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Research Article

Prediction of Peak Velocity of Blasting Vibration Based on Artificial Neural Network Optimized by Dimensionality Reduction of FA-MIV

Zhang Zhongya [1,2,3] **and Jin Xiaoguang** [1,2,3]

[1] *Reservoir Area Environmental Geological Hazard Prevention and Control of National Local Joint Engineering Research Center (Chongqing), Chongqing 400030, China*
[2] *Key Laboratory of New Technology for Construction of China in Mountainous Area, Chongqing University, Chongqing 400045, China*
[3] *School of Civil Engineering, Chongqing University, Chongqing 400045, China*

Correspondence should be addressed to Jin Xiaoguang; 20161601008@cqu.edu.cn

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Blasting vibration is harmful to the nearby habitants and dwellings in diverse geotechnical engineering. In this paper, a novel scheme based on Artificial Neural Network (ANN) method optimized by dimensionality reduction of Factor Analysis and Mean Impact Value (FA-MIV) is proposed to predict peak particle velocity (PPV) of blasting vibration. To construct the model, nine parameters of field measurement are taken as undetermined input parameters for research, while peak particle velocity (PPV) is considered as output parameter. With the application of FA, common factors are extracted from undetermined input parameters. Then, principal components are defined as a linear combination of common factors. The weight of each principal components effected on output parameter is ranked according to the calculation of MIV, and two principal components with minimum weight are eliminated. Ultimately, output parameter (PPV) is explained in a low-dimensional space with four input characteristic parameters. In the prepared database consisting of 108 datasets, 98 datasets are used for the training of the model, while the rest are used for testing performance. The performances of the ANN models are compared with regression analysis, in terms of coefficient of determination (R^2) and mean absolute error (MAE). It is found that the performances of ANN models with using FA-MIV are superior to those of models without using FA-MIV in the prediction of PPV. In addition, the abilities of ANN models are all superior to regression analysis in the prediction of PPV. The result obtained from ELM is more accurate than BPNN and MVRA models.

1. Introduction

Drilling and blasting, the most widely applied in the field of tunneling, mining engineering, and civil engineering projects, have been used for a long time. Although Tunnel Boring Machines (TBMs) are now used in many tunneling projects, most civil, tunneling, and mining engineering projects involving the underground excavation in rock are still performed using blasting [1, 2].

During the explosive charges large quantities of energy are released. There are reports that about 20% of explosive energy is used in actual breakage and displacement of rock mass and the rest reflect in ground vibration, fly rock, noise, etc. [3, 4]. Due to critical damage to surroundings caused by intense vibration, blast-induced ground vibration is considered as one of the most important environmental hazards of mining operations and civil engineering projects [4–6]. Considering this, it is of great importance to properly design the blasting operations, in order to avoid the possible occurrence of rock mass and support damage and instability [7, 8].

In practice, blast-induced ground motion is commonly expressed by a peak particle velocity (PPV) [9, 10]. In order to well predict PPV, a large number of researchers conducted in-depth study and achieved some available results, which are called conventional empirical attenuation equations methods. However the limitations of conventional empirical attenuation equations are soon revealed, that is, the blast-induced ground vibrations are affected by a number of parameters, empirical attenuation equations are sometimes not suitable for the design of blasting patterns [7, 8]. In those cases, artificial neural networks (ANNs), which have been found to be very useful in diverse, real-world applications, are proposed and applied considering various parameters instead of these conventional predictors. Khandelwal and Singh [11] used BPNN for the prediction of ground vibration and frequency by all possible influencing parameters of rock mass and explosive characteristics as well as blast design, specifically including hole diameter (mm), average hole depth (m), average burden (m), average spacing (m), average charge length (m), average explosive per hole (kg), distance of monitoring point from blasting face (m), blastability index, Young's modulus (GPa), Poisson's ratio, P-wave velocity (km/s), velocity of detonation of explosive (km/s), and density of explosive (t/m3), totally 13 input parameters. Mohamed [5] investigated the effect of one, two, and large number blasting variables of inputs in ANN on ground vibration prediction and compared the results with conventional scaling law predictors. Khandelwal and Singh [12] proposed a three-layer, feed-forward backpropagation neural network having 15 hidden neurons, 10 input parameters, and two output parameters to predict PPV and frequency. In their paper, 10 input parameters were considered, i.e., hole depth, burden, spacing, maximum charge per delay, distance of monitoring point from blasting face, compressive strength/tensile strength, Young's modulus, Poisson's ratio, P-wave velocity, and velocity of detonation of explosive, and the results were compared with multivariate regression analysis (MVRA) and conventional predictors. Dehghani and Ataee-pour [13] used artificial neural networks (ANN) and dimensional analysis techniques in prediction of the peak particle velocity (PPV); in addition, different model structures were discussed. Monjezi et al. [14] predicted blast-induced ground vibration using various types of neural networks, including multilayer perceptron neural network (MLPNN), radial basis function neural network (RBFNN), and general regression neural network (GRNN). In this paper, also 6 input parameters were selected, i.e., distance from the blasting location (m), maximum charge per delay (kg), burden/spacing, number of holes per delay (m), UCS (MPa), and delay per rows. One year later, also Monjezi et al. [15] used Artificial Neural Network (ANN) to predict PPV considering 4 input parameters consisting of maximum charge per delay, distance from blasting face to the monitoring point, stemming, and hole depth. Lapčević et al. [16] predicted PPV by ANNs with different number of hidden nodes, and just 5 input parameters were considered, i.e., total charge (kg), maximum charge per delay (kg), distance from blasting shot (m), charge per hole (kg), and delay time (ms). Saadat et al. [17, 18] discussed differential evolution algorithm for predicting blast-induced ground vibrations, and nine input parameters were taken into consideration.

