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A Lasso and Elastic-Net Regularized Generalized Linear Model for Predicting Blast-Induced Air Over-pressure in Open-Pit Mines

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Abstract: Air overpressure (AOp) is one of the products of blasting operations in open-pit mines which have a great impact on the environment and public health. It can be dangerous for the lungs, brain, hearing and the other human senses. In addition, the impact on the surrounding environment such as the vibration of buildings, break the glass door systems are also dangerous agents caused by AOp. Therefore, it should be properly controlled and forecasted to minimize the impacts on the environment and public health. In this paper, a Lasso and Elastic-Net Regularized Generalized Linear Model (GLMNET) was developed for predicting blast-induced AOp. The United States Bureau of Mines (USBM) empirical technique was also applied to estimate blast-induced AOp and compare with the developed GLMNET model. Nui Beo open-pit coal mine, Vietnam was selected as a case study. The performance indices are used to evaluate the performance of the models, including Root Mean Square Error (RMSE), Determination Coefficient (R2), and Mean Absolute Error (MAE). For this aim, 108 blasting events were investigated with the Maximum of explosive charge capacity, monitoring distance, powder factor, burden, and the length of stemming were considered as input variables for predicting AOp. As a result, a robust GLMNET model was found for predicting blast-induced AOp with an RMSE of 1.663, R2 of 0.975, and MAE of 1.413 on testing datasets. Whereas, the USBM empirical method only reached an RMSE of 2.982, R2 of 0.838, and MAE of 2.162 on testing datasets.

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1. Introduction

Open-pit mining projects often have a significant impact on the environment and public health, particularly in neighboring areas. The increase in environmental pollution caused by mining operations has been found in the concentrations of wastewater, emissions, radiation, and related policies [23]. The adverse effects caused by blasting operations in open-pit mine such as ground vibration, air overpressure (AOp), fly rock, and back-break are also dangerous agents for humans and the surrounding environment [12, 20, 29, 31]. Of these side effects, AOp is the most dangerous factor.

Air overpressure (AOp) is one of the side effects of blasting operations in an open-pit mine. It is caused by the vibration of the air adjacent to the explosive block or by vibration from the ground. In the case of explosions on the ground, AOp is created directly by the pressure of the explosive product into the ambient air with high destructive power. This side effect of AOp is caused by a sudden increase in air pressure that is greater than the atmospheric pressure at the passing wave. Similar to explosions caused by bombs or weapons, the blast-induced AOp in open-pit mine is responsible for brain, eyes, ears, nasopharynx, oropharynx, larynx and trachea (URT), lung, heart, abdomen, and genito-urinary [26]. At a high level, some pathologies involving the brain, lung, and heart can lead to death. Thus, accurate control and prediction of blast-induced AOp is an essential issue in order to reduce its adverse effects on the environment and the surrounding community.

Review of the literature shows that studies focused on the physiological, pathological, safety threshold and molecular mechanisms of trauma caused by AOp were performed [11]. In addition, the correlation between air overpressure, duration of the blast wave, body mass, and probability of survival was also found in a study by Bowen, Fletcher [7]. However, these studies mainly serve the mode of treatment without the ability to predict and control AOp.

For estimating blast-induced AOp, many scholars have attempted to develop empirical methods based on the relation of the explosive charge per delay (W) and monitoring distance (R) [24, 27, 28, 30, 32]. However, in some cases, experimental methods are often less accurate because the conditions applied in each region are different [15, 16, 20].

