO using
(a) OK and (b) MLP NN

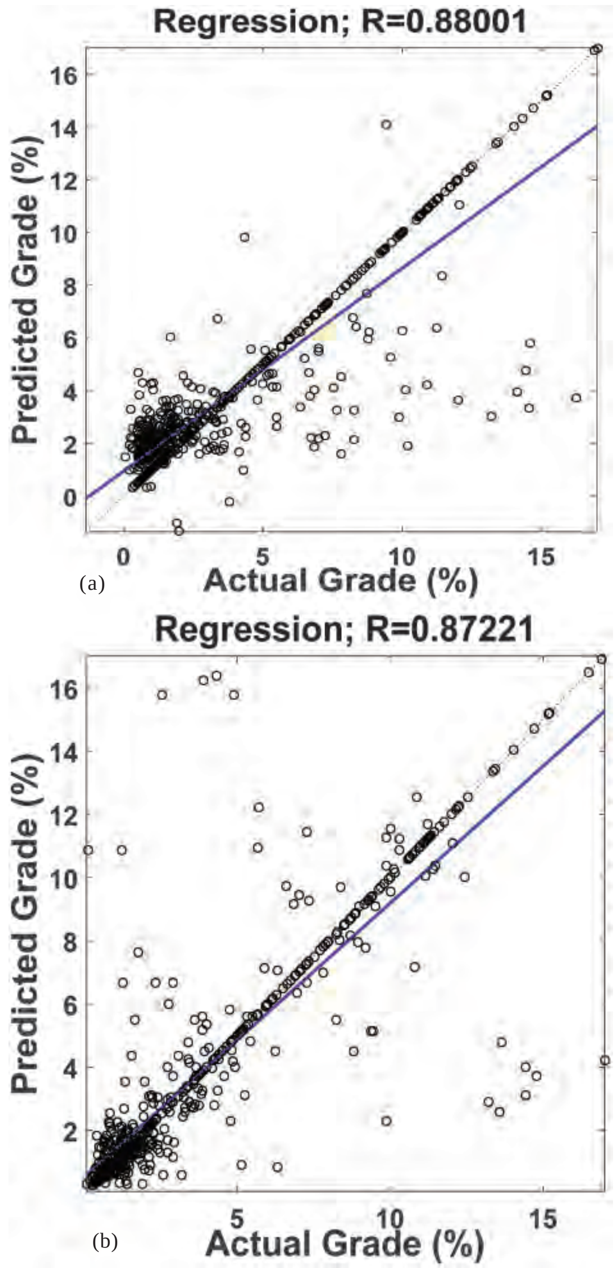

Fig.6 Regression plot for Al_2O_3 using
(a) OK and (b) MLP NN

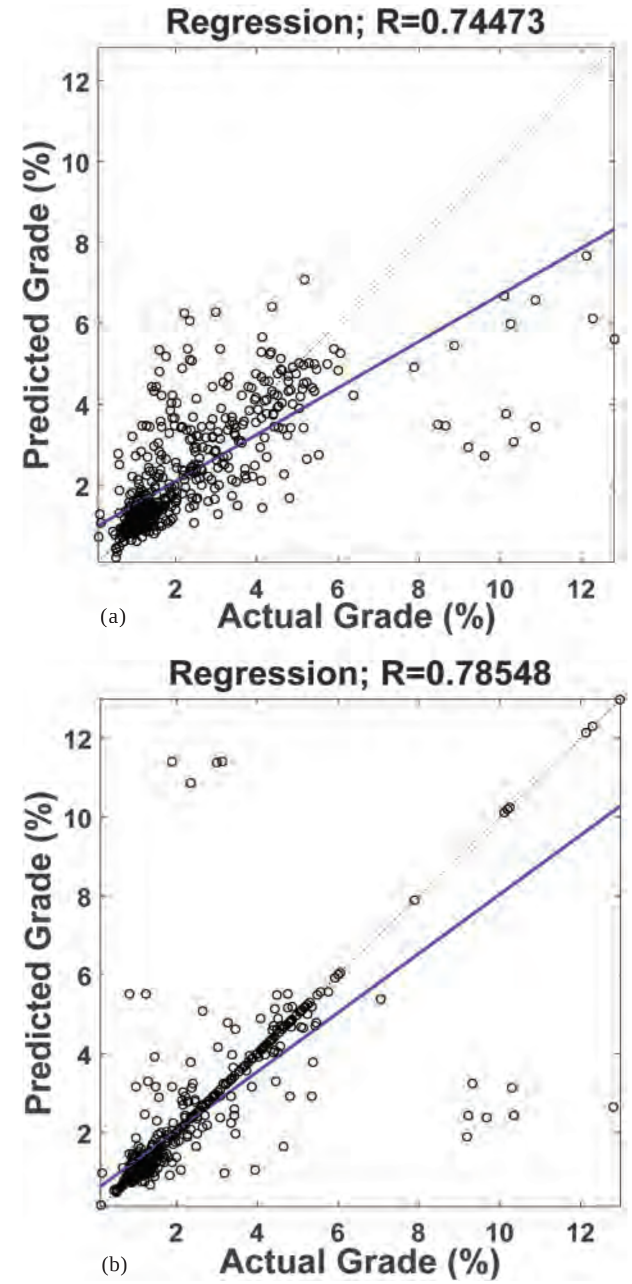

Fig.7 Regression plot for Fe_2O_3 using (a) OK and (b) MLP NN

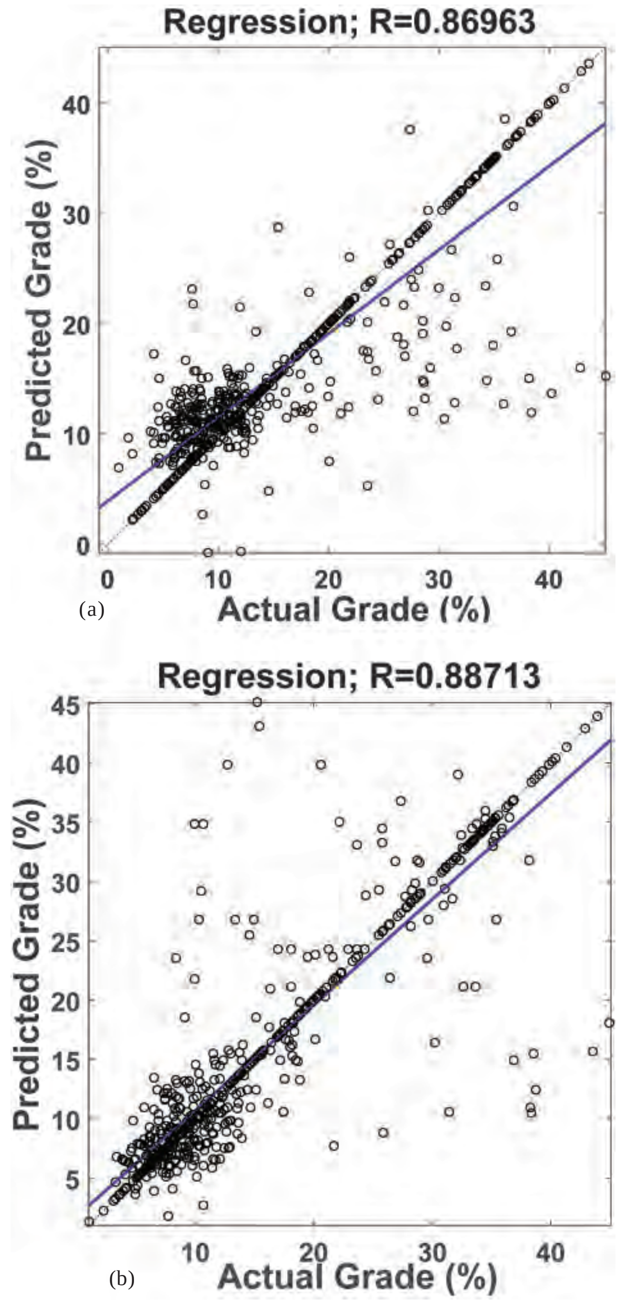

Fig.8 Regression plot for SiO_2 using (a) OK and (b) MLP NN

one to twenty. The pure linear, logarithmic sigmoid, and hyperbolic tangent sigmoid are used as transfer functions in the hidden layer and output layer. The activation functions used in hidden layer and output layer are chosen among pure linear, logarithmic sigmoid, and hyperbolic tangent sigmoid iteratively. It is observed that fifteen neurons in the hidden layer are sufficient to capture the complex interaction among input and output variables. However, logarithmic sigmoid transfer function and symmetric sigmoid transfer function are found suitable in the hidden layer and output layer respectively for the optimized network. Then model's performance is evaluated with test data set. The error statistics on test dataset of MLP NN is presented in the Table 3.

6. Results and Discussion

In this paper, MLP NN is used for improvement in grade estimation of limestone deposit. The performance of MLP NN is compared and validated by the results obtained by OK approach.The ordinary kriging considers only the spatial coordinates for grade estimation, whereas in MLP NN rock types are incorporated as auxiliary information into model for the estimation. The MLP NN considered seven input

