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ARTIFICIAL NEURAL NETWORK EVALUATION AND PREDICTION OF BLAST-INDUCED PEAK PARTICLE VELOCITY - A CASE STUDY OF LIMESTONE MINING

PENILAIAN DAN PREDIKSI JARINGAN SYARAF TIRUAN TERHADAP KECEPATAN PARTIKEL YANG DIINDUKSI PELEDAKAN - STUDI KASUS PENAMBANGAN BATUGAMPING

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ABSTRACT

In recent decades, generation of ground vibrations results from blasting activities in mining sector has been identified as a significant cause of extensive harm to nearby structures, vegetation, and individuals. Hence, it is imperative to closely monitor and accurately forecast the uncertain levels of vibration, and implement the appropriate steps to mitigate their potentially harmful impact. The objective of this study was to establish a correlation between the peak particle velocity and the various parameters that influence it. This study employed the deployment of the artificial neural network approach to assess and forecast the uncertain ground vibrations. In this study, a multilayer perception neural network with three layers and a feed-forward back-propagation architecture was employed. The network consisted of five input parameters, namely the distance from the blast face, maximum charge per delay, spacing, burden, and depth hole. The output of interest was the peak particle velocity. The neural network was trained using the Levenberg–Marquardt algorithm, and the training dataset comprised 29 experimental records and blast event data obtained from the limestone mine in Indonesia. In order to assess the effectiveness and the precision of the artificial neural network model that was created, a total of four conventional predictor models were utilized. These models were proposed by reputable sources such as the US Bureau of Mines, Ambraseys–Hendron, Langefors–Kihlstrom, and the Bureau of Indian Standards. The results collected from the demonstrate study show that the artificial neural network model suggested in this research has the ability to provide more precise estimations of ground vibrations in comparison to existing conventional prediction models. The artificial neural network model yielded a coefficient of determination (R2) of 0.9332 and a root mean square error (RMSE) of 0.4763.

Keywords: peak particle velocity, blast-induced ground vibration, artificial neural network, conventional predictors.

ABSTRAK

Dalam beberapa dekade terakhir, getaran tanah yang dihasilkan dari aktivitas peledakan pada sektor pertambangan telah teridentifikasi sebagai penyebab kerusakan struktur tanah, vegetasi, dan masyarakat sekitar. Oleh karena itu, perlu adanya pemantauan getaran secara akurat untuk memperkirakan tingkat getaran, dan menerapkan langkah-langkah yang tepat untuk mengurangi dampak kerusakan akibat getaran peledakan. Tujuan penelitian ini adalah memprediksi peak particle velocity *(PPV) dan berbagai parameter yang mempengaruhinya. Penelitian ini menggunakan pendekatan jaringan syaraf tiruan untuk menilai dan meramalkan getaran tanah yang tidak menentu. Dalam penelitian ini, jaringan saraf persepsi* multilayer *dengan tiga lapisan dan arsitektur* feed-forward

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back-propagation *digunakan. Jaringan ini terdiri dari lima parameter input, yaitu jarak permukaan ledakan, muatan maksimum per penundaan, spasi,* burden*, dan kedalaman lubang. Keluaran yang diinginkan adalah kecepatan partikel puncak. Jaringan syaraf tiruan dilatih menggunakan algoritma Levenberg-Marquardt, dan kumpulan data pelatihan terdiri dari 29 aktivitas peledakan dan data kejadian ledakan yang diperoleh dari tambang batugamping di Indonesia. Untuk menilai efektivitas dan ketepatan model jaringan syaraf tiruan yang telah dibuat, sebanyak empat model prediktor konvensional digunakan sebagai pembanding. Model prediksi tersebut adalah US Bureau of Mines, Ambraseys–Hendron, Langefors–Kihlstrom, dan Bureau of Indian Standards. Hasil yang diperoleh dari penelitian ini menunjukkan bahwa model jaringan syaraf tiruan memiliki kemampuan untuk memberikan estimasi* peak particle velocity *(PPV) yang lebih akurat dibandingkan dengan model prediksi konvensional yang sudah ada. Model jaringan syaraf tiruan menghasilkan koefisien determinasi (R2) sebesar 0,9971 dan* root mean square error *(RMSE) sebesar 0,08133.*