In recent years, artificial intelligence (AI) system has become popular and widely applied in many fields. In predicting blast-induced AOp, many scientists have studied and developed predictive models with promising results. Armaghani, Hajihassani [4] successfully developed an adaptive neuro-fuzzy inference system (ANFIS) model for predicting blast-induced AOp in three quarry sites in Malaysia using 128 blasting events. Several empirical methods, artificial neural networks (ANN) and multiple regression (MR) techniques were also used to predict blast-induced AOp and compared with the ANFIS model. The results revealed that the ANFIS was the best model for predicting blast-induced AOp in their study with an RMSE of 2.329 and R^2 of 0.971. In another study, Amiri, Amnieh [3] performed a blast-induced AOp predictive study based on ANN and K-nearest neighbors (KNN), i.e., ANN-KNN. 75 blasting events were collected from the Shur river dam, Iran for their study. The United States Bureau of Mines (USBM) empirical and a single ANN model were also developed to predict blast-induced AOp. The results indicated that the developed ANN-KNN is a superior model in comparison with the ANN and USBM models with RMSE = 1.7 and R^2 = 0.95. Based on the hybrid model technique, Hasanipanah, Shahnazar [17] have also successfully developed a blast-induced AOp model using particle swarm optimization (PSO) and support vector regression (SVR) algorithms, namely PSO-SVR. Three forms of equation include linear (L), quadratic (Q) and radial basis (RBF) kernel functions were applied for PSO-SVR model. Multiple linear regression (MLR) technique was also conducted to estimate AOp and compared with PSO-SVR models. For this aim, 83 datasets were recorded at Shur river dam, Iran. However, their results were not so good with an RMSE of 0.45 and R2 of 0.996 on the testing datasets for the most outstanding performance of PSO-SVR-RBF. In recent studies, Mahdiyar, Marto [25], AminShokravi, Eskandar [2], Alel, Upom [1], Armaghani, Hasanipanah [6], and Faradonbeh, Hasanipanah [13] have also successfully developed blast-induced AOp predictive models based on AI techniques such as Monte Carlo, PSO, genetic algorithm, ANN, and gene expression programming. They are really new powerful tools for predicting blast-induced AOp to control the effects on the environment and public health.

The literature shows that the studies of applying and development of the AI system have been studied and implemented quite well. However, the fact that they are not applied for all subjects or in everywhere. Furthermore, no artificial intelligence model can represent all models to predict blast-induced AOp for all regions. Therefore, in this study, a Lasso and Elastic-Net Regularized Generalized Linear Model (GLMNET) is developed for predicting blast-induced air overpressure to minimize impacts on the environment and public health at Nui Beo open-pit coal mine, Vietnam.

The rest of the article is organized as follows: Section 2 describes the study area and data used in this study; Section 3 gives an overview of the GLMNET algorithm; Section 4 carried out the development of blast-induced AOp predictive models; Section 5 presents the results of this work and discussion; Finally, the conclusions and remarks are drawled in section 6.

2. Materials

In this study, Nui Beo open-pit coal mine, Vietnam was selected as a case study for predicting blast-induced AOp. It is located in the central of Halong City, Quang Ninh province, Vietnam, and it lies within latitudes 20057’30”N - 20058’30”N, and longitudes 10707’55”E - 107009’00”E (Figure 1). This mine is one of the sizeable open-pit coal mines in Vietnam with a production of 1,125,000 tons/year; the capacity of overburden is 4.815.000 m3/year [9]. The fragmentation of rock is conducted by blasting method in the mine. Explosives used on the mine are ANFO, Z113 and AN13 emulsion with 250mm for blast hole diameter in rock breakage and 42mm diameter for oversize rock breakage.