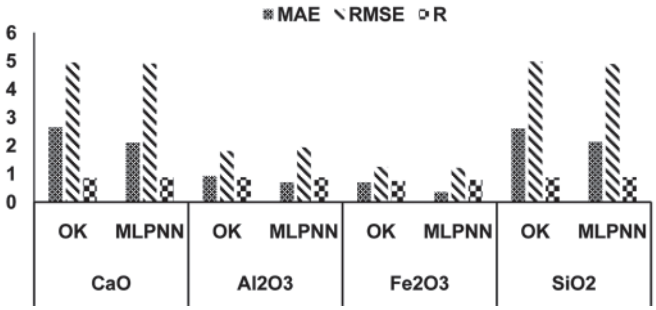

Fig.9 Comparison of ME, MAE, RMSE, R among OK, and MLP NN

variables including three-dimensional spatial coordinates (X, Y, and Z), and four lithological units, whereas grade of four limestone constituents are taken as output variable.

The comparative analysis of distinct estimation techniques are carried out to determine the best estimation for the deposit. The models are evaluated on the basis of their predicted grades with test data set. The mean error (ME), mean absolute error (MAE), mean squared error (MSE), root mean square error (RMSE), correlation coefficient R, and coefficient of determination R^2 are used as performance measures for all three estimators. SE, MAE, MSE and RMSE signify the accuracy and precision of the model. The best network topology is selected in accordance with the highest correlation coefficient and the lowest mean square error (MSE) (Samanta, 2010; Goswami et al., 2017). Table 3 represents error statistics of the models on test data. The MLP NN and OK underestimated CaO and Fe_2O_3 whereas it overestimated Al_2O_3 and SiO_2. Both the models exhibit comparable values of RMSE for each attributes of the limestone deposit. The R and R^2 values indicate that MLP NN performed better