In recent years, a huge number of researchers have performed a train of works on combination of ANNs and principal component analysis [4, 6, 16, 19–31]. Nevertheless, the application of Mean Impact Value and Factor Analysis is exactly rare in previous research. Only in 2016, Marzouk and Elkadi [32] used Factor Analysis and artificial neural networks to estimate water treatment plants costs. Meanwhile, high-dimensional input parameters have made the network structure more complicated and the calculation accuracy decline is often ignored by many researchers. Looking for low-dimensional parameter datasets consisting of most information of all influencing parameters will be a better approach to predict PPV.

In this paper, a new approach to dataset transformation and filtration is proposed, i.e., the combination of Factor Analysis (FA) and Mean Impact Value (MIV). Instead of putting all influencing parameters into the network structure, appropriate transformation and filtration are done before the calculation. The database of measured parameters is taken from paper [3], and nine influencing parameters are prepared for the present study. From the prepared database consisting of 108 datasets, 98 datasets are used for the training of the model, while the rest are used for testing performance. To test the performance of various predictors, the coefficient of determination (R^2) and mean absolute error (MAE) are calculated for an evaluation indicator.

2. Methodology

2.1. The Basic Principle of Factor Analysis (FA). Factor Analysis (FA) is a technology of changing multiple variables into less, which can be regarded as the extension of principal component analysis (PCA). Apparently, it is easier to explain system in a low-dimensional space than high-dimensional space [32]. Factor Analysis (FA) is specially used in dimensionality reduction of high-dimensional variable space. By getting rid of the redundish and repetitive information, high-dimensional space is transformed into low-dimensional space in order to achieve the purpose of simplified calculation.

In order to better interpret the basic principle of Factor Analysis (FA), N samples have been prepared. The model of Factor Analysis (FA) can be expressed in

$$\begin{aligned} X_1 &= \mu_1 + a_{11} f_1 + \cdots + a_{1q} f_q + e_1 \\ X_2 &= \mu_2 + a_{21} f_1 + \cdots + a_{2q} f_q + e_2 \\ &\vdots \\ X_p &= \mu_p + a_{p1} f_1 + \cdots + a_{pq} f_q + e_p \end{aligned} \tag{1}$$

where P stands for the number of technical indicators, X = $(X_1, X_2, \ldots, X_p)^T$ is the random variable which can be observed, and f = $(f_1, \ldots, f_q)$ is the common factors. a_{ii} (i = 1,2,. . .,p, j = 1,2,. . .,q) is the load factor, which expresses correlation coefficient between original variables i and factor variables j.

In the process of Factor Analysis (FA), each common factor will be expressed as the linear combination of variables. Therefore, the value of each common factor, which is called

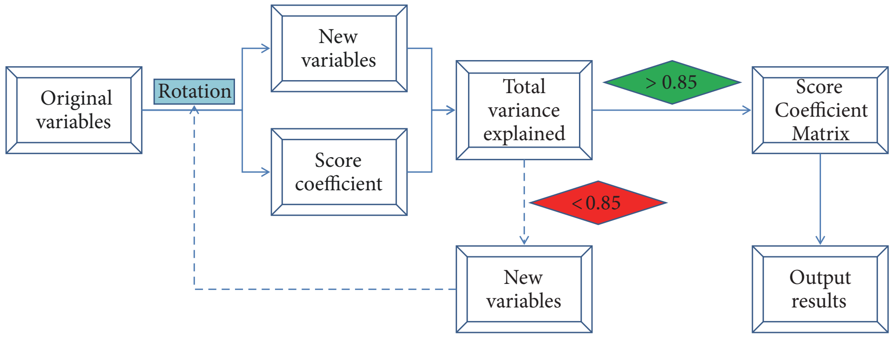


Figure 1: Flowchart of FA.

factor score, will be estimated. The mathematical model of estimating factor score can be expressed in

$$F_i = b_{i1}X_1 + b_{i2}X_2 + \cdots + b_{in}X_n \quad (\mathrm{i} = 1, 2, \cdots, \mathrm{m}) \tag{2}$$

where $\mathrm{F_i}$ stands for the factor score of a factor of i (i = 1,2,. . .,m) and b is coefficient of each original variable.

When common factor has no practical significance, the rotation of the appropriate is necessary, which can change the information distribution of different factors, in order to explain the result. After getting the factor score of each common factor, the less factors that represent most information of the original variables should be extracted. According to the experience value, the factor should be extracted when the total variance explained reached more than 85%, because in this case, most information of the original variables can be brought out exactly. The flowchart of FA is presented in Figure 1.

2.2. The Overview of Mean Impact Value (MIV). Mean Impact Value (MIV) is an index to determine the size of the effect which input neurons act on output neurons. The plus-minus sign of MIV stands for the direction of correlation, while the size of the absolute value stands for relative materiality.

The calculation procedure of Mean Impact Value (MIV) is primely presented as follows:

(i) Step 1: create source dataset P, train the network, and get a simulation result A1.

(ii) Step 2: after the training of network, add a certain proportion such as p(%) to each training sample of P, then repeat training process, and get another simulation result A2.

(iii) Step 3: calculate the differentials between A1 and A2, which is called MIV, and make the ranking of each input.

And the process of MIV is easily realized in the MATLAB program. The flowchart of MIV is presented in Figure 2.

2.3. Artificial Neural Network. Artificial neural network (ANN) is a form of artificial intelligence based on the human neuronal system, which can be used to learn and compute functions for which the analytical relationships between inputs and outputs are unknown [14]. Multilayer perceptron (MLP), the best type of neural networks, consists of at least three layers: input layer, output layer, and intermediate or hidden layer(s) [33]. The number of hidden layers and neurons depends on complexity of the problem to be solved. In this paper, we followed the methods of Monjezi et al. [15]; BPNN and ELM were selected for this research.