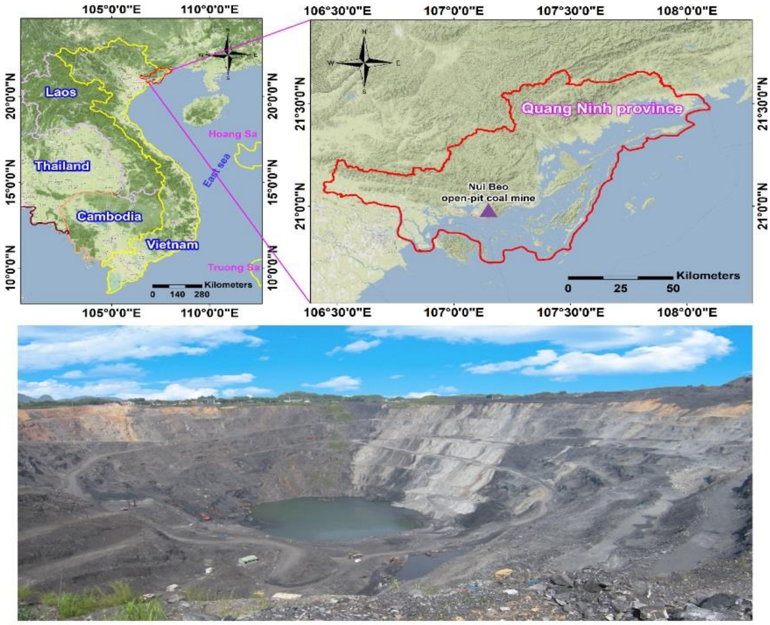

Figure 1. A view of the Nui Beo open-pit coal mine, Vietnam

The study area has complex geological conditions, including many faults and folds. The sedimentary rocks consist of conglomerate, sandstone, claystone, and sandstone with high hardness. The coal seams with average thicknesses are interspersed in clay layers. Figure 2 illustrates the examples of geological cross-sections of the study area.

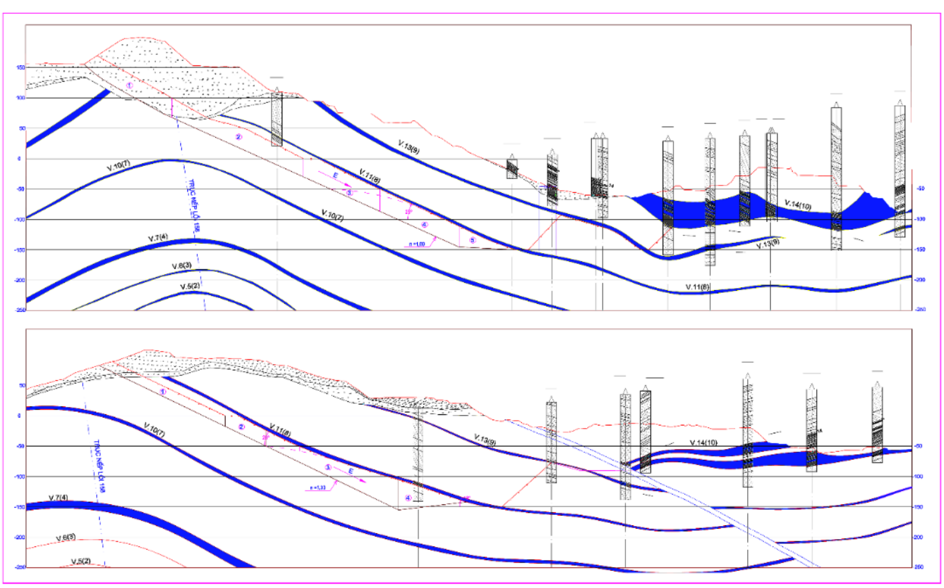

Figure 2. The representative geological cross sections of the Nui Beo open-pit coal mine

For collecting data, the maximum of explosive charge capacity (W), monitoring distance (R), powder factor (P), burden (B), and the length of stemming (T) were considered as the input variables for predicting blast-induced AOp. The Blastmate III (Instantel – Canada) was used to record the values of AOp from blasting operations (Figure 3). A handheld GPS navigation system is used to determine the monitoring distance. The remaining parameters are collected from blast design. Table 1 summarized the datasets used in this study.

Table 1. Summary of the datasets used in this study

W	**R**	**P**
Min. : 1382	Min. :104.0	Min. :0.350
1st Qu.: 4460	1st Qu.:269.5	1st Qu.:0.390
Median : 5932	Median :345.5	Median :0.430
Mean : 5844	Mean :369.0	Mean :0.426
3rd Qu.: 7250	3rd Qu.:451.8	3rd Qu.:0.460
Max. :10143	Max. :740.0	Max. :0.500
B	**T**	**AOp**
Min. :6.600	Min. :6.600	Min. : 79.96
1st Qu.:7.000	1st Qu.:6.900	1st Qu.: 90.76
Median :7.450	Median :7.300	Median : 94.76
Mean :7.442	Mean :7.288	Mean : 95.59
3rd Qu.:7.900	3rd Qu.:7.600	3rd Qu.:100.44
Max. :8.200	Max. :8.000	Max. :115.78

In this study area, the maximum of AOp value is 115.78 decibels (dB) at 104m for the monitoring distance, the mean of AOp value is 95.59 dB. Whereas, the nearest distance to the surrounding residential is 100m. The allowable noise level in the recommended occupational is 85 dB, whereas, the people and the workers in the mine must be continuously exposed to noise beyond the allowable limits caused by the blast. Hearing difficulties and other cardiovascular diseases can arise. Therefore, they need to be controlled and predicted to minimize the negative impact on public health.