as compared to that by OK for CaO, Fe_2O_3 and SiO_2. Both models exhibit nearly same values for Al_2O_3. These observations is reflected in the scatter plot of predicted grades against actual values for various limestone constituents Figs. 5-8. Fig. 9 represents the pictorial form of comparison between OK and MLP NN on the basis of ME, MAE, RMSE and R values for all grade attributes.

7. Conclusion

The applicability of MLP NN model for grade estimation of limestone deposit from limited borehole data is evaluated. A total 1686 borehole samples with spatial coordinates along with their lithological units (input) and assay values of limestone constituents (output) are considered. The F-test exhibit statistical similarity between the training and testing data set at 5% level of significance. The RMSE values for CaO, Al_2O_3, Fe_2O_3 and SiO_2 by MLP NN are 4.9093, 1.9374, 1.2108 and 4.8954 respectively, whereas corresponding values by OK are 4.9439, 1.8096, 1.2485 and 4.9793. The correlation coefficients for these attributes by MLP NN 0.8721, 0.8722, 0.7855, and 0.8696 for CaO, Al_2O_3, Fe_2O_3 and SiO_2. Similarly the R values for CaO, Al_2O_3, Fe_2O_3 and SiO_2 by OK 0.8541, 0.8800, 0.7447 and 0.8696 respectively. The RMSE values exhibit higher accuracy in estimation of limestone grade attributes in majority of elements with the inclusion of lithology as compared to that by OK.