Kata kunci: peak particle velocity*, getaran tanah,* artificial neural network*, model prediksi konvensional.*

INTRODUCTION

Mineral exploitation in the framework of infrastructure development in Indonesia tends to increase. Drilling and blasting is one of the exploitation efforts that have economic value in excavating rock masses. Until recently, explosives were a valuable source of energy required for the breaking, excavation and displacement of rock masses. Explosives detonate in the blast hole, releasing a large amount of energy, when converted to a pressure of up to 50 GPa and a temperature of up to 5000 K released (Chen and Huang, 2001; Hajihassani, Jahed Armaghani, Marto, *et al.*, 2015). Although there have been significant developments in explosives technology, the utilization of explosives energy has not progressed much due to the complexity of various rock parameters (Armaghani *et al.*, 2014). In blasting, only about 20% -30% of the energy used is used for breaking and moving rock masses, the rest of the energy is lost to ground vibrations, fly rocks, noises, back breaks, over breaks, and so on. Several variations of vibration parameters to predict and reduce the effects of blasting have been carried out. The vibration parameters are displacement, velocity and acceleration (Khandelwal and Singh, 2009; Dindarloo, 2015). When these explosives are used, people living around the mining area get disturbed. It is possible because of the high level ground vibrations, their homes can be damaged and there is always a confrontation between the mine manager and the community around the mine area (Ram Chandar, Sastry and Hegde, 2017). Problems High ground vibrations not only cause problems for the people in the vicinity, but also have a negative impact on structures in the mining area. These problems can provoke residents and close the mine. High-intensity vibrations also damage and clog the existing groundwater channels and damage the ecology of the surrounding area. If ground shaking is not controlled or minimized, it may become one of the main causes of deforestation in the future (Ragam and Devidas S. Nimaje, 2018). Ground vibration is influenced by several parameters such as the physico-mechanical properties of the rock mass, blast characteristics and blast design (Priyadarshi *et al.*, 2023). The influence of these parameters is very important to know as an effort to efficiently utilize explosive energy and minimize unwanted effects of explosions. Design parameters such as maximum payload per delay, delay time, load, distance, payload length, initiation sequence and load decoupling, greatly change the seismic energy dispersion (Pal Roy, 2021). Therefore, it is necessary to optimize the design parameters of the blast and the characteristics of the explosives based on the rock mass properties, such as strength, density, porosity, longitudinal wave velocity, impedance, stress-strain response and the presence of structural discontinuities. Through these parameters, it is necessary to have a predictive method that provides safe peak particle velocity (PPV) values in the context of safe, smooth and environmentally friendly excavation of rock masses for mining and civil construction projects (Shirani Faradonbeh *et al.*, 2016). One of these prediction methods is an Artificial Neural Network. By using the method artificial neural networks (ANN), PPV frequency can be predicted before the explosion and produces the highest significance value which is 99% or more accurate than conventional methods such as USBM, MLR etc. (Prashanth and Nimaje, 2018; Ragam and Devidas Sahebraoji Nimaje, 2018). The detonation design can be modified in such a way that detonation disturbance can be minimized, efficient utilization of detonation energy will be achieved (Bakhshandeh Amnieh, Siamaki and Soltani, 2012; Bui *et al.*, 2021; Bui, Nguyen and Nguyen, 2021). Several researchers have conducted investigations and put forth various conventional vibration predictors to predict PPV. These predictors are outlined and summarized in Table 1 below.