2.3.1. Backpropagation Neural Networks (BPNN). Backpropagation algorithm, the most common network in the field of prediction, is an example of supervised learning procedures [15]. In this technique the strengths or weights of the interneuron connections are adjusted according to the difference between the predicted and actual network outputs. In a feed-forward backpropagation algorithm, the signals flow from input layer to the output layer (forward pass). Then the output is compared to the actual measured values and the difference or error is calculated. The obtained error is propagated back through the network (backward pass) updating the individual weights. This process is repeated until the error is converged to a level defined by a cost function such as root mean square error (RMSE) [12].

2.3.2. Extreme Learning Machine (ELM). Extreme learning machine (ELM) is an efficient learning algorithm of SLFNs [8]. For N distinct samples (x_i, y_i), $i = 1, \ldots, N$, $x_i \in R_j$ and $y_i \in R_m$, the ELM model structure had j input layer nodes, n hidden layer nodes, m output layer nodes, and a hidden layer activation function $g(x)$. The outputs of hidden layer can be expressed as (3), and the relationship between the outputs of hidden layer and the outputs of output layer can be expressed as (4):

$$\mathrm{h} = \mathrm{g}\,(\mathrm{ax} + \mathrm{b}) \tag{3}$$

$$\mathrm{h}\,(x_i)\,\beta = y_i, \quad where\ i = 1, 2, \ldots, N \tag{4}$$

The above equation can be rewritten as

$$\mathrm{H}\beta = \mathrm{Y} \tag{5}$$

where $\mathrm{H} = \begin{bmatrix} \mathrm{g}(a_1,b_1,x_1) & \cdots & \mathrm{g}(a_1,b_1,x_n) \\ \vdots & \vdots & \vdots \\ \mathrm{g}(a_n,b_n,x_1) & \cdots & \mathrm{g}(a_n,b_n,x_n) \end{bmatrix}^T$.

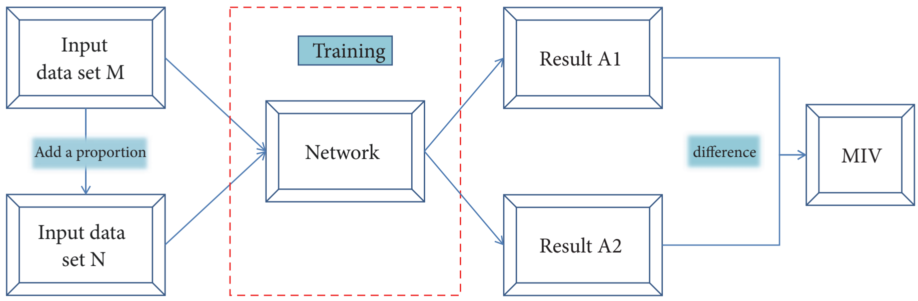


Figure 2: Flowchart of MIV.

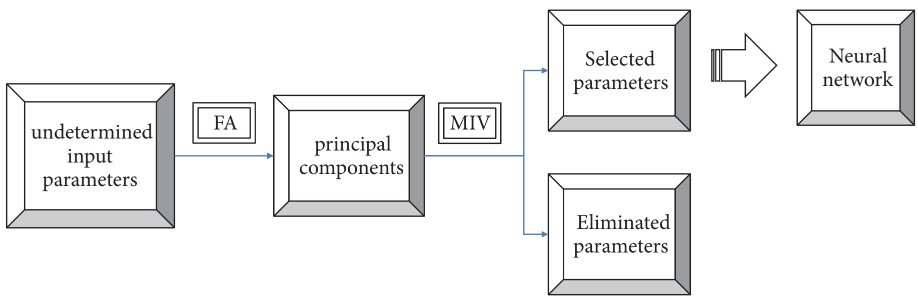


Figure 3: Technology roadmap of FA-MIV approach.

Finally, ELM utilized the generalized inversion method to obtain the output weights. So ELM model had the advantage of fast training rate and better generalization.

2.4. The Combination of FA and MIV. In this paper, Factor Analysis (FA) and Mean Impact Value (MIV) are integrated and applied to dimension reduction process of input neurons in the Artificial Neural Network for the first time. Through the application of Factor Analysis (FA), the high correlation of original variables can be reduced considerably, thus less but accurate variables will be used for input neurons in Artificial Neural Network. After Factor Analysis, each factor extracted in the process of Factor Analysis (FA) will be quantitatively evaluated through Mean Impact Value (MIV) and then an accurate ranking of each factor extracted in the process of Factor Analysis (FA) is designed. The effect that each input neuron acts on output can be well shown in the accurate ranking; thus the final and the most effective input variables could be extracted with little hindrance. Due to the combination of FA and MIV, dependent variable could be explained in a low-dimensional space; thereby a more accurate prediction results could be obtained, authentically. The technology roadmap of the combine of FA and MIV called FA-MIV in this paper is shown in Figure 3.

3. Dataset and Dimensionality Reduction of FA-MIV

3.1. Selection of Input Parameters. It is of great importance to select a sound input dataset for ANN predictions [34, 35]. In order to make this decision, we carefully analyze the characteristics of blasting in the following. Firstly, we pay attention to the classical prediction formula