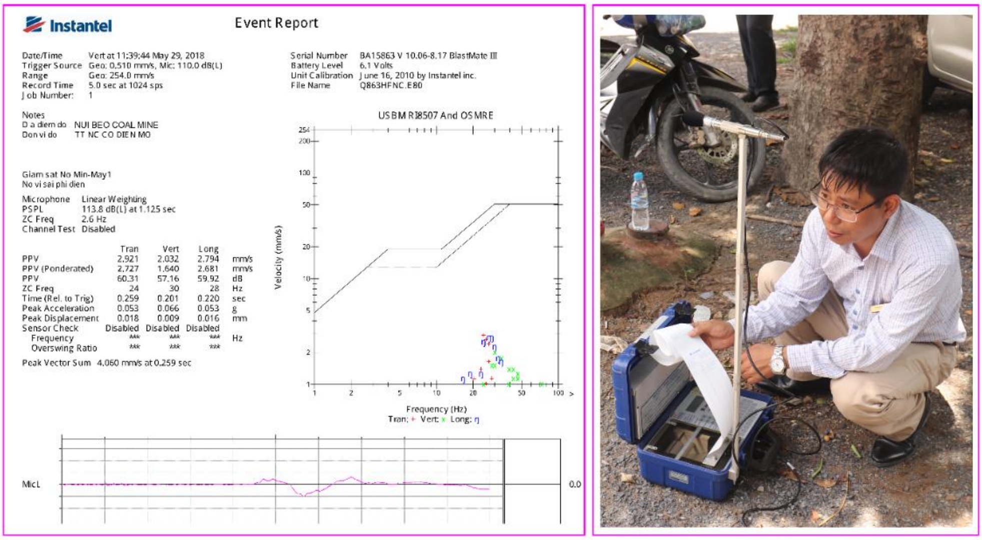

Figure 3. Collecting data by Blastmate III – Instantel

3. Details of GLMNET

The Lasso and Elastic-Net Generalized Linear Model (GLMNET) is one of the machine learning algorithms in the artificial intelligence system introduced by Friedman, Hastie [14]. The GLMNET algorithms continuously optimize the objective function on each parameter; the remaining parameters are fixed. It uses cyclical coordinate descent and executes continuously until convergence [18]. For predicting blast-induced AOp, the GLMNET can be described as follows:

Let y_i is the value to forecast, i.e., AOp; x_i is a matrix consisting of input variables such as W, R, P, B, and T; $x_i = (x_{i1}, x_{i2}, ..., x_{\mathrm{ij}}, ..., x_{ik})^T$ with k denotes the number of descriptors. A linear model for each predicted AOp result is assumed as follows:

$$y_i = x_i^T \beta + \varepsilon_i \tag{1}$$

Where β is a coefficient, $\beta = (\beta_1, \beta_2, \ldots, \beta_j, \ldots, \beta_k)^T$; ε_i is the error between the actual and the predicted AOp values. The coefficients β are determined that ε_i is minimized. The residual sum of squares is minimized as follows:

$$E(\beta) = \sum_{i=1}^{n} (y_i - x_i^T \beta)^2 \tag{2}$$

The minimizing coefficients are defined by ordinary least squares method [10] as follows:

$$\hat{\beta} = (X^T X)^{-1} X^T y \tag{3}$$

Where $X = (x_1^T, x_2^T, \ldots, x_i^T, \ldots, x_n^T)$ and $y = (y_1, y_2, \ldots, y_i, \ldots, y_n)^T$.