References

1. Chatterjee S., Bhattacherjee A., Samanta B., Pal S.K. (2006): "Ore grade estimation of a limestone deposit in India using an artificial neural network", *Applied GIS*, Vol. 2:1, pp. 03.1–03.20
2. Chatterjee S., Bandopadhyay S., Ganguli R., Bhattacherjee A., Samanta B., Pal S.K. (2007): "General regression neural network residual estimation for ore grade prediction of limestone deposit", *Mining Technology*, Vol. 116:3, pp. 89–99
3. Chatterjee S., Bandopadhyay S., Machuca D. (2010): "Ore grade prediction using a genetic algorithm and clustering based ensemble neural network model", *Mathematical Geosciences*, Vol. 42, pp. 309–326
4. David M. (1977): "Geostatistical Ore Reserve Estimation", Amsterdam, Elsevier Scientific Publishing, pp. 384
5. Dutta S., Bandopadhyay S., Ganguli R., Misra D. (2010): "Machine learning algorithms and their application to ore reserve estimation of sparse and imprecise data", *Journal of Intelligent Learning Systems & Applications*, Vol. 2, pp. 86–96
6. Dutta S., Mishra D., Ganguli R., Samanta B., Bandopadhyay S. (2006): "A hybrid ensemble model of kriging and neural network for ore grade estimation", *International Journal of Mining*, reclamation, and Environment, Vol.20:1, pp. 33–45
7. Goswami D.A., Mishra K.M., Patra D. (2017): "Investigation of general regression neural network architecture for grade estimation of an Indian iron ore deposit", *Arabian Journal of Geosciences*, Vol. 10:4, pp. 1–14
8. Goswami D.A., Mishra K.M., Patra D. (2017): "Adapting pattern recognition approach for uncertainty assessment in the geologic resource estimation for Indian iron ore mines", In Signal Processing, Communication, Power and Embedded System (SCOPES), 2016 International Conference on (pp. 1816-1821) IEEE
9. Haykins S. (1999): "Neural Networks: A comprehensive foundation", New Jersy, Prentice Hall, pp.824
10. Hyun J., Saro L. (2010): "Application of Artificial Neural Network for Gold–Silver Deposits Potential Mapping: A Case Study of Korea", *Natural Resources Research*, Vol. 19:2, pp. 103–124.

