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Prediction of Seismic Wave Intensity Generated by Bench Blasting Using Intelligence Committee Machines

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ABSTRACT

In large open pit mines prediction of Peak Particle Velocity (PPV) provides useful information for safe blasting. At Sungun Copper Mine (SCM), some unstable rock slopes facing to valuable industrial facilities are both expose to high intensity daily blasting vibrations, threatening their safty. So, controlling PPV by developing accurate predictors is essential. Hence, this study proposes improved strategies for prediction of PPV by maximum charge per delay and distance using the concept of Intelligent Committee Machine (ICM). Besides the Empirical Predictors (EPs) and two Artificial Intelligence (AI) models of ANFIS and ANN, four different ICMs models including Simple and Weighted Averaging ICM (SAICM and WAICM) and First and Second order Polynomial ICM (FPICM and SPICM) in conjunction with genetic algorithm, proposed for the prediction of PPV. Performance of predictors was studied considering R^2, *RSME* and *VAF* indices. Results indicate that ICM methods have superiority over EPs, ANN and ANFIS, and among the ICM models while SAICM, WAICM and FPICM performing near to each other SPICM overrides all the models. R^2 and RSME of the training and testing data for SPICM are 0.8571, 0.8352 and 11.0454, 12.3074, respectively. Finally, ICMs provides more accurate and reliable models rather than individual AIs.

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NOMENCLATURE

AD	Aerial Distance	MCD	Maximum Charge weight per Delay
ANFIS	Adaptive Neuro-Fuzzy Inference System	PPV	Peak Particle Velocity
ANN	Artificial Neural Network	R^2	R square
BIGV	Blast Induced Ground Vibration	RSME	Root Mean Square Error
EP	Empirical Predictor	SAICM	Simple Averaging ICM
FL	Fuzzy Logic	SPICM	Second order Polynomial ICM
ICM	Intelligence Committee Machine	VAF	Variance account for
FPICM	First Order Polynomial ICM	WAICM	Weighted Averaging ICM

1. INTRODUCTION

Blasting is the most acknowledged and practiced technique of breaking rocks due to the rational use of destructive energy of the explosive. Simultaneously some negative impacts on environment such as ground vibrations, airblast, flyrock and generation of fines, fumes and dust. Among these environmental effects, Blast Induced Ground Vibration (BIGV) is the serious problem in mining industry, and predicting it, gives an important help in minimizing the public complaints. BIGV in the form of repetitive dynamic loading, may cause damage to the nearby structures [1]. Hence, some regulations associated with the ground motion to structural damage have been developed [2]. These regulations mainly are based on the Peak Particle Velocity (PPV) criteria. Many researchers and engineers have studied PPV prediction by developing some Empirical Predictors (EPs) which are based on the Maximum Charge weight per Delay (MCD) and the

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distance between blasting center and monitoring point (D) [3, 4]. These models are highly dependent on the geo-mining conditions and experimental site–specific studies should be performed to obtain necessary data.

Scholars have shown that, it is good enough to predict the vibration level by EPs through regression analysis but inadequate in finding optimum form of the non-linear relation between the influencing parameters of the BIGV. In statistical analysis, data are studied bearing in mind a particular geometry, which may or may not be satisfactory to recognize the non-linearity among various input/field parameters [5]. Hence, new approaches on the basis of soft computing techniques have been used to predict and control the BIGV, to overcome non-linearity problem. These methods include Artificial Neural Network (ANN) [5-8], Fuzzy Logic (FL) and Adaptive Neuro-Fuzzy Inference System (ANFIS)[9-11], genetic programming [12], support vector machine [6] and hybrid methods such as neuro-evaluative methods. In neuro-evaluative methods an evolutionary algorithm, such as Particle Swarm Optimization (PSO) algorithm [13], imperialist competitive algorithm (ICA), combines with ANN to improve ANNs efficiency, which lead to more reliable and accurate models in comparison with ANN and EPs. Armaghani, et al. [13], Hajihassani, et al. [13, 14] incorporated PSO algorithm with ANN and Hajihassani, et al. [15] combined ANN with ICA to predict PPV All three studies used optimization algorithm to find the weights and biases of ANN to minimize the learning error, while the networks architecture were fixed. There are also few studies focused on developing or improving EPs using regression analysis. Agrawal and Mishra [16] employed a probabilistic analysis to consider the impact of cap scattering in initiating system, on the calculation of MCD used by the well-established United States Bureau of Mines [2] EP, which leaded to a significant reduction in prediction errors. et al. [17], tried to incorporate burden besides MCD and distance as input variables for PPV prediction in format of EP. Their results showed that although burden has some influence on PPV but it is not significant. Arthur, et al. [18] used Gaussian Process Regression (GPR) method with different kernel functions to predict PPV. Their model overrides the ANN and EPs methods using the same data. Summery of recent works on PPV prediction using Artificial Intelligence (AI) and statistical techniques are given in Table 1. Comparison of the researches suggests the superiority of AI methods over the EPs. However, these methods are representative of all individual approaches being capable of predicting PPV. Results show that various AI models, offer acceptable efficiency near to each other but with different characteristic advantages and disadvantages. So, utilizing the synergy among models with higher performance is an attractive idea, if the positive features of various techniques can be collaborated. One such technique is Intelligence Committee Machine (ICM) models [19-22]. ICM provides an AI-based multi-approach interface to benefit their synergy. ICM consists of a collection of intelligent systems, which merges the outputs of each system and thus reaps the advantages of all systems. thus, ICM's performance could be better than the best single intelligent system [20, 21]. Combination of the intelligent systems outputs can be done in different ways. Averaging the committee constituents is one of the common combining methods in the ICMs, namely; simple averaging with equal weights [22] and weighted averaging with optimized weights, which were usually determined using an optimization approach such as GA [20, 21]. Weighted averaging was found to provide superior performance over the simple averaging [20, 21]. In addition to the averaging ICM models, the present proposed using a first and second order polynomial combinations of committee constituents (AI models) outputs which were provided more accuracy than the averaging methods.