Should be noted that, this equation cannot be solved in the case of $k > n$ because$X^T X$ becomes singular. Therefore, the regularized regression technique can be employed for instead. The loss function for a type of regularized regression, i.e., Elastic-Net is defined as follows:

$$E(\beta) \sum_{i=1}^{n} (y_i - x_i^T \beta)^2 + \lambda \sum_{i=1}^{k} (1-\alpha)\beta_j^2 + \alpha|\beta_j| \tag{4}$$

By minimizing the loss function of Elastic-Net in equation (4), the coefficients β can be estimated. The factors that are not important to AOp can be eliminated, even if $k > n$. It can be seen that, α and λ are parameters that determine the performance of the forecasting model and adjusted for the purpose of the user $(0 < \alpha < 1)$. If $\alpha = 0$, this model corresponds to ridge regression [19]. In the case of $\alpha = 1$, this model corresponds to LASSO regression [33]. For each value of α, the λ and β parameters are defined so that the loss function $E(\beta)$ is minimized. The values of λ are determined by leave-one-out cross-validation method (LOOCV) [8].

By continuously optimizing the objective function on each parameter while other parameters are fixed, GLMNET has the high-speed computing power and sparse resolution in the input matrix x_i [18] for predicting blast-induced AOp.

The literature review showed that GLMNET had not been developed to predict blast-induced AOp. Therefore, it was conducted in this study to assess its applicability and accuracy level in predicting blast-induced AOp.

4. Developing the AOp predictive models

For developing the AOp predictive models, a randomized data splitting procedure is performed. Accordingly, the initial datasets with 108 blasting events are divided into two parts: 80% of the whole datasets (including 88 blasting events) are used as the training datasets for developing the predictive models; the remaining 20% (equivalent to 20 blasting events) are used as the testing datasets for evaluating the performance of the developed models. For the comparison purposes, the United States Bureau of Mines (USBM) empirical technique is also applied for estimating blast-induced AOp. Should be noted that all AOp predictive models are developed on the same set of training data.

To avoid overfitting in the development of the predictive models, a resampling technique is used, i.e., repeated k-fold cross-validation [21]. For the number of data in the training datasets are 88 observations, we chose k = 10 fold for resampling technique, namely 10-fold cross-validation with 3 repeats. The detailed of 10-fold cross-validation resampling technique can be explained in reference [34].

4.1. Empirical

Empirical is one of the methods used to estimate the blast-produced AOp in an open-pit mine. It is realized by collecting the datasets of blasting operations and using a statistical method to find out the site factors and forecasting equations. Kuzu, Fisne [22] conducted AOp predictions by identifying scaled-distanced (SD) based on the United States Bureau of Mines (USBM) empirical equation to calculate the site factors. Among the empirical methods, USBM method is the experimental technique was widely used to predict AOp in open-cast mine based on the relationship between the monitoring distance (R) and the maximum explosive charge capacity (W), and site factors [5, 15]. The relationship between W and R is determined through the SD values as below [22]:

$$SD = RW^{-0.33} \tag{5}$$

Where R denotes the monitoring distance (m); W is the maximum explosive charge capacity (kg); SD is the scaled distance factor (m kg-0.33).

From the scaled distance, AOp can be calculated as follow [22]:

$$AOp = k(SD)^{-\beta} \tag{6}$$

Where AOp is measured in decibels (dB), k and β are site factors and computed by the regression analysis method. Depending on the specific conditions of each mine, the site factors are different.

In this study, the training datasets with 88 blasting events are used to calculate the site factors of the Nui Beo open-pit coal mine, Vietnam. Eviews software version 8.0 was used for multivariate regression analysis to determine the site factors in this study. As a result, the site factors are determined as $k=175.307$ and $\beta=0.203$ for USBM empirical equation. The USBM equation for predicting blast-induced AOp in this study is described as follows:

$$AOp = 175.307(SD)^{-0.203} \tag{7}$$

4.2. GLMNET

In GLMNET, α and λ are the parameters of the algorithm used to control the quality of the forecasting model as mentioned. It is complicated to know that which model is the best for predicting blast-induced AOp in this study. Therefore, a "trial and error" procedure was performed with 1000 different GLMNET models in the R software environment version 3.4.4. Should be noted that the values of α being in the range of 0 to 1; corresponds to each value of α, λ is defined by the LOOCV method so that the loss function was minimized. The performance of the predictive models on the training datasets is assessed based on the Root Mean Square Error (RMSE) metric. Figure 4 demonstrated the performance of 1000 GLMNET models with various of α and λ parameters in the “trial and error” procedure. Finally, a best GLMNET model was found with $\alpha=0.974$ and λ=0.117.