11. Kapageridis I.K. (2005): “Input space configuration effects in neural network-based grade estimation”, *Computers & Geoscience, Vol. 31, pp.704–717*
12. Koike K., Matsuda S., Suzuki T., Ohmi M., (2002): “Neural Network-Based Estimation of Principal Metal Contents in the Hokuroku District, Northern Japan, for Exploring Kuroko-Type Deposits”, *Natural Resources Research*, Vol. 11:2, pp. 135–156
13. Mahmoudabadi H., Mohammad I., Mohammad B.M. (2009): “A hybrid method for grade estimation using genetic algorithm and neural networks”, *Computers & Geosciences*, Vol.13, pp. 91–101
14. Samanta, B., Bandopadhyay, S. and Ganguli, R., (2004): “Sparse Data Division Using Data Segmentation and Kohonen Network for Neural Network and Geostatistical Ore Grade Modeling in Nome Offshore Placer Deposit”, *Natural Resources Research,* Vol. 13: 3, pp.189–200
15. Samanta B., Ganguli R., Bandopadhyay S. (2005): “Comparing the predictive performance of neural networks with ordinary kriging in a bauxite deposit”, Mining Technology: *Transactions of the Institutions of Mining and Metallurgy*: Section A, Vol. 114, pp.129–139
16. Samanta B., Bandopadhyay S., Ganguli R., (2006): “Comparative Evaluation of Neural Network Learning Algorithms for Ore Grade Estimation”, *Mathematical Geology,* Vol. 38:2, pp. 175–197
17. Samanta B., Bandopadhyay S. (2009): “Construction of a radial basis function network using an evolutionary algorithm for grade estimation in a placer gold deposit”, *Computers & Geoscience*, Vol.19:2, pp.1592–1602
18. Samanta B. (2010): “Radial basis function network for ore grade estimation”, *Natural Resources Resaerch*, Vol.19:2, pp. 91–102
19. Shahoo M., Ramazia H.R., Moradi S. (2014): “Estimation of Iron concentration by using a support vector machine and an artificial neural network - the case study of the Choghart deposit southeast of Yazd, Yazd, Iran”, Geopersia, Vol.4:2, pp. 201–212
20. Singh J., Verma A.K., Banka H., Singh T. N., Maheshwar S., (2016): “A study of soft computing models for prediction of longitudinal wave velocity”, *Arabian Journal of geosciences*, Vol.9:224, pp.3-11
21. Tahmasebi P., Hezarkhani A., (2010): “Comparison of optimized neural network with fuzzy logic for ore grade estimation, *Australian Journal of Basic and Applied Sciences*, Vol. 4:5, pp.764–772
22. Tahmasebi P., Hezarkhani A. (2011), “Application of a Modular Feed forward Neural Network for Grade Estimation”, *Natural Resources Research*, Vol.20:1, pp. 25–32
23. Tahmasebi P., Hezarkhani A. (2011): “Application of adaptive neuro-fuzzy inference system for grade estimation; case study, Sarcheshmeh Porphyry Copper Deposit, Kerman, Iran”, *Australian Journal of Basic and Applied Sciences*, Vol.4:3, pp. 408–420
24. Tahmasebi P., Hezarkhani A. (2012): “A hybrid neural networks-fuzzy logic-genetic algorithm for grade estimation”, *Computers & Geosciences*, Vol.42, pp. 18–27
25. Wu X., Zhou Y. (1993): “Reserve estimation using neural network techniques”, *Computer and geosciences*, Vol.19:4, pp. 567–575.

MINE ACCIDENT INVESTIGATION IN INDIA: A SYSTEM APPROACH

(Continued from page 748)

33. Paul, P. S. and Maiti, J. (2008): “The Synergic Role of Sociotechnical and Personal Characteristics on Work Injuries in Mines,” *Ergonomics*, Taylor & Francis, UK, Vol. 51, No. 5:737-767.
34. Paul, P. S. and Maiti, J. (2007): “The role of behavioral factors on safety management in underground mines.” *Safety Science*, 45(4), 449-471.
35. Paul, P. S. (2013): “Investigation of the role of personal factors on work injury in underground mines using structural equation modeling.” *International Journal of Mining Science and Technology*, 23(6):815-819.
36. Rasmussen, J. (1997): “Risk Management in a Dynamic Society: A Modelling Problem,” *Safety Science*, Vol. 27, No. 2/3:183-213.
37. Reason, J. (1990): Human Error Cambridge University Press, Cambridge,UK.
38. Sari, M., Selcuk, A. S., Karpuz, C. and Duzgun, H. S. B. (2009): “Stochastic modeling of accident risks associated with an underground coal mine in Turkey,” *Safety Sci.* 47:78-87.
39. Sklet, S. (2004): “Comparison of some selected methods for accident investigation.” *J. Hazard Mater.* 111(1-3):29-37.
40. Stoop, J. and Dekker, S. (2012): “Are safety investigation proactive?” *Safety Science*, 50: 1422-1430.
41. Woods, D. D. and Cook, R. I. (2006): Incidents: Are they markers of resilience or brittleness? In E. Hollnagel, D.D. Woods and N. Leveson, eds., Resilience Engineering: Concepts and Precepts. Ashgate, Aldershot, UK, 69-76.
42. Zahid, H. Qureshi (2007): A Review of Accident Modelling Approaches for Complex Socio-Technical Systems. 12th Australian Workshop on Safety Related Programmable Systems (SCS’07), Vol. 86.

Printed by Pradip Kumar Chanda at The Indian Press Pvt. Ltd. 93A Lenin Sarani, Kolkata 700 013 and published by him for Books & Journals Pvt. Ltd. from 6/2 Madan Street, Kolkata 700 072.