In this study, the data of production blasting seismic monitoring at Sungun Copper Mine (SCM) were utilized. At first, conventional EPs, ANFIS and ANN were used to determine an attenuation law for BIGV represented by PPV intensity. In these models MCD and Aerial Distance (AD) between blasting center and monitoring station were used as inputs while trying to predict PPV. Then the ICM approach was used for prediction of PPV intensity exploiting the two ANFIS and ANN models considering averaging and polynomial combinations of outputs. Finally, the efficiencies of the seven methods were compared.

TABLE 1. Recent studies on PPV prediction using AIs and statistical techniques

Reference	Technique	Inputs*
Iphar, et al. [23]	ANFIS	MCD , D
Khandelwal [6]	SVM	MCD , D
Mohamed [10]	ANN, FIS	MCD , D
GHasemi, et al. [9]	ANFIS	B, S, ST, NR, MCD , D
Monjezi, et al. [7]	ANN	MCD, D. TC
ARmaghani, et al. [13]	ANN-PSO	S, B, ST, PF, Di, NR, RD, SDr
HAjihassani et al. [15]	ANN-ICA	BS, ST, PF, C, D, Vp, E
Samareh, et al. [24]	Reg-PSO-GA	MCD , D, GSI, σ_{cm} , VOD
Faradonbeh, et al. [25]	GP	B, S, ST, D,HL, PF, MCD, D
Torres, et al. [26]	MLP	MCD , D
Agrawal, et al. [16]	Reg	MCD , D
Murmu, et al. [17]	Reg	MCD , D, B
Nguyen, et al. [8]	ANN	MCD , D,
Arthur, et al. [18]	GPR	B,S,PF,D,HL,NB

* Burden (B); Spacing (S); Hole Length (HL); Stemming (ST); Powder Factor (PF); Rock Density (RD); Hole Diameter (Di); Burden to Spacing ratio (BS); Number of Row (NR); Number of Blast holes (NB); Subdrilling (SDr); Distance from the blast face (D); Total Charge (TC); Young's modulus (E); P-wave velocity (Vp); Joint Spacing (Js); Specific Charge (SC); Delay Per Row (DPR); compressive strength of the rock mass (σcm); Velocity Of Detonation (VOD); Support Vector Machine (SVM); Multiple Linear Regression(MLP); Fuzzy Inference System(FIS); Regression (Reg);Genetic Programming (GP)

The reminder of the paper is organized as follows. In section 2 blast vibration mechanism and site condition are explained. Section 3 presents the methodology. Then results of different prediction models are presented. Finally discussion and conclusions are given.

2. BLAST INDUCED GROUND VIBRATION AND EMPIRICAL PREDICTORS

When an explosive is detonated in a blast hole, enormous dynamic stresses are released in the rock space. Approximately 20–30% of blasting energy is used for rock fragmentation. When the energy level is less than rock strength, it can only deform the rock and this elastic deformation is transmitted from one rock particle to the other rock particle, is called ‘‘seismic energy’. Seismic waves have two main types, i.e. body waves and surface waves. Body waves propagate through the rock mass (P-waves and S-waves). While surface waves transmitted along the surface and are further divided into Rayleigh, Love and coupled waves [4]. Differences in propagation path and delay time in blasting operation result in overlapping of the onset of wave fronts and wave types. These vibrations may cause a resonance in a structure where the amplitude of resonance may surpass the amplitude of the initial vibrations. The resonance made in any structure would trigger damage. In rock mass blasting, it has been found suitable to express the intensity of vibration by the PPV. The motive for this choice is the well-established correlation between PPV and observed cosmetic cracking; this is described theoretically by the fact that the strain induced in the ground during shaking is relative to the PPV. The PPV at the monitoring station is usually measured in three perpendicular directions (the vertical, longitudinal and transverse directions). The resultant intensity of vibrations is stated either as the maximum value of three directional components (PPV) or by the true vector sum of the squares of maximum of the three components [4]. Up to now many scholars have studied BIGV and some EPs have been proposed to determine the PPV, as a function of distance (D) and MCD (Q_{max}), and some of the widely used EPs are given in TABLE 2.

2. 1. Experimental Site and Monitoring System

Sungun Copper Mine (SCM) is one of Iranian porphyry copper mine, located 75 km northwest of Ahar in the East Azerbaijan Province in the north west of Iran. At SCM open pit mining method is used for ore extraction with overall pit slope of 37 degree. The geotechnical studies show that the major fault systems of the area have WW- SE, N-S and ENE-WSW strikes. Geotechnical studies show that the strength of intact rock increases directly with siliceous and indirectly with argilic alterations [1]. BIGV study was done at SCM to investigate the effect of blasting on some important industrial and rock structures around the mine, such as industrial site, concentrating plant, belt conveyors, crushing site, waste dump and rock slopes overlooking the concentration plant (Figure 1).

