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Prediction of roof falls and induced caving in continuous miner panel using Machine Learning.

Mr D.Laxmi Narayana, Assistant Professor

Dr.M.S.Venkataramayya, Professor

Department of Mining Engineering
Malla Reddy Engineering College,
Maisammaguda, Secunderabad, 500010

{Email: dabbulaxminarayana015@gmail.com : vr.musunuri@gmail.com}

ABSTRACT

Continuous Miners are deployed in underground mining for extraction of coal by caving method. The safety conditions require regular caving in the goaf to release the stress in the roof. These falls depend upon various geo-mining and specific characteristics in the area under extraction. Prediction of roof cavability is conducted by emprerical calculations and also numerical modeling. The cavability is assesed by monitoring of convergence in the front abutment zone. A threshold limit of 5mm convergence is considered for cavabilty in the goaf. In some cases, the roof fall does not occur beyond the threshold limit and requires induced caving of the roof in the goaf. In this paper 336 data sets of roof falls in five continuous miner panels were analyzed by logistic regression and machine learning algorithms, to predict the need for induced caving or not. The comparison of the field data in 336 sets, with the logistic regression was found to be about 74%. The variation is because of the varying depths and dimensions of the five panels in the mine under study. It is concluded that the logistic regression and machine learning algorithms of prediction is a useful tool for the decision of induced caving in a continuous miner panel based on the sufficient field data of 336 sets.

Keywords - Continuous miner panel; roof falls; induced caving; machine learning; logistic regression.

1. INTRODUCTION

Coal seams at the deeper depths are suitable for underground mining technologies. It is suggested that, “the Power Roof Support Longwall mining and Continuous Miner technology” would be used successfully in several mines, and there is a requirement to propagate and develop it as the primary underground coal mining technique for mass production [1]. The Continuous Miner Technology has been used for development (i.e., virgin seam or developed pillar) and depillaring (i.e., split & fender or fishbone) with caving method for extraction of coal. In the case of the caving method after the extraction of coal from the developed pillars, the roof is allowed to fall into the goaf, this fall occurs periodically (i.e., periodical roof falls)

[2]. But sometimes the roof will not fall periodically and increase the hanging goaf area which interrupts the mining operations and also cause problems like crushing of goaf edge pillar, air blast, trapping of machinery inside the goaf because of advanced fall and accidents in depillaring panels [3]. To avoid these problems induced blasting is conducted, if necessary for caving and filling the goaf. The caving due to natural or induced periodic falls will increase, the productivity, safety, and overall performance of mining activities in the panel. Prediction of roof falls in the goaf has been carried out in different approaches such as Experiences from previous panels, Empirical Formulas, Numerical Modeling methods, and Machine Learning Techniques.

In this paper, Machine Learning Techniques of Supervised Learning with Logistic Regression with 336 datasets of roof falls in five panels of continiuious miner working of GDK 11 Inc mine of SCCL is used for the prediction of roof falls in the goaf [4]. Factors considered for prediction of roof falls in the goaf are:

1. Extracted Area in the Panel in Sq.m (EA)
2. Hanging Goaf Area in Sq.m (HG)
3. Fall Area in Sq.m (FA)
4. Roof Convergence before falling in mm (RC)
5. Induced Blasting (IB)

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Panel No	Panel Size in Sq.m	Panel Depth in m		No of Pillars	Panel Dimensions in m (D x S)	Total No of falls
		Min	*Max*			
A-1A	98,980	160	217	74	157 x 630	81
A-1B	91,462	162	221	80	139 x 658	80
A-2	86,955	166	225	75	128 x 682	64
A-3	1,00,195	172	237	93	145 x 691	63
A-4	72,000	172	235	58	120 x 600	48
Overall Data	-	160	237	380	140 x 640	336

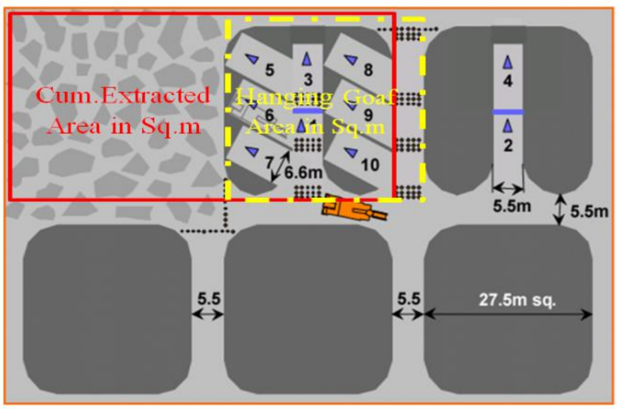

Fig. 1 Extracted Area & Hanging Goaf Area

2. Induced Blasting

Induced caving by blasting has received narrow attention. Induced caving by blasting (induced blasting) is critical to fetch downcast the hanging goaf roof area during the depillaring stage. In the mechanized bord & pillar system of coal extraction, a wide-ranging area of overlying roof strata is generally uncovered after depillaring. The weight accumulation characteristic ahead of the working face is neutralized by regular caving of underlying strata [5]. This is unlikely to happen if extraction is unfolding under a competent roof. Hard roof management schemes in underground coal mines could benefit from induced blasting.

