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A Study on Prediction of Blast Induced Air Overpressure by different Approaches

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ABSTRACT

In this paper, a comparative study on performance of empirical equation, artificialneural network (ANN) and fuzzy logic in prediction of blast induced air overpressure is conducted. For this purpose, a total of 26 blasting data sets for prediction of air overpressure are collected from a limestone mine in India. The monitoring distance and maximum charge/delay is taken as two input variables and the air overpressure (dB) as the output variable. Root mean square error (RMSE) is used as a performance index to measure the performance of the proposed models. The results indicated that ANN is more accurate when compared to fuzzy logic and empirical equations.

KEYWORDS: Artificial neural network, Empirical equation, Fuzzy logic, Air overpressure,Root mean square error.

1. INTRODUCTION

In open-pit mining, there are several methods which are used for fragmentation of the rocks. Among them drilling and blasting is most employed method by considering its technological and productive aspects [1-3]. A large amount of fragments of rocks are produced by the blasting operations which are used for loading and transportation at cheap cost. Around one fourth of the explosive energy is utilised for the rock fragmentation and remaining three fourth energy considered as unwanted environmental effects such as blast induced ground vibrations, fly rock, dust, blast induced air overpressure, etc [5-9]. These environmental issues may affect nearby infrastructure.

Air overpressure is considered as one of the most dangerous among the various side effects in case of causing of damage. During blasting, explosive gases are rapidly released into the atmosphere, in the form of pressure waves. These pressure waves which are greater than the normal atmospheric pressure and known as the blast induced air overpressure. Air overpressure has an impact on structures as well as humans and can cause damage [10-12].

Different types of methods are used in this study to forecast air overpressure values such as empirical equation, artificial neural networks and fuzzy logic models are developed for the prediction of air overpressure.Empirical models struggle to make reliable predictions when the level of air overpressure surpasses specified limitations. As a result, the deployment of an artificial intelligence network is crucial for predicting air overpressure.

Artificial neural networks (ANNs) are a form of artificial intelligence that work similar to human nerve systemsand can guess existing function based on real-world data. The nodes in the ANN models are

similar to the biological neurons and such nodes are called as artificial neuron. ANN mainly consists of three layers namely input layer, output layer and hidden layer.An artificial neuron takes inputs from the input layer and passes them to the hidden layer to process the inputs in order to generate an output. The output that is generated passes to the output layer through the artificial neurons [13].

Fuzzy systems are being used in a variety of industrial and scientific applications at the moment.Fuzzy models are logical models that construct qualitative correlations among the variables in the model using "if–then" rules [14]. Because fuzzy models are rule-based, they can incorporate information represented in natural language statements, which makes them more usefulamong the variables in the model using "if–then" rules.

The values predicted from empirical equation, ANN model and fuzzy logic model are compared with measured values by using performance index such as root mean square error (RMSE) and suggested suitable method in prediction of air overpressure.

2. REALATED WORK

Several researchers are worked on prediction of air over pressure by using several techniques and suggested suitable methods for prediction of air over pressure. Hoang Nguyen et al (2020) [15], used empirical technique and machine learning algorithms such as gradient bosting machine (GBM), random forest (RF) and cubist to predict the AOp and concluded that cubist model predicted more accurately. ManojKhandelwal, P.K. kantar (2011) [16],used support vector machine (SVM) to predict the AOp by using SUM predictions which are composed with the generalized predictor equations. Mohsen Hajihassani et al (2015) [17], compared the empirical equations, a hybrid model of anartificial neural network (ANN) and a particle swarm optimization algorithm to predict the air overpressure and concluded that proposed model of hybrid ANN accurate tool to predict the air overpressure.Manoj Khandelwal et al (2005) [18], in their research the air overpressure is predicted by using neural network (NN) and to know the accuracy of approach, the predictions are compared with generalized equations. Edy Ton nizam Mohmmad et al (2016) [19], predicted the air overpressure by using the empirical equations, artificial neutral network (ANN), and hybrid model of genetic algorithm GA-ANN and it was found that GA-ANN as higher accuracy compared to others.

3. METHODOLOGY

3.1 Empirical approach for AOp prediction

There are number of empirical equations that are suggested to predict AOp, among them United States Bureau of Mines (USBM) proposed equation is the most appropriate and widely used. The following is the equation for predicting the AOp:

$$AOp = K(SD)^{-\beta} \quad (1)$$

Where, AOp is air overpressure measured in decibels, K and β are the site constants and SD is the scaled distance measured in m/kg and is calculated by using the below equation.

$$SD = DW^{-0.33} \quad (2)$$

Where, D is monitoring distance measured in meters, W is maximum charge/delay measured in kgs.

The site constants are calculated by doing regression analysis between scaled distance and air overpressure values. This calculation is done in MS Excel Worksheet.