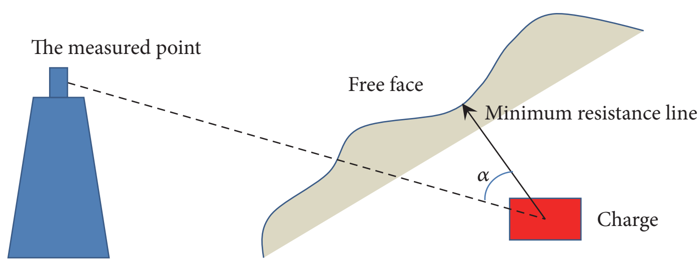
$$v = K\left(\frac{\sqrt[3]{Q}}{R}\right)^{\alpha} \tag{6}$$

where v is PPV, Q is maximum amount of charge at one time (kg), and R is the distance to the explosion center. K and α are coefficient related to engineering geology. Clearly, the amount of charge and distance information should be taken into consideration from this classical formula. Therefore, maximum amount of charge at one time (kg), total amount of charge (kg), horizontal distance (m), and elevation difference (m) can be easily selected. Among them, maximum amount of charge at one time and total amount of charge can be found in the design, while horizontal distance and elevation difference should be measured in site. However, many researchers have pointed out that this is not enough to accurately forecast the PPV [26, 27]. Instead of using regression coefficient, more measured data should be adopted. For example, front row resistance line (m), presplit penetration ratio (%), integrity coefficient, angel of minimum resistance line to measured point (°) and detonation velocity (m/s). In terms of front row resistance line and angel of minimum resistance line to measured point, these two parameters are all distance parameters and can be obtained via blasting design and field measurement. Among them, front row resistance line represents the minimum distance between the charge center of the front row and free face, as shown in Figure 4. And the measured method can also be obtained from Figure 4.

The angel of minimum resistance line to measured point represents the relative position between the measured point

Table 1: Range of input parameters (from paper [3]).

Serial no.	Input parameter	U.	Range	Mean
1	maximum amount of charge at one time	kg	160-5590	1080.843
2	total amount of charge	kg	936-9000	4248.093
3	horizontal distance	m	47.1-444.3	173.2306
4	elevation difference	m	6-109.3	54.48194
5	front row resist line	m	4-7	5.407407
6	presplit penetration ratio	%	0-100	30
7	integrity coefficient		0.3-0.78	0.558241
8	angel of minimum resistance line to measured point	°	0-180	128.0556
9	detonation velocity	m/s	2800-4200	3448.148



α: The angel of minimum resistance line to measured point

Figure 4: Sketch of the minimum resistance line.

and the explosion zone. Note that this value is between 0° and 180°, where 0° represents the same direction with minimum resistance line and 180° represents the opposite direction with minimum resistance line. In fact, front row resistance line and minimum resistance line are two of main parameters in the process of blasting design. To a great extent, these two parameters determine the effect of blasting. As regards integrity coefficient, it can be found in geological survey report. This value is also called fissure coefficient, which is calculated as the square of the ratio of the longitudinal wave velocity of rock mass and rock. And the longitudinal wave velocity of rock mass and rock can be measured by dynamic method. The larger this value is, the higher the integrity of rock mass is. Note that this parameter is closely related to the engineering geology and can be regarded as a representation of K and α in (6). In addition, detonation velocity is the basis of other parameters of detonation. Generally, detonation velocity is influenced by charge diameter, charge density, explosive particle size, and explosive shell. Finally, presplit penetration ratio represents the effect of presplitting blasting. In order to quantify this effect, the presplit penetration ratio is adopted. Note that presplit penetration ratio is the ratio of the hole number of hole width which is less than 1 cm and total hole number. Clearly, the effect of presplitting blasting is best when this ratio is equal to 0. In fact, the above parameters are more or less related to geology and engineering conditions because of that each parameter is determined according to hydrology and geology of certain engineering.

3.2. Parameters from Field Measurements. Excavation of rock mass by blasting is comprised of two processes: releasing of explosive energy and movement of surrounding rock and soil [18, 36]. The effect on rock and soil can be regarded as wave mechanics process that can be treated as stress wave spreading in the medium and disturbing to the medium [17, 37, 38]. After a comprehensive consideration, maximum amount of charge at one time (kg), total amount of charge (kg), horizontal distance (m), elevation difference (m), front row resistance line (m), presplit penetration ratio (%), integrity coefficient, angel of minimum resistance line to measured point (°), and detonation velocity (m/s) are chosen as differentiating parameters prepared for inputs, presented as X1 (kg), X2 (kg), X3 (m), X4 (m), X5 (m), X6 (%), X7, X8 (°), and X9 (m/s), respectively, as arranged in Table 1. Peak particle velocity (PPV) is chosen as the characteristic parameters to predict blasting vibration. The value of differentiating parameters and PPV are taken from paper [3, 29]. While training of the network was carried out using 98 datasets collected from dataset, the other 10 datasets were kept for testing the model.

Table 2: Component score coefficient matrix.

Input parameter	Component Score Coefficient					
	Facl-1	Facl-2	Facl-3	Facl-4	Facl-5	Facl-6
X1	0.021628	0.576030	0.073062	-0.089619	-0.051766	-0.044531
X2	-0.065673	0.618741	0.014271	0.188095	-0.003991	0.071065
X3	0.544394	0.006002	0.105118	0.142102	0.171140	-0.192944
X4	0.584546	-0.043643	-0.070355	-0.199844	-0.093659	0.178693
X5	-0.055301	-0.106954	-0.449728	0.287387	0.195003	-0.025068
X6	-0.012397	0.000079	0.789898	0.125918	0.255600	0.022631
X7	-0.036287	0.066257	0.014703	0.795024	-0.123264	-0.035259
X8	0.055798	-0.016083	0.223241	-0.143820	0.950645	-0.110411
X9	0.006169	0.020209	0.032738	-0.074159	-0.124897	0.985197

3.3. Dimensionality Reduction of Dataset by FA-MIV. As introduced in Section 2, dimensionality reduction of dataset by FA-MIV was realized in SPSS and MATLAB software. Firstly, the FA is adopted to reduce the dimensionality of original dataset. As we all know, the aim of FA is to describe connection of various input parameters using a small number of factors. In other words, it is to merge a lot of parameters which are of high correlation. According to Sections 3.1 and 3.2, one can see that some potential connections between many parameters exist, such that X1 and X2 are all about the charge. Therefore, FA is performed to remove these connections. In this way, the dimensionality of original dataset can be preliminarily reduced. As described in Section 2.1, nine parameters are set as original variables (X_n) in FA. Therefore, the number of n in (2) is equal to 9. After getting the factor score of each common factor, the less factors that represent most information of the original variables should be extracted. According to the experience value, the factor should be extracted when the total variance explained reached more than 85%, because in this case, most information of the original variables can be brought out exactly. In this way, the new factors can be expressed using the linear combination of original variables. And, the coefficient of each factors can also be obtained, which is called score coefficient matrix in FA. The resultant of FA is arranged in Table 2. Note that the total variance explained is 91 % at this moment. This process can be easily realized in SPSS or MATLAB.