The paramount purpose of induced blasting is to avoid rock bursts at the working faces, which is similar to pre-conditioning/distressing in deep mines [6]. By drilling holes into the uncaved roof and blasting with explosives, the roof rock can be brought down or fractured so that caving can be controlled. In the case of induced blasting, blast fragmentation is not the most important factor. However, the rock should be fractured by the induced blast to facilitate roof fall [7]. Once the roof span exceeds 120–190 Sq.m, induced blasting is commonly done regularly unless the overhanging roof does not fall inside the goaf by its weight. Roof convergence and stress on the goaf edge pillars are monitored continuously. Induced blasting will be used to avoid uncontrolled roof collapse with associated air blast once the daily rise in roof convergence is > 5 mm or the strata pressure increases by 2 t [8].

3. Field Study

The field study has done from GDK-11 Inc in Ramagudam-I Area, Singareni Collieries Company Limited where 1 seam is working with Continuous Miner Technology. Total Block-A property is divided into 6 panels for the continuous miner and 5 panels that have been successfully completed. Details of Continuous Miner Panels worked in 1 seam are:

Table.1 Details of Continuous Miner Panels worked in 1 seam

In this paper, a statistical approach of Supervised Machine Learning’s logistic regression using machine learning is adopted for the prediction of roof falls in the goaf.

4 Machine Learning

Machine learning technology-enabled computer programs to study without been explicitly trained. Machine learning is widely used in almost many fields in the world including healthcare sector. Machine learning is an application of artificial intelligence (AI) that provides systems the ability to automatically learn and improve from experience without being explicitly programmed [9]. Further, machine learning at its most basic is the practice of using algorithms to parse data, learn from it, and then make a determination or prediction about something in the world [10]. There are two major categories of problems often solved by machine learning i.e. regression and classification. Mainly, the regression algorithms are used for numeric data and classification problems include binary and multi- category problems [11].Machine learning algorithms are further divided into two categories such as supervised learning

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and unsupervised learning [12]. Basically, supervised learning is performed by using prior knowledge in output values whereas unsupervised learning does not predefined labels hence the goal of this is to infer the natural structures within the dataset [13]. Therefore, selection of machine learning algorithm need to carefully evaluated.In machine learning, data is the key driving element for analysis.

4.1 Data Collection

The data collected from the field study is formulated to a CSV file and imported to the machine learning program of Logisitic regression using liberires and Sklearn codes which are equipped with statistical paramters of different algorithms.

S No	Extracted Area in Sq.m	Hanging Goaf Area in Sq.m	Fall Area in Sq.m	Strata Parting in mm	Nature of Fall	Induced Blasting (IB)
1	5339	5339	684	6	Induced Fall	1
2	5829	5145	1017	5	Induced Fall	1
3	7970	6269	2459	5	Induced Fall	1
4	10663	6503	568	4	Periodic Fall	0
5	11953	7225	2410	25	Induced Fall	1
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
332	54692	1168	1168	5	Induced Fall	1
333	57794	3102	1570	5	Periodic Fall	0
334	58850	2588	818	3	Periodic Fall	0
335	58850	1770	1102	7	Periodic Fall	0
336	60996	2814	668	6	Periodic Fall	0

Table.2 Dataset Collected from Continuous Miner Panels

4.2 Analyzing Data

Data analysis is crucial in the area to identify challenges that such an organization has and to evaluate information in relevant ways. Data is nothing more than facts and numbers. Data analysis is the process of organizing, interpreting, structuring, and presenting a dataset into valuable evidence that gives meaning to the information[14].