3.2 ANN approach for AOp prediction

This problem is solved using a feed-forward network, which is said to be suited for problems involving heterogeneous databases. The network model is a two-input model, with monitoring distance and the maximum charge/delay as two input variables, as illustrated in Fig 1. The model was trained using 19 blasting data points, and it was tested and validated using 7 data points.

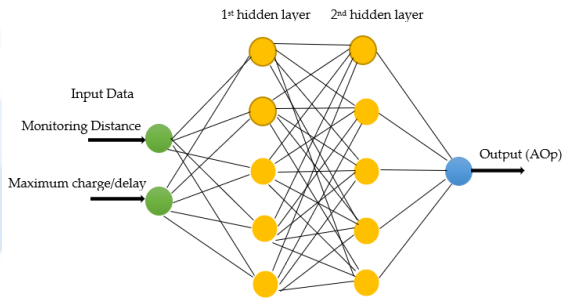

Fig 1: ANN model developed for prediction of air overpressure.

3.3 Fuzzy Logic approach for AOp prediction

The current fuzzy model developed for prediction of air overpressure by using two input parameters and one output parameter. The input parameters were monitoring distance and maximum charge/delay,with air overpressure as the output parameter. The membership functions are used separately for input and output

parameters. Basically, fuzzy logic is rule based hence if-then rules are written to link between the inputs and output. The number of rules is determined by number of data sets and their range.The number of membership functions for the monitoring distance and maximum charge per delay is 1 and 17, respectively.

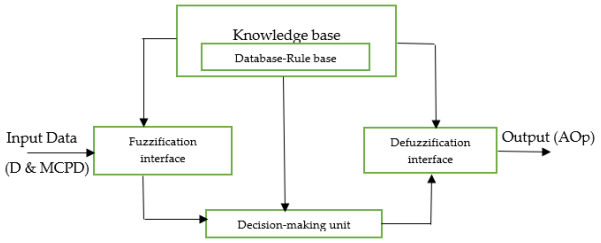

Fig 2: Fuzzy Logic modelling process for AOp prediction.

4. CASE STUDY AND DATA COLLECTION

A limestone mine in Andhra Pradesh, India have been evaluated for a total of 26 blasting operations. In the study site, the drilling is carried with ROC L6[30] down-the-crawler mounted equipment and then blasting is done with Ammonium Nitrate explosive. As a stemming material, fine gravels were used. There are three benches with 18m high among the first bench with 4m top soil and remaining two limestone benches with 7m height. The data was collected during two months period, from February to march (2022).

AOp was measured with the help of ISEE linear microphones linked to the AOp channels of NOMIS Seismographsequipment (Fig 3) during each blasting operation.

Fig 3: Data collection using NOMIS Seismographs for predicting AOp.

5. RESULTS AND EVALUATIONS

The main objective of this paper is to reveal the potential of the applied approaches (empirical equation, ANN, and fuzzy logic) to predict the air overpressure. Two input factors, such as monitoring distance and maximum charge/delay, are used to build models of empirical equation, ANN, and fuzzy logic. Fig 4 shows a graph of predicted AOp values using an empirical technique vs measured AOp values for all 26 datasets. The low R^2 value of 0.59 and the high RMSE value of 23.48 Fig 6 illustrates predicted air overpressure values using fuzzy logic against the measured air overpressure values. All datasets had R^2 and RMSE values of 0.69 and 9.75, respectively, indicating that fuzzy logic shows a reasonable level of accuracy in prediction of air overpressure. Furthermore, R^2 and RMSE values of 0.73 and 8.99 for all datasets imply that this model is superior in predicting AOp using ANN (Fig 5).

To measure the performance of the predicted models, RMSE is considered as the performance index and it is evaluated by using the following formula:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(m-p)^2} \quad (4)$$

Where, m and$p$ represent measured and projected values, and N is total number of blasting data sets. The model is considered as accurate whose RMSE value is near to zero. Table 1 shows the RMSE values of each model.

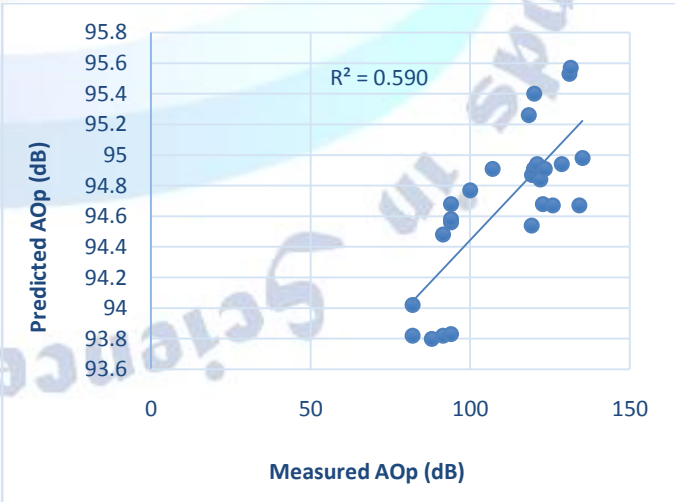

Fig 4: Predicted AOp values using empirical vs MeasuredAOp values.