As shown in Table 2, six factors are extracted according to FA. After factor rotation, each factor could be of well interpretation. From Table 2, the following conclusions could be obtained:

(i) The load of Facl-1 acting on X3 and X4 is relatively larger than the others; that is, Facl-1 stands for the characteristic of horizontal distance and elevation difference, which means the spatial distance in blasting.

(ii) The load of Facl-2 acting on X1 and X2 is relatively larger than the others; that is, Facl-2 could be considered as the index of the maximum amount of charge at one time and total amount of charge, which represents the charge.

(iii) The load of Facl-3 acting on X5 and X6 is relatively larger than the others; that is, Facl-3 could be suggested as technique data of front row resistance line and presplit penetration ratio, because X5 and X6 are related to a large extent, which is closely related to the principle of minimum resistance line.

(iv) Facl-4, Facl-5 and Facl-6 represent the integrity coefficient, angel of minimum resistance line to measured point and detonation velocity, respectively, as shown in Figure 5.

(v) From Table 2, each factor can be represented as a linear combination of every input parameter (X1-X9), and the coefficient is just the score of each factor. In this way, six new inputs are calculated and defined, as listed in Table 3.

After preliminarily reduction by FA, six new input parameters are obtained. However, the prediction of PPV using these six parameters seems to be unsatisfactory because the presence of low correlation and high error. This is likely due to that some less important parameters still exist, compared to the others. To deal with this problem, MIV is adopted to further investigate these six parameters. Aiming at finding out the less important parameters, MIV is the most appropriate index to evaluate the impact. As elaborated in Section 2.2, the network is trained using the dataset of these six parameters in step 1, and a result set (A1) is obtained. Then, a new dataset which is the last dataset adding a certain proportion (5%) is used to train the same network, and another result set (A2) is obtained. Note the A1 and A2 are all dataset, not one value. Finally, the difference of A1 and A2 is calculated, namely, MIV. The computed results of MIV are shown in Figure 6.

From Figure 6, it is found that the impacts of Facl-4 and Facl-6 acting on PPV are much smaller than the others; thus they are eliminated in the present study. The reasons why these two factors are eliminated are presented in the following:

(1) As for Facl-4, namely, the integrity coefficient, it is likely due to the fact that the most geology

Table 3: Range of factors extracted according to FA.

Fac no.	Practical significance	Min	Max	Mean
Fac1-1	spatial distance in blasting	-473.39	161.81	-103.3037
Fac1-2	the charge	900.57	7214.68	3317.1492
Fac1-3	related to the principle of minimum resistance line	168.91	634.79	316.3706
Fac1-4	the integrity coefficient	-92.21	1311.15	447.2407
Fac1-5	angel of minimum resistance line to measured point	-583.09	-154.16	-349.2670
Fac1-6	detonation velocity	2774.22	4673.30	3612.1705

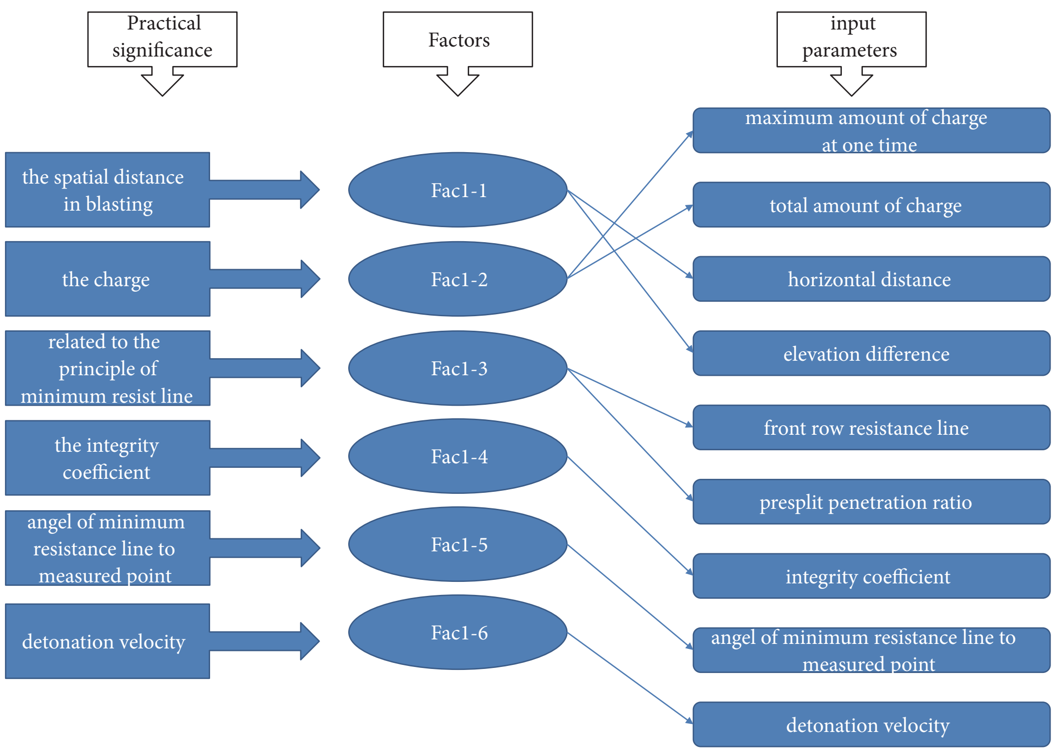


Figure 5: Practical explanation of each factor.

conditions have been considered in the determination of other parameters, such as amount of charge and minimum resistance line. Compared to other parameters, integrity coefficient seems to be less importance.