A total of 70 blast vibration events from 25 blasts, on 26 different locations, were gathered with the help of one “Blastmate III” and three “Minimate plus” seismographs having two “Standard Triaxial Geophone” for PPV measurement. In blasting operations at this site, ANFO and Emulite as the column charge for dry and wet blastholes respectively, emolan as primer and gelatin dynamite as booster and bottom charge are used. Detonating cord is used as initiation system and delay time between blasting rows includes 13ms, 20ms, 50ms and combination of these. Other common blasting parameters during monitoring period are as following; hole diameter ranges between 90 - 127 (mm), hole length ranges between 13-15 (m), bench height was 12.5 (m), burden and spacing patterns used include 2×2, 2×3, 2.5×3.5, 4×5 (m×m), one third of hole filled by stemming, specific charge ranges between 300-800 (g/m^3)and maximum instantaneous charge ranges between 100-3300 (Kg) [1].

TABLE 2. Different EPs mostly used in literature

Name of predictor equation	Formula
USBM (Duvall and Fogelson, 1962) [2]	$PPV=K(D/Q^{1/2})^{-\beta}$
AH (Ambraseys–Hendron, 1968) [27]	$PPV=K(D/Q^{1/3})^{-\beta}$
LK (Langefors–Kihlstrom, 1978) [28]	$PPV=K[(Q/D^{2/3})^{1/2}]^{\beta}$
BIS (Bureau of Indian Standard 1973) [29]	$PPV=K(Q/D^{2/3})^{\beta}$
CMRI (Pal Roy, 1993) [30]	$PPV=n+K(D/Q^{1/2})^{-1}$

3. METHODOLOGY

In this study seven approaches including EPs, ANN, ANFIS, simple and weighted average ICMs and first and second order polynomial ICMs, have been used to predict PPV at SCM (Figure 2). As mentioned before AD and MCD are used as input variables. The PPV measured at SCM ranges from 0.76 to 114.60 mm/s. The raw data of the PPV monitoring were published before by Azimi [31].

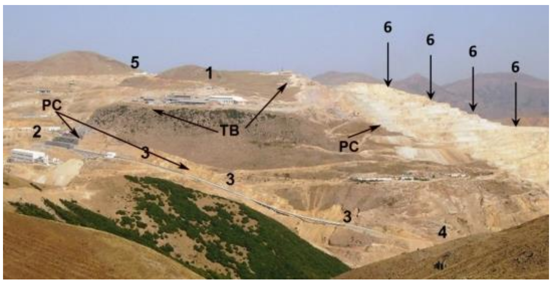


Figure 1. Surface structures close to the pit; 1- Industrial site 2- Concentrating Plant 3- Belt Conveyors 4- Crushing Site 5- Administration Office 6- Waste dump

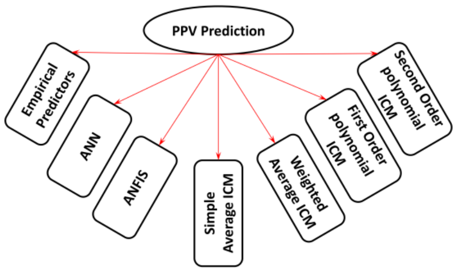


Figure 2. Prediction approaches

3. 1. ANN ANN is biologically stirred information processing systems emulating the computational powers of human brain, by adopting numbers of highly interlinked simple processing units, named as neurons. Nowadays, ANN is an intelligent device for solving non-linear problems. Back propagation, is a common approach of training ANN to learn how to accomplish a given task. It's a supervised learning approach [32]. This means that it requires a set of training data that has the desired output for given inputs. ANN computes the difference between the calculated output and the desired output from the training data set as shown in Equation (1).

$$E=\sum_{i=1}^{n}E_i=\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{m}\left(T_j(i)-Y_j(i)\right)^2 \tag{1}$$

where E is the sum of the mean square error *(MSE)*, m is the number of output nodes, n is the number of training samples, $T_j(i)$ is the expected output, $Y_j(i)$ is the actual output and , E_i is the mean squared error of each training sample. The error is then propagated backward through the network and the weights are attuned during a number of iterations, called epochs. The training stops when the calculated output values best approximate the desired values [33]. In this study the Multilayer Perceptron Model (MLP), a variant of the original perceptron model, is used as the basic component of the prediction system. MLP is a feed forward network that contains an input layer, an output layer, and a one or more middle or hidden layer.

3. 2. ANFIS If an unusual noise or uncertainties exists in the monitored data of PPV, statistical models have difficulty in making accurate predictions. In recent years the capability of fuzzy set theory and logic to deal with uncertainty and noise has given rise to its use in control and prediction problems. Since FL does not require precise, noise-free inputs, it is intrinsically robust. It is most reliable if the mathematical model of the system to be controlled is unavailable, and the system is known to be significantly nonlinear [9, 10, 23]. ANFIS is one of the first hybrid neuro-fuzzy systems for function approximation, which benefits from advantageous of learning capabilities of ANN and superior modeling of FL simultaneously. ANFIS can construct an input–output mapping based on both human knowledge in the form of fuzzy rules and specified input–output data pairs [34-36]. ANFIS presented a Sugeno-type fuzzy system in five-layer network. Figure 3 depicts ANFIS with two inputs x and y and one output z.