4.2.1 Exploratory Data Analysis

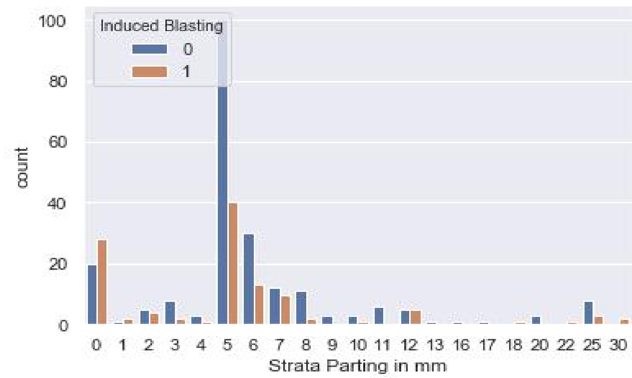

Fig.2 Count plot of Induced blasting and Strata parting

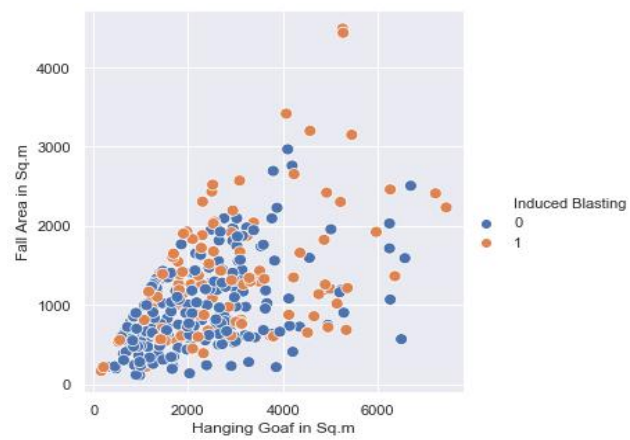

Fig.3 Correlation graph of Hanging Goaf and Fall Area Induced Blasting

Interpreted or combined graphs are used for the graphical representation of two or more variables in a single plot. Here induced blasting and strata parting readings are interpreted in count plot figure 3. From the graphs, it is seen that the majority of induced blasting is conducted between the 0 to 6 mm strata parting and the periodical roof falls are noted between 5 to 8 mm and also in some cases periodical roof and induced blasting are correlated at the same strata readings which are difficult to predict. By combining variables of the induced blast with correlation graph of Hanging goaf and Fall area shows that the outliers are major problems in the depillaring stage with a large area of hanging goaf with fewer strata parting reading figure 3.

4.2.2 Predictive Data Analysis

Predictive analytics is to establish the probability of upcoming occurrences depending on historical data. The purpose is to provide the best judgment of what will happen in the

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future, rather than actually acknowledging what has happened. Predictive models generate (or train) a model that could forecast values for various or new data based on previous findings shown in figure 4. Modeling generates predictions, which indicate the probability of the response variable based on the anticipated consequence of a collection of input variables. In these models the training and testing data is divided into 70:30 ratio i.e., out of 336 datasets, 235 datasets are given to train the dataset to predict the dependent variable induced blasting, and the remaining 101 datasets are later used for testing of the model with its predicted values. In these 101 datasets, actual falls are 71 periodic falls and 30 induced falls but the model predictions are concluded that there are 89 periodic falls and only 12 were induced falls. So the evaluation of the model or program is validated based on the accuracy of predictive values to actual values in the testing dataset.

Model Building

```
In [27]: from sklearn.linear_model import LogisticRegression

In [28]: lr=LogisticRegression()

In [29]: lr.fit(x_train,y_train)

Out[29]: LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                    intercept_scaling=1, l1_ratio=None, max_iter=100,
                    multi_class='auto', n_jobs=None, penalty='l2',
                    random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                    warm_start=False)

In [30]: y_pred=lr.predict(x_test)

In [31]: y_pred

Out[31]: array([0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0,
                0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
                0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0], dtype=int64)

In [33]: y_test.values

Out[33]: array([0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 1, 0,
                0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0,
                1, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1,
                0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0,
                1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0], dtype=int64)
```

Fig.4 Logistic Regression Predictive model

The roof falls are categorized according to the panels in which there are occurred. Predictions of these roof falls are also carried out panel-wise. This panel-wise roof falls analysis is carried out with 70% data with the training subset and 30% data for the testing purpose. The outcomes from the different panels are tested and predicted data values are given with no. of Periodical falls and no. of Induced falls occurring in their respective panels are shown in table 3. And the graphical representation of periodical falls and induced falls with the tested and predicted values according to the panels in which there are occurred in figures 5 & 6 respectively.

Panel No	Total No of Falls	Total		Test Data		Predicted Data	
		Train Data 70%	*Test Data 30%*	*No of Periodic falls*	*No of Induced falls*	*No of Periodic falls*	*No of Induced falls*
A-1A	81	56	25	20	5	19	6
A-1B	80	56	24	20	4	22	2
A-2	64	44	20	9	11	14	6
A-3	63	44	19	17	2	16	3
A-4	48	33	15	6	9	5	10
Overall Data	336	225	101	71	30	89	12