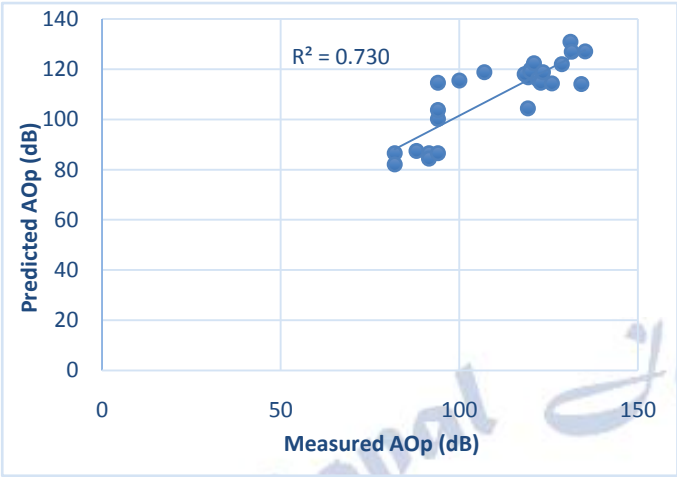

Fig 5: Predicted AOp values using ANN vs Measured AOp values.

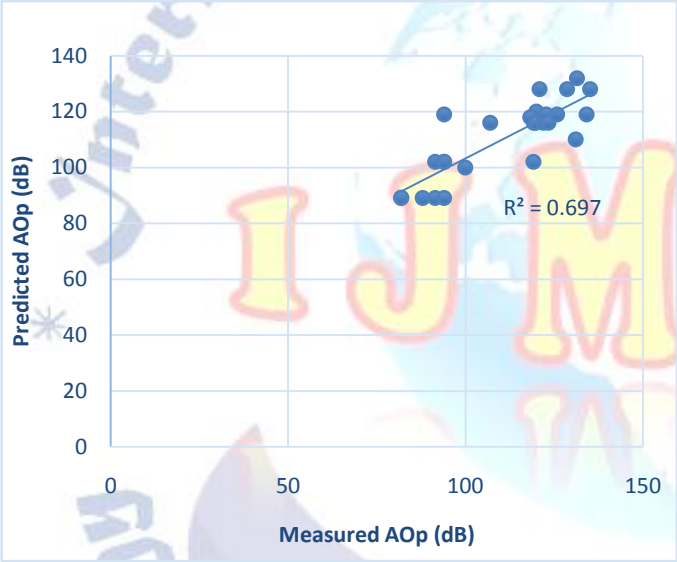

Fig6: Predicted AOp values using Fuzzy logic vs MeasuredAOp values.

Table 1: Comparison between the measured and predicted AOp values (dB).

S.NO	MEASURED AOP VALUES (dB)	PREDICTED AOP VALUES (dB) USING EMPIRICAL MODEL	PREDICTED AOP VALUES (dB) USING ANN MODEL	PREDICTED AOP VALUES (dB) USING FUZZY LOGIC MODEL
1	81.9	93.82	86.53	89.1
2	81.9	94.02	82.12	89.2
3	119.3	94.87	116.82	116
4	107	94.91	118.82	116
5	88	93.8	87.47	89.1
6	120	95.4	120	120
7	91.5	93.82	86.53	89.1
8	91.5	94.48	84.43	102
9	94	94.56	100.26	102
10	94	94.58	103.81	102
11	94	94.68	114.57	119
12	100	94.77	115.49	100
13	118.3	95.26	118.05	118
14	119.2	94.54	104.45	102
15	119.9	94.91	119.05	116
16	120.9	94.94	122.46	128
17	122	94.84	116	116
18	122.8	94.68	114.6	119
19	123.4	94.91	118.82	116
20	94	93.83	86.53	89.1
21	125.9	94.67	114.4	119
22	128.7	94.94	122	128
23	131.1	95.53	131	110
24	131.44	95.57	127	132
25	134.2	94.67	114.12	119
26	135.2	94.98	127.18	128
RMSE		**23.48**	**8.99**	**9.475**

6. CONCLUSION

The study proposed models for the prediction of blast induced air overpressure in a lime stone mine. The main objectivewas achieved by collecting the field measurements. For prediction of air overpressure, ANNand Fuzzy logic models were developed with the helpof MATLAB software by using the measurements collected in the field. Then the AOp values are predicted with developed models and the empirical equations and their performance in prediction of blast induced air overpressure was compared. The results shown that ANN prediction model was giving the values which are near to the measured values when compared to other.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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