Suppose that the rule base comprises two fuzzy if–then rules of Takagi and Sugeno's type:

$$R1: IF\ x\ is\ A_1\ and\ y\ is\ B_1\ THEN\ f_1=p_1x+q_1y+r_1 \tag{2}$$

$$R2: IF\ x\ is\ A_2\ and\ y\ is\ B_2\ THEN\ f_2=p_2x+q_2y+r_2 \tag{3}$$

where p_i , q_i and r_i are the consequent parameters. The ANFIS can be summarized in the following steps [34].

Layer 1, (fuzzification layer): The input layer is the adaptive nodes which calculate the membership grades of the inputs, considering membership functions.

$$O_i^1=\mu_{Ai}(x)\ i=1,2\ ;O_{i+2}^1=\mu_{Bi}(x)\ i=1,2 \tag{4}$$

x and y are crisp input of *ith* node; μ_{Ai} and μ_{Bi} are membership function A_i and B_i; and O_i^1 and O_{i+1}^1 are outputs of 1st layer.

Layer 2, (product layer): This layer comprises rule nodes with AND/OR operator, to calculate different combinations of the decision rules (w_m). The output of the 2nd layer (O_m^2) is given as follows

$$O_m^2=w_m=\mu_{Ai}(x).\mu_{Bj}(y); m=1,\ldots,4; i=1,2; j=1,2 \tag{5}$$

Layer 3, (normalized layer): The *ith* node calculates the ratio of the *ith* rule's firing strength to the sum of all rules' firing strength. For ease, outputs of 3rd layer (O_i^3) will be called normalized firing strengths.

$$O_i^3=\overline{w}_i=\frac{w_i}{\sum_{i=1}^{4}w_i}\quad i=1,\ldots,4 \tag{6}$$

Layer 4, (defuzzification layer): Nodes in the 4th layer are adaptive nodes of first order Sugeno type polynomials. The output of *4th* layer (O_i^4) is;

$$O_i^4=\overline{w}_i f_i=p_ix+q_iy+r_i\quad i=1,\ldots,4 \tag{7}$$

p_i , q_i and r_i are coefficients of this linear combination.

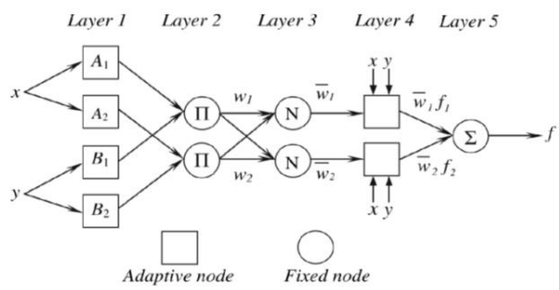


Figure 3. An ANFIS architecture [34]

Layer 5, (output layer): Computing the single output node through sum of all the rules' outputs, system output (O_1^5) is generated.

$$O_1^5 = z = \sum_{i=1}^{4} \overline{w}_i f_i = \frac{\sum_{i=1}^{4} w_i f_i}{\sum_{i=1}^{4} w_i} \tag{8}$$

For learning of ANFIS, a combination of back-propagation (gradient descent) and least squares estimate are employed. [34]. Fuzzy C-Means (FCM) clustering is used to produce the initial Fuzzy Inference System (FIS) and a set of rules that replicas the data behavior. FCM tries to find the most specific point in each cluster which can be deemed as the ''centroid'' of the cluster. Then each data can be fitted to all groups with different membership degree between 0 and 1. This is reached by minimizing the weighted within group sum of squared error function. Then ANFIS is applied on the clustered data [37].

3. 3. Intelligence Committee Machine (ICM)

An ICM consists of a collection of intelligent systems, which merges the outputs of each system and thus reaps the advantages of all systems. Thus, ICM's performance could be better than the best single intelligent system. Combination of the intelligent systems outputs can be done in different ways. Simple and weighted averaging are two common combining methods in the ICM. In Simple Averaging ICM (SAICM), after training the committee constituents, the final output can be attained by averaging the output of the committee constituents. This method is more beneficial when the variances of the group constituents are different, since the simple averaging can decrease the variance of the nets [38]. In Weighted Averaging ICM (WAICM), which was found to provide superior performance, every committee constituents has an appropriate weight related to their ability to generalization [20, 21]. The weight of each committee member can be found by trial and error operation or incorporating an optimization algorithm such as GA and PSO [20, 21]. In this study in addition to conventional combination of ICM (SAICM and WAICM) two new combinations namely, first and second order polynomial combinations of intelligent members were also performed and compared with other.

The ICM consisting of two committee constituents (Figure 4), is constructed in two major steps: in the first step the PPV will be predicted from input data by using the committee constituent models, including ANN and ANFIS. In the next step, four different combinations of the ICM will be constructed using the outputs of ANN and ANFIS models, as shown in Figure 4. GA is used to determine the weight of each committee individuals for WAICM, first order Polynomial ICM (FPICM) and second order Polynomial ICM (SPICM). GA initially was developed by Holland [39], and now is one of the important evolutionary computation techniques, used in engineering to find approximate solutions for optimization and search problems [39-41]. To obtain the optimal weights for WAICM with the GA, the fitness function is defined as follows:

$$\begin{aligned} & MSE = \sum_{i=1}^{N} \frac{1}{N}\left(\left(w_1 \times ANN_i + w_2 \times ANFIS_i\right) - T_i\right)^2 \\ & 0 < w_1 \le 1 \\ & 0 < w_2 \le 1 \\ & w_1 + w_2 = 1 \end{aligned} \tag{9}$$

This function shows the mean squared error (MSE) of committee machine where ANNi and ANFISi are the output of the ANN and ANFIS on the *ith* input or *ith* training pattern, w_1 and w_2 are the weight of ANN and ANFIS, respectively. T_i is the target value of the *ith* input, and N is the number of training data.