(2) As for Fac1-6, namely, detonation velocity, it is influenced by charge diameter, charge density, explosive particle size, and explosive shell. Similarly, the information has been concluded in the design of other parameters. In the process of training network, the influence of detonation velocity is less than those of other factors.

Overall, the final selected factors are reasonable for the prediction of PPV. By the combination of FA and MIV, these factors are a good representation of the charge, distance, and engineering geology conditions, which were also emphasis in classical formula. Ultimately, better prediction performance could be obtained by using these selected factors.

4. ANN Models Predictors

As shown in Figure 6, four new input characteristic parameters from dataset were selected and used for the final input parameters via dimensionality reduction of FA-MIV that are Fac1-1, Fac1-2, Fac1-3, and Fac1-5. A database consisting of 98 datasets was utilized for input parameters, whereas testing was carried out with the rest of datasets. A satisfactory

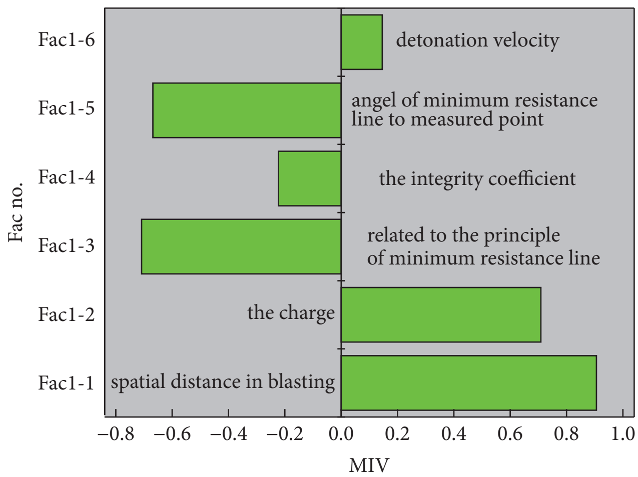


Figure 6: Rank of each factor.

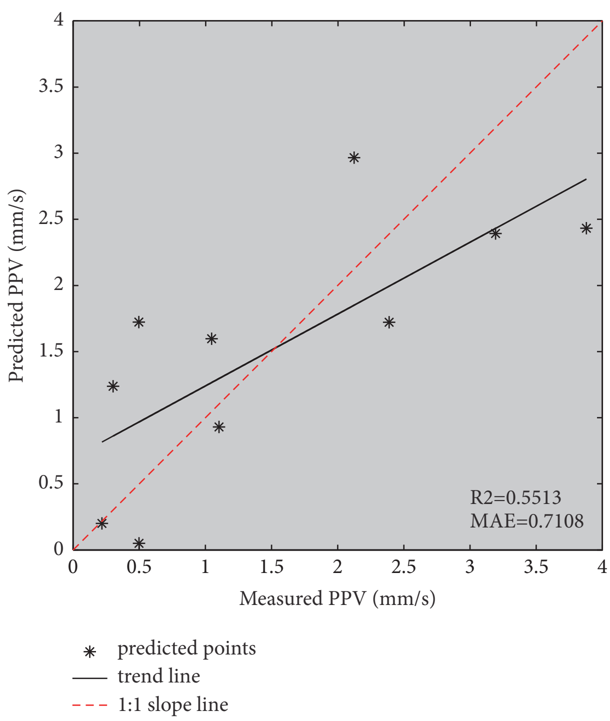


Figure 7: Correlation between predicted and measured PPV for BPNN model without using FA-MIV.

well-trained model was obtained after a series of ANNs training.

In order to evaluate the model performance, the correlation and between the predicted and real measured values of PPV was determined. The higher the coefficient of determination (R^2) is, the better performance of the proposed network demonstrates. Simultaneously, mean absolute error (MAE) can be also considered for evaluation of the model performance. Nevertheless, the MAE is just opposite to the coefficient of determination. The computed result of R^2 and MAE are shown Figures 7–10.

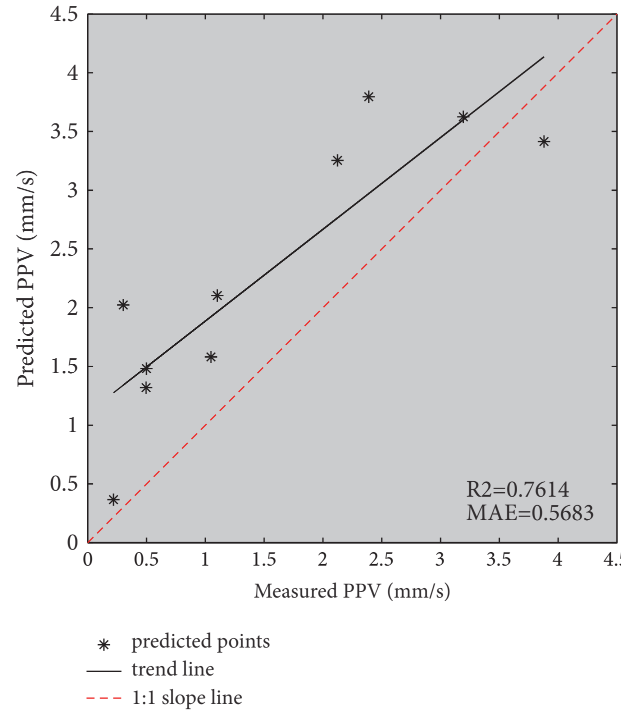


Figure 8: Correlation between predicted and measured PPV for BPNN model using FA-MIV.