Table 1. The conventional formula used for predicting PPV

Name	Formula
United State Bureau of Mines (Duvall and Petkof, 1959)	$PPV = K\left[\frac{D}{\sqrt{Q_{max}}}\right]^{-B}$
Langefors–Kihlstrom (Langefors and Kihlstrom, 1963)	$PPV = K\left[\sqrt{\left(\frac{Q_{max}}{D^{2/3}}\right)}\right]^{-B}$
Ambraseys–Hendron (Ambraseys and Hendron, 1968)	$PPV = K\left[\frac{D}{Q_{max}{}^{1/3}}\right]^{-B}$
Bureau of Indian Standards (Indian Standard Institute (ISI), 1973)	$PPV = K\left[\sqrt{\left(\frac{Q_{max}}{D^{2/3}}\right)}\right]^{-B}$

The proposed conventional predictor equations can estimate the PPV based on two specific parameters: the distance between the blasting face and the monitoring point and the maximum charge per delay. While a few studies have overlooked the incorporation of attenuation/damping factor, it is essential to note that the PPV is influenced by several geological, geotechnical, blast geometry, and explosive properties (Armaghani *et al.*, 2014). These aspects have yet to be accounted for in the current predictors. The impacted parameters, such as distance, maximum charge per delay, spacing, burden, etc., exhibit significant magnitudes and intricate interrelationships. Consequently, conventional predictor methods may not be appropriate in this context, and the existing predictors cannot forecast other significant parameters such as frequency, air noise, and flying rocks.

The objective of this study was to utilize ANN for the purpose of forecasting ground vibrations resulting from blasting activities at the limestone mine in Gresik, Indonesia. The findings produced from the ANN were compared with those of four conventional vibration predictors.

METHODOLOGY

A selection was made of 29 explosion events that were recorded at various monitoring locations located in and around mine A, specifically within the distance ranges of 100 – 200 m and 200 – 300 m. The PPV values were measured using the Blassmate III instrument, which has a measurement range of 0-254 mm/s. The precision of the measurements is reported to be 0.5 mm/s. The device is equipped with a transducer that operates in three dimensions and a sensor for capturing sound from the surrounding air. These components are utilized to quantify PPV as well as airborne noise levels. The instrument should be securely attached to both the microphone and the geophone through the wires. It is imperative that it be situated in a location that ensures safety. The positive predictive values (PPVs) was influenced by several parameters, including the physico-mechanical properties of the rock mass, explosive characteristics, and blast design. Table 2 presents the input parameters and their corresponding ranges, which have been derived from the field investigation and the blasting process (Figure 1).

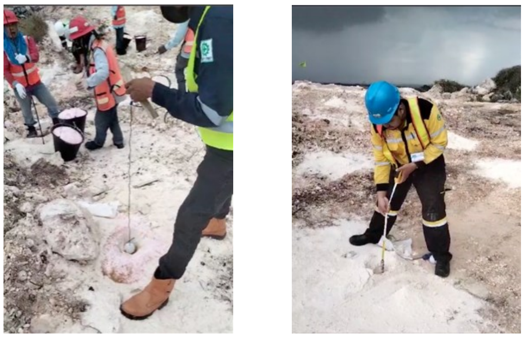

Figure 1. Blasting proses

Table 1 is a compilation of standard vibration prediction equations proposed by a range of scholars, scientists, researchers, and field engineers. The equation for calculating PPV was established by the United States Bureau of Mines (USBM) as follows (Ataei and Sereshki, 2017):

$$PPV = K \left[\sqrt{\frac{D}{Q_{max}}}\right]^{-B} \text{ or } PPV = K_{[SD]^{-B}}$$

Where PPV is the Peak Particle Velocity, SD is the scaled distance, and K and B are the site constants. The site constants K and B were determined by plotting graph between PPV and different scaled distance (SD) (Tarumasely, Wardana and Prastowo, 2024). The general equation of straight line is
y = mx + C

This implies that the PPV and SD data should demonstrate a linear relationship when plotted on a logarithmic scale graph paper. Consequently, $y = PPV$, $x = SD$, intercept $C = k$, and slope $-B = m$.

ANNs have shown excellence in predicting blast-induced ground vibration due to their ability to capture complex nonlinear relationships between the input parameters and the output responses. The ANNs have been widely used in the field of rock mechanics and geotechnical engineering for ground vibration prediction with high accuracy. Several studies have demonstrated the effectiveness of ANNs in blast-induced ground vibration prediction. Various types of neural networks was applied to predict blast-induced ground vibration and found that the ANN models outperformed traditional empirical models (Monjezi *et al.*, 2010; Lawal and Kwon, 2021). Similarly, particle swarm optimization-based ANN approach achieved accurate predictions of blast-induced ground vibration (Hajihassani, Jahed Armaghani, Monjezi, *et al.*, 2015).