Consequently, the fitness function for FPICM and SPICM are as shown in Equations (10) and (11). There are no constraints on the weights of these two combiners.

$$MSE = \sum_{i=1}^{N} \tfrac{1}{N}((w_1 \times ANN_i + w_2 \times ANFIS_i + w_3) - T_i)^2 \tag{10}$$

$$\begin{aligned} MSE = \sum_{i=1}^{N} \frac{1}{N}((w_1 \times (ANN_i)^2 + w_2 \times (ANFIS_i)^2 + w_3 \\ \times ANN_i \times ANFIS_i + w_4 \times ANN_i + w_5 \\ \times ANFIS_i + w_6) - T_i)^2 \end{aligned} \tag{11}$$

3. 4. Model Performance Criteria

Coefficient of determination (R^2), Root Mean Square Errors (*RMSE*), and variance account for (*VAF*) were chosen for performance evaluation. The desired value for these criteria are 100%, 0 and 100%, respectively [42]. Equations of these criteria are as following.

$$R^2 = 1 - \sum_{i=1}^{n}(T_i - Y_i)^2 / \sum_{i=1}^{n}(T_i - mean(T_i))^2 \tag{12}$$

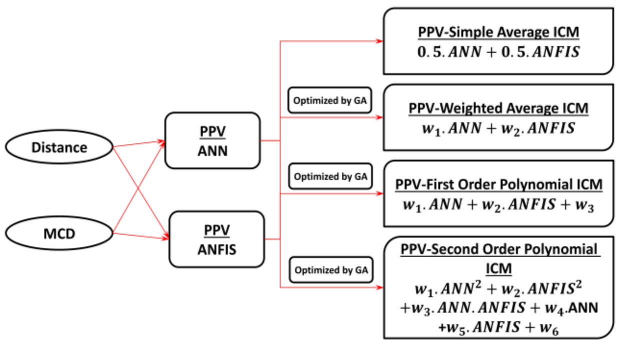


Figure 4. The structure of the ICM model

$$MSE = \sqrt{1/n \times \sum_{i=1}^{n} (T_i - Y_i)^2} \tag{13}$$

$$VAF = \left[1 - var(T_i - Y_i) / var(T_i)\right] \times 100 \tag{14}$$

in which $T_j(i)$ is the expected output, $Y_j(i)$ is the measured output and n is the number of data.

4. RESULTS

At the following section data monitored at SCM are used to develop the mentioned models.

4. 1. Prediction of PPV Using Eps In this study, the most well-known EPs were used for PPV prediction. Site constants in Table 3 (k, n, a, b and c) are computed by using regression analysis using Matlab Curve Fitting Toolbox benefitting Levenberg-Marquardt (LM) algorithm.

The R^2, correlation coefficient (R) and $RMSE$ are given in Table 3. Results show that the prediction capabilities of empirical models are in the average range. Among the EPs, the Ambraseys–Hendron [27] (AH) model, is the best EP to predict PPV at SCM.

4. 2. Prediction of PPV Using ANN The ANN model for PPV prediction at SCM was found by trial and error method. Almost 300 ANN models were constructed varying number of neurons, number of hidden layers, type of transfer function and considering random selection of data. For ANN modelling 70% and 15% of data used for model training and validation, respectively and the rest 15% of data used for model testing. These networks were trained using the Levenberg–Marquardt training algorithm (trainlm). The best ANN selected as the one which scored the best total rank considering all three performance indices for training and testing data. The histogram of the 300 alternative ANN training performance indices is shown in Figure 5. The best ANN found as a MLP with two hidden layers, with 20 and 22, neurons in hidden layers.

TABLE 3. The EPs and their constant values

Name of predictor equation	Constant Values			Statistical Indexes		
	K	*β*	*n*	R^2	R	RMSE
USBM	101.6	0.9389	-	0.541	0.736	15.133
AH	341.9	1.004	-	0.561	0.749	14.809
LK	34.64	-1.779	-	0.520	0.721	15.483
BIS	34.64	-0.8897	-	0.520	0.721	15.483
CMRI	110.3	-	-1.13	0.541	0.736	15.142

In the selected ANN, tribas, tansig and satlins were the transfer functions between input layer and first layer, first layer and second layer and finally between the second layer and output layer, respectively. The performance indices including R^2, RMSE and VAF for the trained ANN considering the training, validation and test data were calculated and are shown in Table 4. Comparisons between measured and predicted PPV by ANN approach is shown in Figure 6.