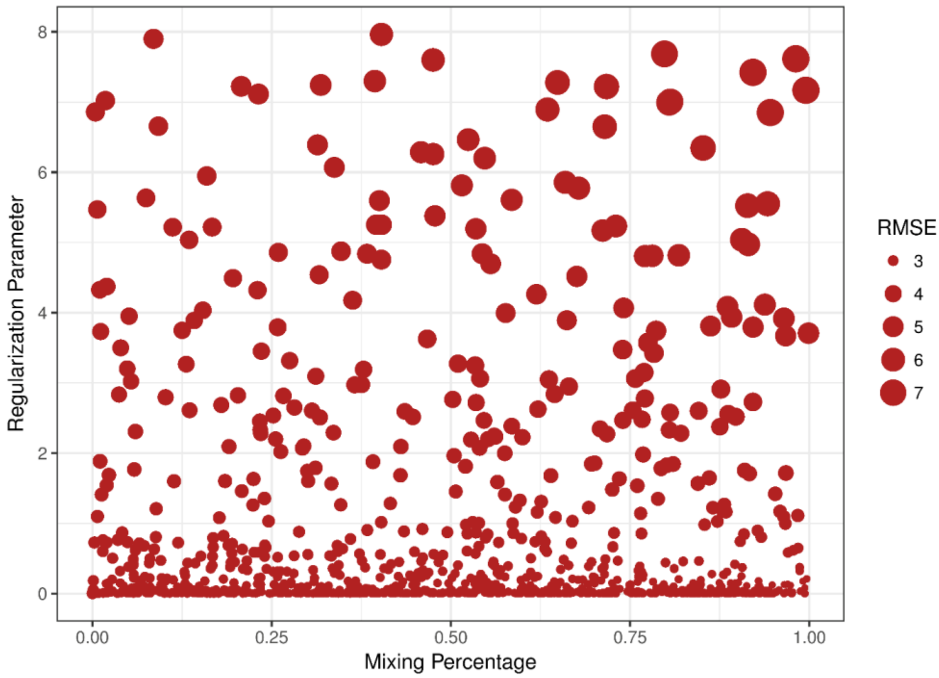

Figure 4. The performance of the GLMNET models on the training datasets

5. Results and discussion

As regarded, the performance of the blast-induced AOp predictive models was compared and evaluated on both the training datasets and the testing datasets. The performance indices include Root Mean Square Error (RMSE), Determination Coefficient (R2), and Mean Absolute Error (MAE) are used to evaluate the performance of the predictive models and computed as follow:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{8}$$

$$R^2 = 1 - \frac{\sum_i (y_i - f_i)^2}{\sum_i (y_i - \bar{y})^2} \tag{9}$$

$$MAE = \frac{1}{n}\sum_{j=1}^{n} |y_i - \hat{y}_i| \tag{10}$$

Where n is the total number of data, y_i is the measured value, $\hat{y}_i$ is the predicted value, and $\bar{y}$is mean of measured values. In the most optimal model, R^2 should be equal to 1, and the RMSE and MAE should be equal to 0, respectively.

Based on the developed models and equations (8-10), the performance of the predictive models on the training and testing datasets are computed as shown in Table 2.

Table 2. Performance indices of the AOp predictive models

Model	Training datasets			Testing datasets		
	RMSE	R2	MAE	RMSE	R2	MAE
Empirical (USBM)	4.195	0.682	2.548	2.982	0.838	2.162
GLMNET	2.837	0.822	1.713	1.663	0.975	1.413

From Table 2, it can be seen that the GLMNET model outperformed the empirical model on both the training datasets and the testing datasets. The performance of the GLMNET model reached an RMSE of 2.837, R^2 of 0.822, and MAE of 1.713. Whereas, the empirical model only achieved an RMSE of 4.915, R^2 of 0.682, and MAE of 2.548 on the training datasets.

As mentioned, the testing datasets as the unseen data are used to evaluate the performance of the developed models. Accordingly, the selected GLMNET model provided very high performance with RMSE = 1.663, R^2 = 0.975, and MAE = 1.413 on the testing datasets. Whereas, the empirical model only achieved performance with RMSE = 2.982, R^2 = 0.838, and MAE = 2.612 on the testing datasets. Figure 5 interpreted the relationship between measured and predicted values on the testing datasets.