5. Regression Analysis for a Comparison

To compare with the performance of ANN models, multivariate regression analysis (MVRA) is carried out on the same 98 datasets which were used for the training of the ANN models. In this way, a mathematical relationship is generated to predict the PPV using statistical method (see (7)) and (see (8)):

$$\begin{aligned} \text{PPV} = &-1.0954 + 0.0004\,[\text{X1}, \text{kg}] - 0.000001\,[\text{X2}, \text{kg}] \\ &- 0.007\,[\text{X3}, \text{m}] - 0.00383\,[\text{X4}, \text{m}] \\ &+ 0.0906\,[\text{X5}, \text{m}] - 0.00597\,[\text{X6}, \%] \\ &+ 3.3337\,[\text{X7}] + 0.004049\,[\text{X8}, {}^\circ] \\ &+ 0.000187\,[\text{X9}, \text{m/s}] \end{aligned} \tag{7}$$

$$\begin{aligned} \text{PPV} = &\ 0.195878 - 0.0062\,[\text{Fac1} - 1] \\ &- 0.00046\,[\text{Fac1} - 2] + 0.004479\,[\text{Fac1} - 3] \\ &- 0.00153\,[\text{Fac1} - 5] \end{aligned} \tag{8}$$

To test and validate the regression model, the same datasets which were applied in the ELM model were used. Correlation between the measured and predicted PPV is illustrated in Figures 11 and 12. As seen in Figures 11 and 12, performance of the regression model is poorer compared to the ANN models. Mean absolute error between measured

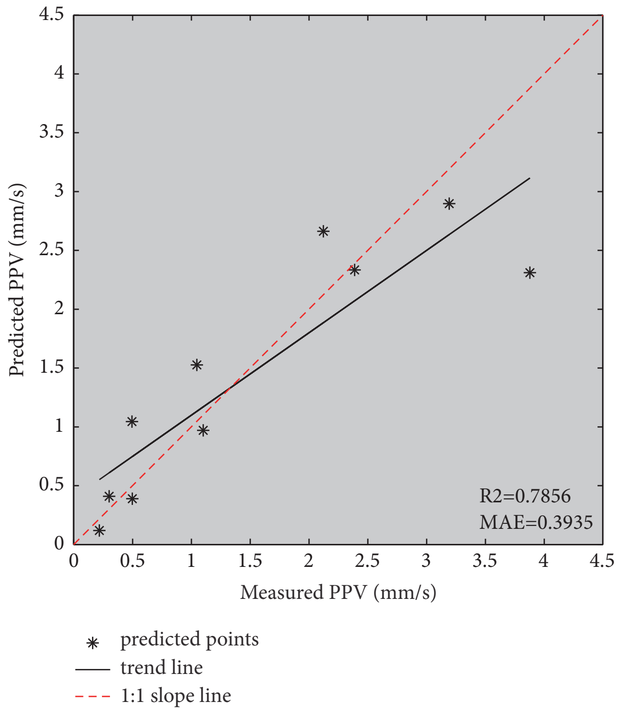


FIGURE 9: Correlation between predicted and measured PPV for ELM model without using FA-MIV.

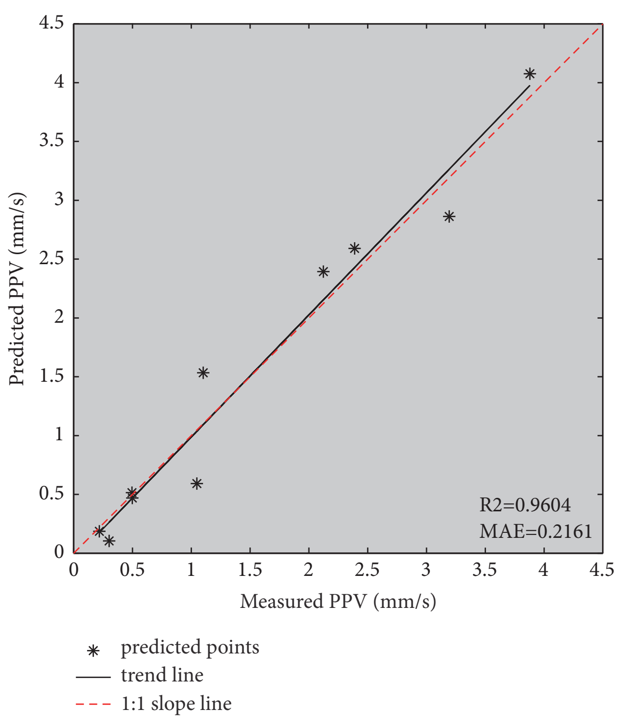


FIGURE 10: Correlation between predicted and measured PPV for ELM model using FA-MIV.

and predicted PPV was calculated 0.8612 and 0.7340 which also shows poorer performance of the MVRA model. In the process of regression analysis, the superiority and accuracy of

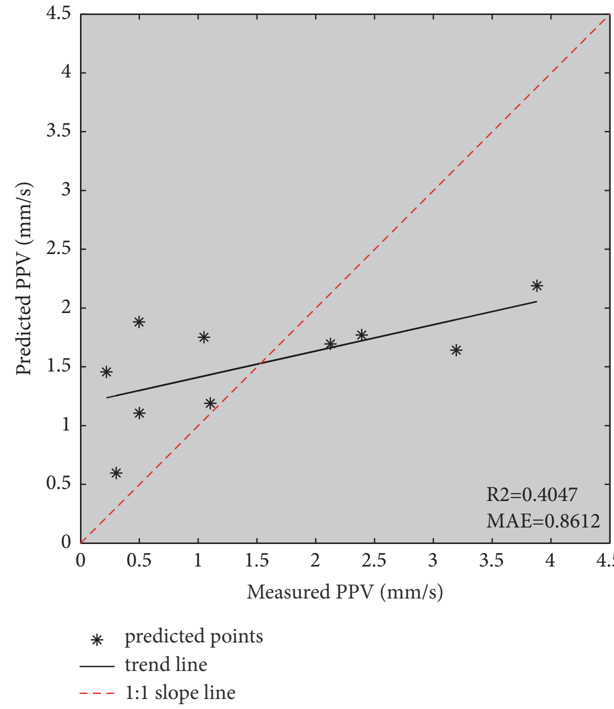


FIGURE 11: Correlation between predicted and measured PPV for MVAR model without using FA-MIV.