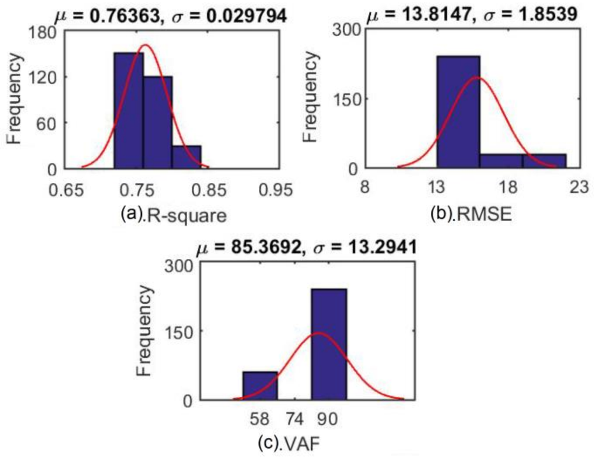


Figure 5. Histogram plots of the ANN performance indices on the basis of 300 independent models (a) R-square (b) RMSE (c) VAF

TABLE 4. Results of ANN model PPV prediction at SCM

Data	R^2	RMSE	VAF
ALL	0.7802	13.1607	86.5617
Train	0.8058	13.0865	87.6779
Test	0.8191	12.5569	92.4478

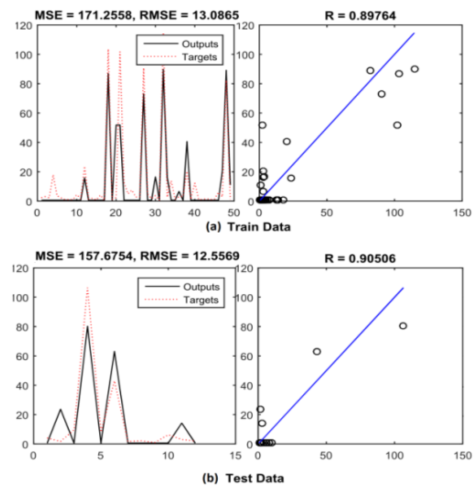


Figure 6. Analysis of measured and predicted values of PPV by ANN model (a) training data, (b) test data

4. 3. Prediction of PPV Using ANFIS An ANFIS based models were developed using the same input variables and the same training, and testing data used in previous analyses. To find the optimum number of fuzzy rules, several models with cluster numbers of 2 to 10 were trained and evaluated and the best one is selected considering R^2 *RSME* and *VAF* values. Among cluster numbers of 2 to 10, ANFIS model with five clusters has the best performance. Figure 7 show the membership function of input1 (MCD) and input2 (AD) with five clusters. The measured and predicted value of PPV for training and testing stages of ANFIS is shown in Figure 8.

4. 4. Prediction Using ICM For constructing the ICMs, the results of predicted PPV from the ANN and ANFIS are combined. In SAICM approach, each expert has equal contribution in constructing the ICM (Equation (15)).

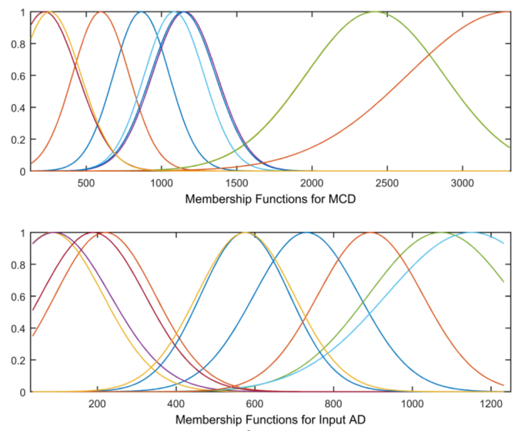


Figure 7. Membership functions, (a) MCD, (b) AD

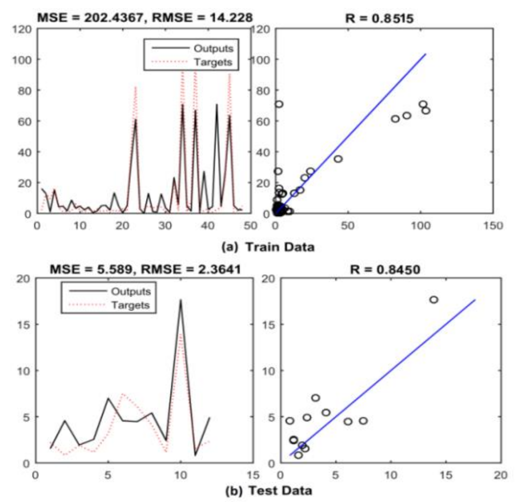


Figure 8. Analysis of measured and predicted values of PPV for the best ANFIS model (a) training data, (b) test

$$PPV_{SAICM} = \frac{1}{2}\left(PPV_{ANN} + PPV_{ANFIS}\right) \quad (15)$$

Applying Equation (15) has provided the R^2 and *RSME* of 0.8499, 11.5363 and 0.802, 13.1867 for training and test datasets, respectively.