Table.3 Panel wise Predictive analysis of falls

Fig.5 Panel wise Tested & Predicted Periodical Falls

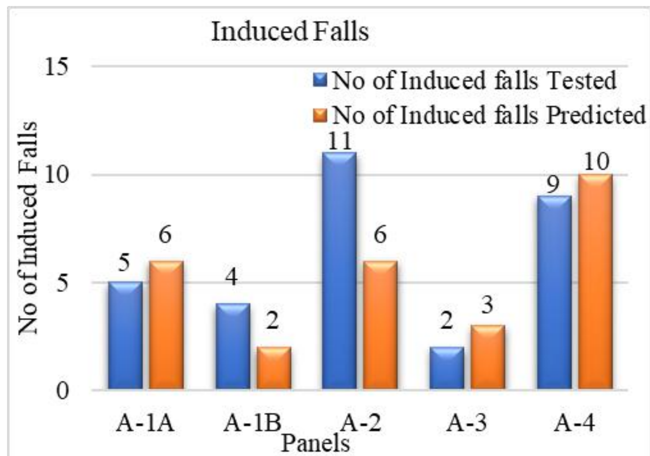
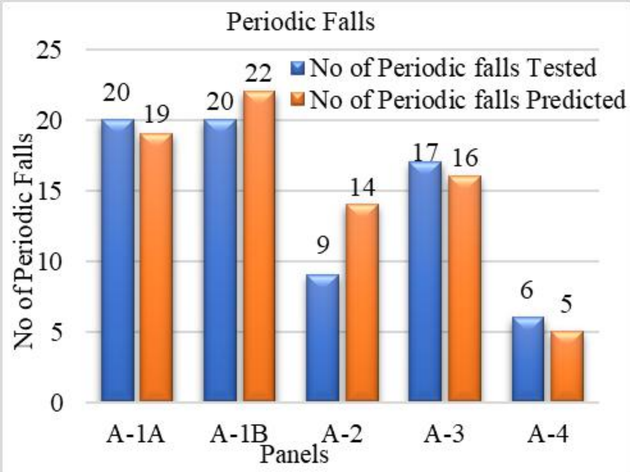


Fig.6 Panel wise Tested & Predicted Induced Falls

4.2.3 Confusion matrix

The confusion matrix is used for the description of the relationship between the tested values and predicted values of the dependent variable i.e., Induced blasting. The confusion matrix and its heatmap of the above model are shown in figure 7. And also the classification report of the model is provided along with the confusion matrix.




```
In [36]: from sklearn.metrics import confusion_matrix

In [37]: confusion_matrix(y_test,y_pred)
Out[37]: array([[67,  4],
                [22,  8]], dtype=int64)

In [42]: sns.heatmap(confusion_matrix(y_test,y_pred),annot=True)
Out[42]: <matplotlib.axes._subplots.AxesSubplot at 0x25d03ec3b48>
```

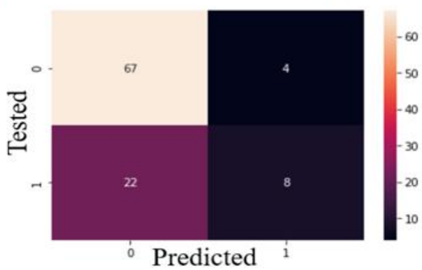


Fig.7 Confusion matrix

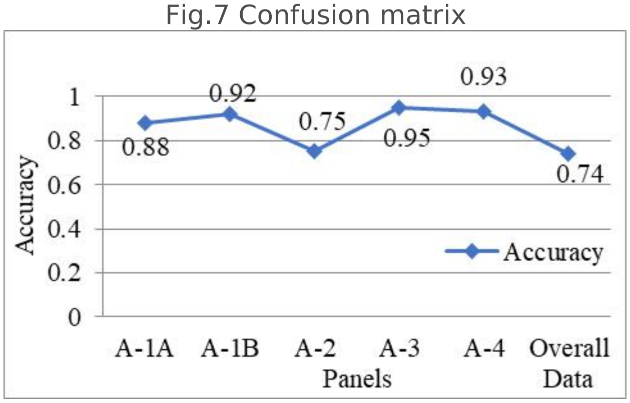


Fig.8 Panel-wise Accuracy of the prediction model.

In the case of panel-wise accuracy analysis, the accuracy levels of 4 panels i.e., A1-A, A1-B, A-3, A-4 are above 0.90 but for the A-2 panel, the accuracy is about 0.75 only. This A-2 panel's data result in the problem of decreasing the accuracy of prediction falls in the model [4].

CONCLUSIONS

1.Analysis of 336 falls in different depillaring panels of continuous miner working of GDK-11 Incline mine shows that there are 221 Periodic falls and 115 induced falls.
2.The induced falls reduce the overall hanging goaf area and avoid problems like crushing of goaf edge pillar, air blast, and accidents in depillaring panels.
3.The predictions model generated using logistic regression generates a decision to induce the roof or not.
4. The accuracy of prediction of roof falls by logistic regression model is 0.742 only. The predictive analysis is carried out panel-wise in which their are occurred and model accuracy levels of 4 panels are above 0.90 but for one i.e., A-2 panel the accuracy is about 0.75.

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