ELM based on FA-MIV over traditional regression analysis are demonstrated.

6. Results and Discussion

Figure 13 shows a comparison between predicted and measured PPV by ANNs and MVRA predictor with using FA-MIV approach or not. Here, predictors optimized by FA-MIV demonstrate the certain superiority and accuracy over the same methods without using FA-MIV approach. Simultaneously, ELM model is closer to the measured PPV than BPNN and MVRA models.

The figure revealed that prediction methods with using FA-MIV predicted PPV are more close to the measured PPV line, whereas methods without using FA-MIV show very high level of error. This is due to the fact that the imports of high-dimensional and redundish input data have made the prediction structure more complicated and the accuracy of results greatly decline.

Table 4 shows the CoD and MAE of PPV predicted by various predictors. It can be concluded that prediction capability of ELM model with using FA-MIV optimizing approach is quite remarkable. Meanwhile, the performances of ANN models are all superior to that of MVRA models.

7. Conclusions

In this paper, a new approach (FA-MIV) to optimize and simplify network inputs was proposed. This proposed approach

Table 4: CoD and MAE of PPV by various models.

model	CoD	MAE
BPNN without using FA-MIV	0.5513	0.7108
BPNN with using FA-MIV	0.7613	0.5683
ELM without using FA-MIV	0.7855	0.3935
ELM with using FA-MIV	0.9603	0.2161
MVRA without using FA-MIV	0.4047	0.8612
MVRA with using FA-MIV	0.5811	0.7340

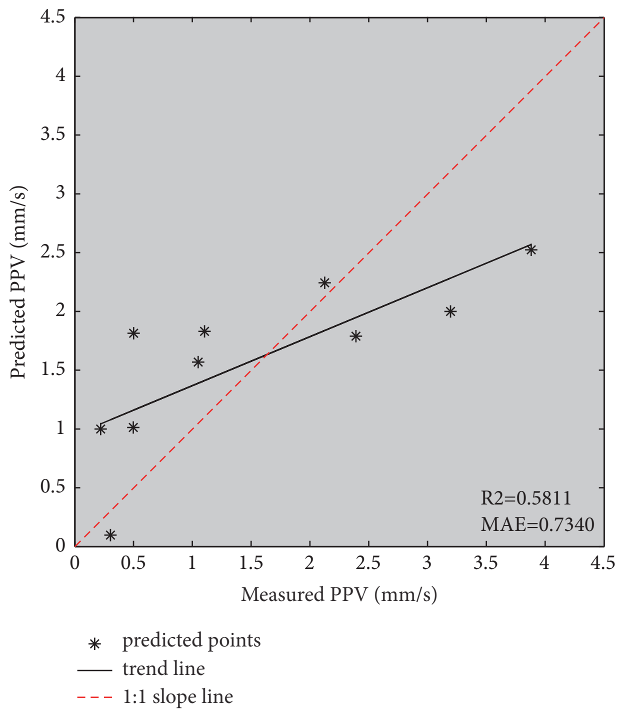


Figure 12: Correlation between predicted and measured PPV for MVAR model using FA-MIV.

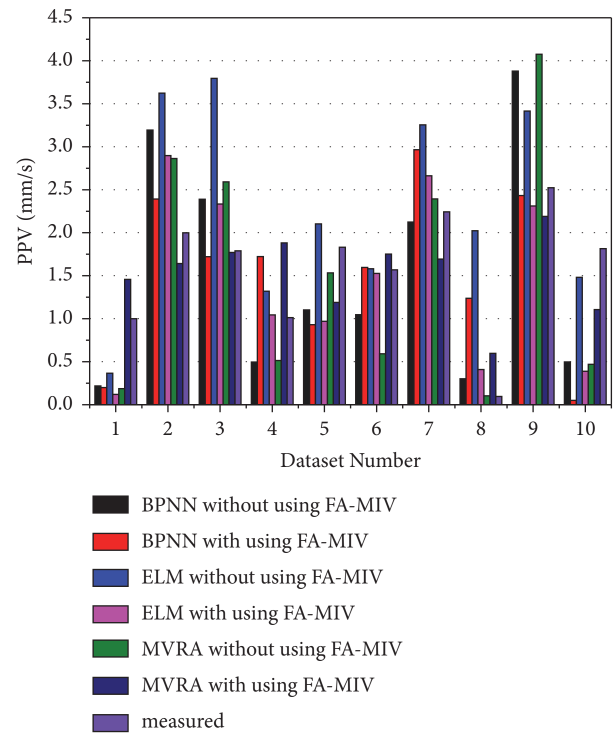


Figure 13: Comparison of PPV.

was applied to ANN prediction of PPV. The optimizing approach proved to be more accurate and remarkable in comparison to the same methods without using FA-MIV. With the application of FA-MIV, coefficient of determination and mean absolute error between measured and predicted PPV were calculated 0.9604 and 0.2161 in ELM, which was 0.7614 and 0.5684 in BPNN and 0.5811 and 0.7340 in regression analysis, respectively, whereas the values without using FA-MIV were 0.7855 and 0.3935 in ELM, 0.5513 and 0.7108 in BPNN, and 0.4047 and 0.8612 in regression analysis, respectively. The results obtained in this paper well demonstrate the reliability and correctness of the application of FA-MIV approach. In addition, ELM model is more accurate than BPNN and MVRA models in the prediction field of PPV. Meanwhile, the program of FA-MIV approach could be easily designed and realized in MATLAB software and will be commendably used to other artificial neural networks (ANNs).

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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