In the next step, GA was used to create WAICM, FPICM and SPICM models and obtain a better combination of the individual AI models. In WAICM each AI models have a weight factor which specifies its participation in PPV prediction. For this purpose, the objective function developed in Equation (9) introduced to the GA. In GA, the initial population is created with a random process, and its size was set to 100 with initial range of [0, 1]. The maximum number of generations was set at 500. The next generation is created using "Scattered" crossover and "Gaussian" mutation functions and some of the individuals in the current population are chosen based on the lower fitness value as elite employing tournament selection, employing GA toolbox (MATLAB, 2015). Ten percent of the population size was filled by elites, while the probability for crossover operation was set at 0.8. This process is repeated until a predetermined termination criterion (maximum iterations) is met.

$$PPV_{WAICM} = w_1 \times PPV_{ANN} + w_2 \times PPV_{ANFIS} \quad (16)$$

After performing GA, the optimized weight coefficients are utilized to the test data. The GA procedure for optimizing the weights/coefficients of FPICM and SPICM is similar to the WAICM using Equations (10) and (11), respectively. It is worth noting that there are no constraints on the magnitude of weights in FPICM and SPICM. Figure 9 to Figure 12 depict the correlation coefficient between the measured and ICM predicted results for training and testing dataset for SAICM, WAICM, FPICM and SPICM, respectively. The results are shown in Table 5. The optimized weights proposed that the overall outputs of the WAICM, FPICM and SPICM are a slightly affected more by ANFIS rather than ANN. This is beacause of the better performance of the ANFIS model in training. After performing the weights optimization, final equation for WAICM, FPICM and SPICM methods are as shown in Equations (17) to (19).

$$PPV_{WAICM} = 0.4028 \times PPV_{ANN} + 0.5972 \times PPV_{ANFIS} \quad (17)$$

$$PPV_{FPICM} = 0.4646 \times ANN_i + 0.6238 \times ANFIS_i - 1.0682 \quad (18)$$

$$\begin{aligned} PPV_{SPICM} = & -0.0105 \times \left(ANN_i\right)^2 - 0.0113 \times \left(ANFIS_i\right)^2 \\ & + 0.0236 \times ANN_i \times ANFIS_i + 0.2715 \\ & \times ANN_i + 0.6809 \times ANFIS_i - 0.0545 \end{aligned} \quad (19)$$

TABLE 5. Results of employing SAICM and WAICM for prediction of PPV at SCM

Methods	Weights	Data	R^2	RMSE	VAF
SWICM	w_1=0.5 w_2=0.5	All	0.8225	12.7829	81.9902
		Train	0.8499	11.5363	84.3989
		Test	0.802	13.1867	80.1254
WAICM	w_1=0.4028 w_2=0.5972	All	0.8371	12.2395	82.5844
		Train	0.8505	11.4907	84.5053
		Test	0.7918	13.5779	78.9810
FPICM	w1=0.4646	All	0.8225	11.7389	82.1765
	w2=0.6238	Train	0.8509	11.2740	85.0848
	w3=-1.0682	Test	0.7954	13.9025	78.1360
SPICM	w1= -0.0105 w2= -0.0113	All	0.8303	11.4723	83.0037
	w3= 0.0236 w4= 0.2715	Train	0.8571	11.0454	85.7011
	w5= 0.6809 w6= -0.0545	Test	0.8352	12.3074	82.8960