Furthermore, the ANNs have been combined with other optimization algorithms to enhance their performance. The ANN is optimized by the imperialist competitive algorithm to predict ground vibration in quarry blasting, and the results showed improved accuracy compared to the traditional methods (Hajihassani, Jahed Armaghani, Marto, *et al.*, 2015; Das and Chakrabortty, 2021).

The activation function is used as a determinant of the neuron output. One of the training methods in the ANN is supervised learning. The main goal of the artificial neural network (ANN) training procedure is to minimize the quantified error (Abd Elwahab, Topal and Jang, 2023; Taiwo *et al.*, 2023). Prior to analyzing and drawing conclusions from newly obtained data, it is imperative to ensure that the neural network has undergone appropriate training. In this study, a back-propagation (BP) training algorithm that encompasses four distinct stages: weight initialization, feed-forward computation, error back-propagation, and weight and bias updating is examined (Wang *et al.*, 2023).

This study utilized a feed-forward back-propagation neural network, and the ANN model was implemented using the Python3 software. The analysis was conducted in two distinct stages, specifically served as training and validation. The data set, consists of 29 samples, is partitioned into two distinct datasets, namely the training dataset and the validation dataset. The former consists of 24 samples, while the later comprises the remaining 5 samples.

The performances of several traditional predictor models were assessed using several common statistical performance evaluation criteria. The statistical measurements that are commonly employed include the coefficient of determination (R^2), mean absolute deviation (MAD), mean squared error (MSE), mean absolute percentage error (MAPE), and root mean square error (RMSE) (Ragam and Devidas Sahebraoji Nimaje, 2018).

RESULTS AND DISCUSSION

The ANN model in mining has been carried out mainly on PPV prediction. Through the input parameters hole depth, spacing, burden, distance, Charge per delay, the PPV prediction using the ANN model, PPV predicted by ANN model is very close to the measured data. This study demonstrates a comparative analysis of the precision positive predictive values (PPVs) obtained from artificial neural networks (ANN) and various predictor equations (Figure 2).

In the Artificial Neural Network method, this study chose the 5-10-1 Architecture model, seen in Table 3, and Iterations/epoch = 500 times, while Programming uses Python3. The input parameters are distance, spacing, burden, hole depth, and charge per delay (Table 2). The architectural model is shown in Figure 3.

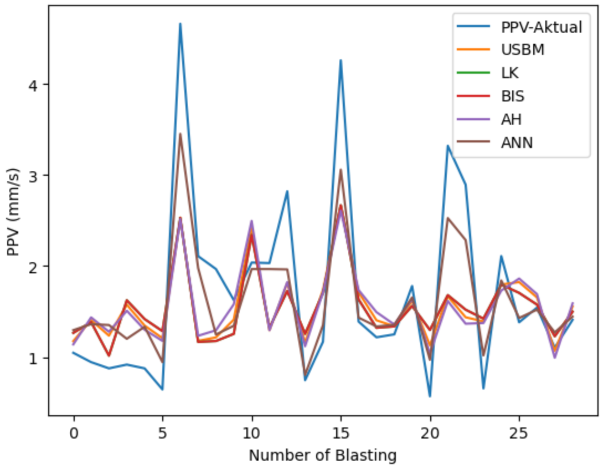

Figure 2. Predictor models' measured and forecasted PPVs

Table 2. Parameter of monitoring in Limestone Mine

No	Parameter	Symbol	Unit	Minimum	Maksimum	Mean	Standar Deviation
1	Spacing	S	m	3	5	3.90	0.54
2	Burden	B	m	2	3	2.38	0.32
3	Hole Depth	HD	m	3.5	8	6.01	0.65
4	Distance	D	m	404	943	588.58	115.19
5	Charge per Delay	Q	kg	427.2	8287.2	2918.46	2157.32
6	Peak Particle Velocity	PPV	mm/s	0.57	4.66	1.70	1.04