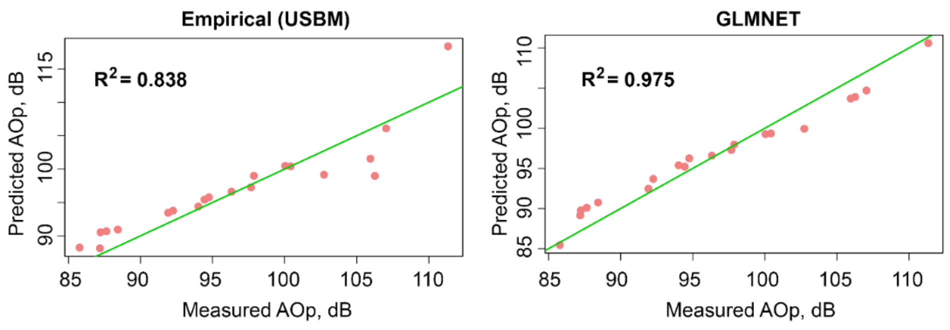

Figure 5. The relationship between measured and predicted values

As set out in this study, high levels of accuracy are needed for predicting blast-induced AOp to minimize the impact on the environment and public health. Figure 6 demonstrated that the developed GLMNET model provides very high levels of accuracy for predicting blast-induced AOp in comparison with empirical models and measured values for the testing of datasets.

It can be seen that the GLMNET model works very well in this study with the number of input variable is high (5 input variables). Whereas, the USBM empirical technique uses only two input variables for predicting blast-induced AOp. Therefore, a technique for analyzing the influence of input variables on the performance of the GLMNET model was implemented in this study. As a result, W, R, P, and T are the input variables that affect the performance of the GLMNET model with the overall effect level of W is 0.076; R is 6.269; P is 0.303; and T is 0.083. The results of the analysis also showed that B is a parameter that does not affect the performance of the GLMNET forecasting model and should be considered for elimination during the development of the AOp forecasting model.

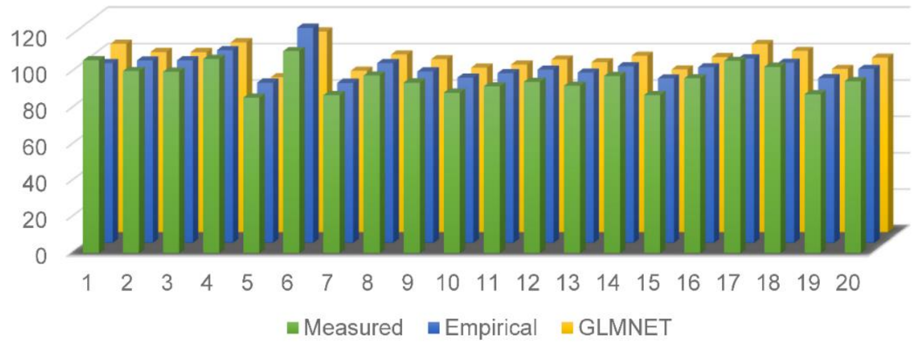

Figure 6. Comparison of predicted values by empirical and GLMNET models

6. Conclusions and remarks

Blasting is an indispensable task for rock fragmentation in an open-pit mine. However, its undesirable effects need to be controlled to minimize adverse effects on the environment and public health, especially air overpressure. Based on the results of this study, we draw some conclusions:

- GLMNET is an advanced artificial intelligence system for predicting blast-induced AOp in open-pit mine with high accuracy. It is possible to explain the linear relationship between multiple input variables that affect the performance of the AOp predictive model. However, the development of the GLMNET model is often complex and takes much time to find the optimal parameters for the model. In addition, higher input variables require more careful and thorough data collection.

- The input parameters include maximum explosion charge capacity (W), monitoring distance (R), powder factor (P), and the length of stemming (T) are the main parameters that affect the performance of the AOp predictive model. Burden (B) parameter should be considered for elimination during the development of AOp predictive models.

- The selected GLMNET model in this study is the best of the 1000 GLMNET models developed. However, some of the other GLMNET models also yielded relatively high performance. Their combination should be studied and considered to improve the accuracy of the blast-induced AOp model.

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