Table 3. Characteristics of the ANN architecture

Network type	Feed-forward back-propagation
Number of neurons in the input layer	5
Number of neurons in the hidden layer	10
Number of neurons in the output layer	1
Number of layers	3

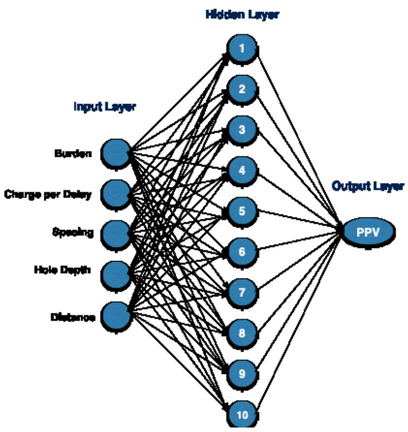

Figure 3. ANN architecture

The 500 iteration results show a significant reduction in error and the final loss result is 0.2322. The iteration shows the number of repetitions of the train data so that it approaches the test data (Figure 4).

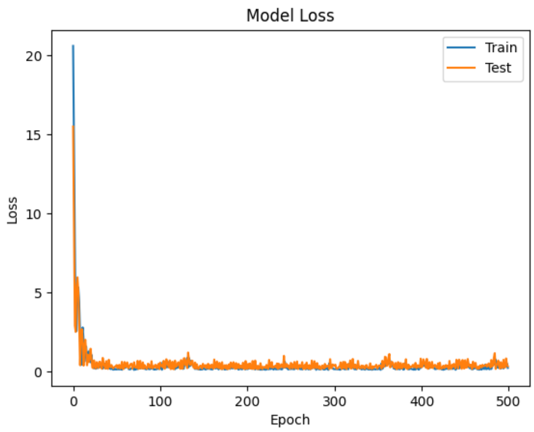

Figure 4. Loss Model

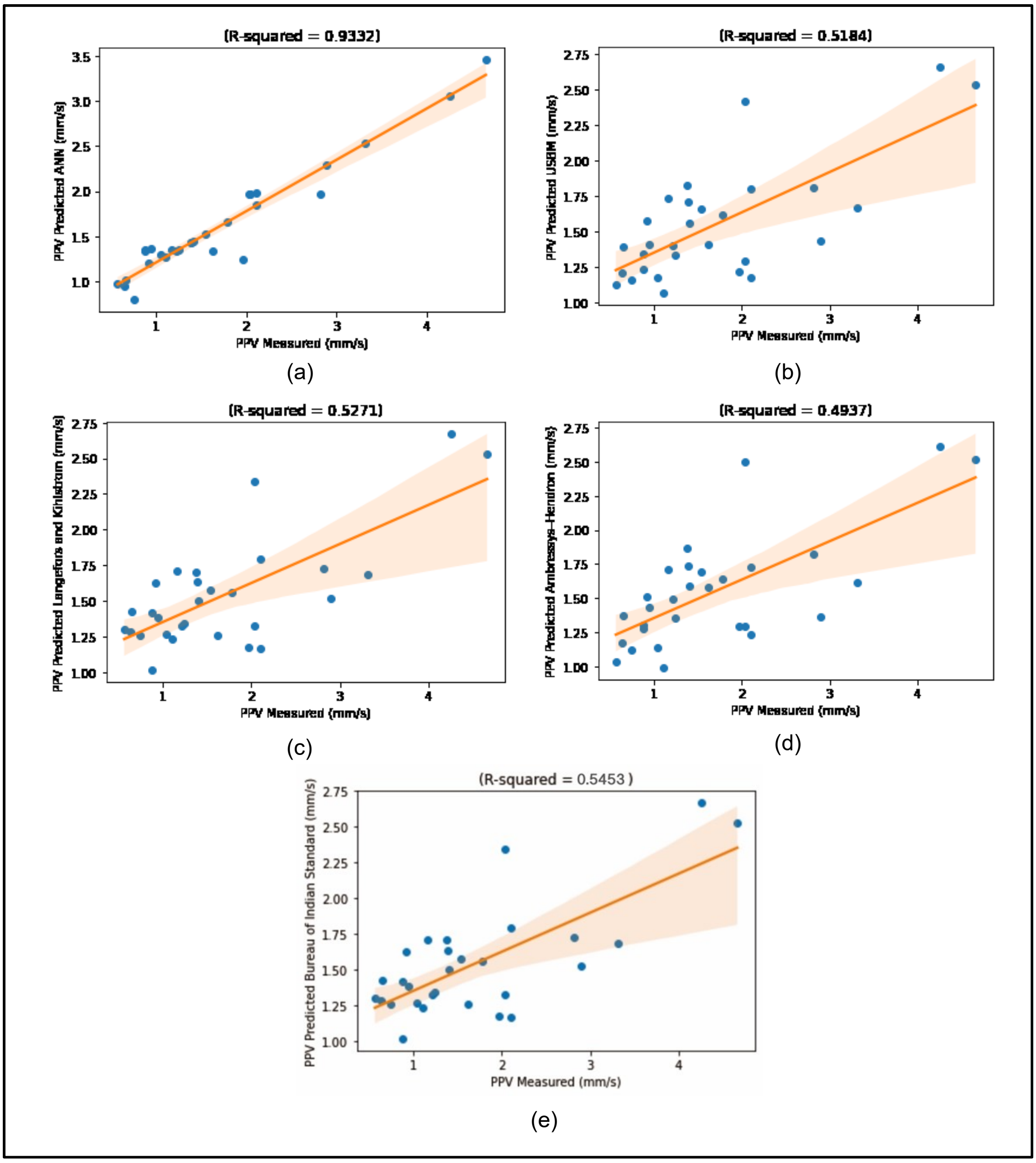

Figure 5. (a) ANN predictor, (b) USBM predictor, (c) Langefors–Kihlstrom predictor, (d) Ambraseys–Hendron predictor, (e) Bureau of Indian Standards predictor

Table 4. Performance of developed statistical models

No	Model	R^2	MAD	MSE	RMSE	MAPE
1	ANN	0.9332	0.0915	0.2269	0.4763	0.1079
2	USBM	0.5184	0.1517	0.6314	0.7946	0.2887
3	Langefors–Kihlstrom	0.5271	0.1601	0.6403	0.8002	0.3104
4	Ambraseys–Hendron	0.4937	0.1500	0.6410	0.8007	0.2814
5	Bureau of Indian Standards	0.5453	0.1661	0.6703	0.8355	0.3304

ANN: artificial neural network; USBM: US Bureau of Mines; MAD: mean absolute deviation; MSE: mean square error; RMSE: root mean square error; MAPE: mean absolute percentage error

R^2, MAD, MSE, MAPE, RMSE, and MAPE are summarized in Table 4 for ANN and numerous conventional vibration equations. Here, the Bureau of Indian Standards predictor yields the highest RMSE while the ANN yields the lowest.

All conventional predictors have site-specific constants, making them incapable of predicting the safe charge for equivalent mining conditions in other locations. As the earth conditions changed, the site and attenuation constant values also varied. In addition, these are derived from just two parameters, namely the maximum charge per delay and the distance between the monitoring point and the explosion face. Based on a linear relationship between scaled distance (D/Qmax) and PPV, these empirical predictors are linear (Khandelwal and Singh, 2009).

CONCLUSION AND SUGGESTION

An assessment was conducted to evaluate the blast-induced ground vibration at limestone mine, specifically focusing on the peak particle velocities (PPV) associated with different blast occurrences. In this study, a set of four conventional vibration predictor equations and one by artificial neural network (ANN) predictor were utilized and suggested for the estimation PPV. In order to assess the precision of the constructed model, five performance indicators were utilized and determined. These indicators include R2, MAD, MSE, RMSE, and MAPE. The results obtained indicate that the ANN predictive model exhibits a substantial R2 value of 0.9332, a low mean squared error (MSE) of 0.2269, and a smaller root mean squared error (RMSE) of 0.4763. In addition, it yields improved predictive outcomes and demonstrates a satisfactory level of accuracy in comparing projected and measured positive predictive values (PPVs).

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