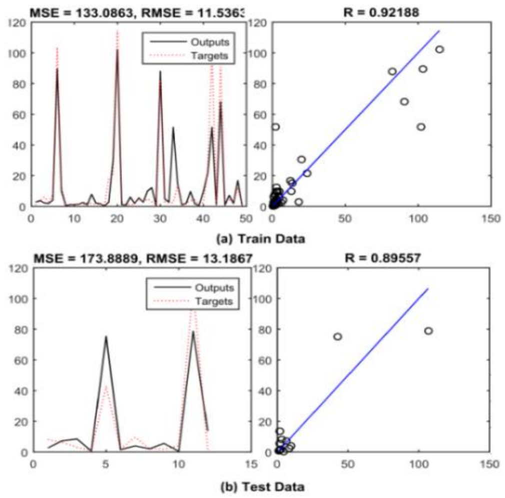


Figure 9. Prediction by SAICM (a) training (b) test data

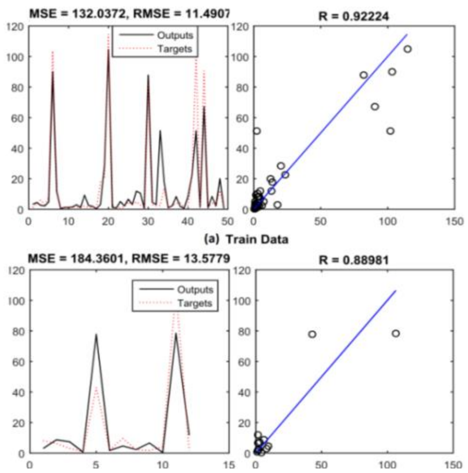


Figure 10. Prediction by WAICM (a) training (b) test data

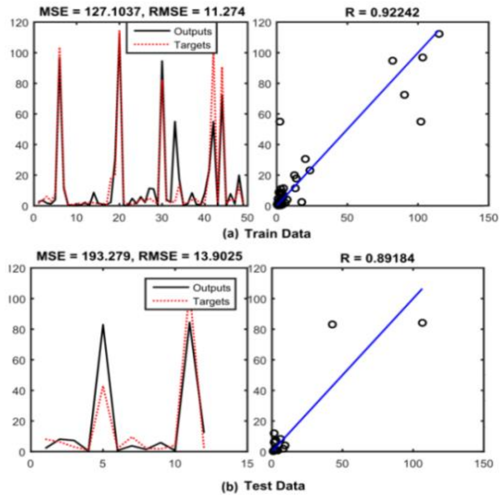


Figure 11. Prediction by FPICM (a) training (b) test data

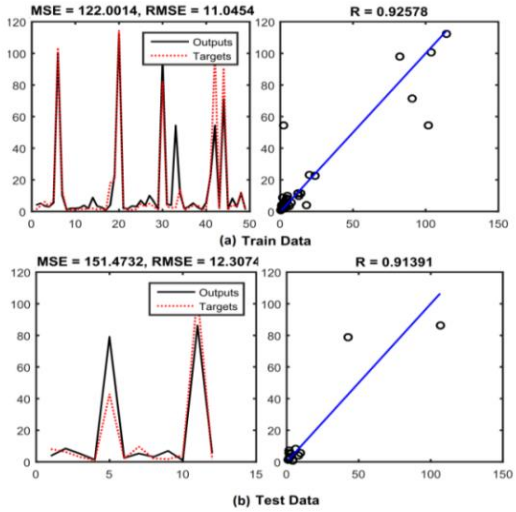


Figure 12. Prediction by SPICM (a) training (b) test data

Actually, the GA decreases the influence of the poorly performing experts and increases the contribution of the high performance experts. It is seen that SPICM has superior performance in comparison with the other three ICM methods. The R^2 and *RSME* of the SPICM predicted PPV for training and testing datasets are 0.8571, 0.8352 and 11.0454, 12.3074, respectively.

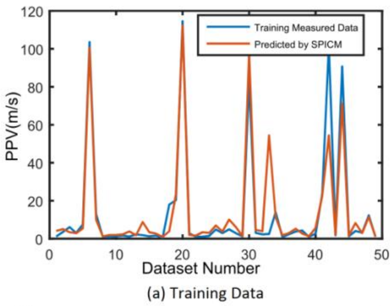
5. DISCUSSION

The statistical performances of the six methods were summarized in Table 6. Comparing the results in TABLE indicate that ICM methods have superiority over the individual ANN and ANFIS models. Comparing the two AI models, ANFIS has better performance in training step in two indices of R^2 and RSME, but ANN proposes higher VAF for training data sets while the ANN outperforms the ANFIS in testing step considering all performance indices.

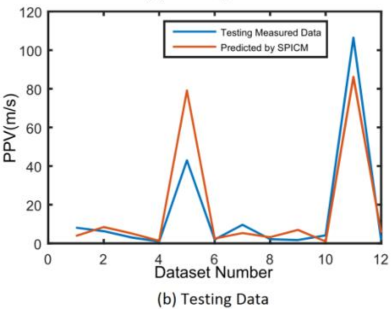
TABLE 6. Performance of the AI and ICM approaches in predicting PPV

Method	Data	R^2	RMSE	VAF
ANFIS	Training	0.8271	12.2395	82.5844
	Testing	0.7326	15.9115	71.4588
ANN	Training	0.8058	13.0865	87.6779
	Testing	0.8191	12.5569	92.4478
SAICM	Training	0.8499	11.5363	84.3989
	Testing	0.802	13.1867	80.1254
WAICM	Training	0.8505	11.4907	84.5053
	testing	0.7918	13.5779	78.9810
FPICM	Training	0.8509	11.2740	85.0848
	testing	0.7954	13.9025	78.1360
SPICM	Training	0.8571	11.0454	85.7011
	testing	0.8352	12.3074	82.8960

Table 6 shows that, the performances of SAICM, WAICM and FPICM are close to each other, while FPICM is slightly performs better, and WAICM performs slightly better than SAICM. But SPICM model overrides the performances of all the models implemented in this study. As explained earlier, SPICM provides a second order polynomial relation between the committee members. The comparison of the measured and predicted values for training and testing datasets is shown Figure 13 for the SPICM method.



(a) Training Data



(b) Testing Data

Figure 13. Comparison between the measured and predicted PPV by SPICM (a) Training (b) Testing

6. CONCLUSION

In this study seven different prediction models were developed based on the monitored data at SCM. Using EPs, the attenuation laws of PPV and site factors were determined at SCM. But to provide prediction with higher accuracy, ANN, ANFIS, SAICM, WAICM, FPICM and SPICM were developed for prediction of PPV at SCM. According to the some efficiency indices, it was found that the ICM models override the EPs and AI models and amongst, GA optimized SPICM model is the best predictor. It is also seen that the ICM models in corporation with GA are fast, accurate and cost-effective for prediction of blast induced vibration. However it should be taken into account that only distance and amount of charge are included in this research. So many other parameters such as ground topography, blast design parameters and geo-mechanical characteristics can be used to increase the accuracy of the prediction models. Moreover, using supervised ICM or integrating more than two committee members can improve the performance of the ICM method.

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Prediction of Seismic Wave Intensity Generated by Bench Blasting Using Intelligence Committee Machines

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چکیده

پیش‌بینی حداکثر سرعت ذره‌ای (PPV) ارتعاش زمین ناشی از انفجار در معادن، روباز بزرگ می‌تواند اطلاعات مفیدی را برای انجام عملیات انفجاری ایمن فراهم کند. در معدن مس سونگون یکسری شیب‌های سنگی با پتانسیل ناپایداری مشرف به برخی تاسیسات صنعتی باارزش هر دو در مواجهه با لرزش روزانه انفجارها قرار دارند، که ایمنی آن‌ها را تهدید می‌کند. از این‌رو کنترل شدت لرزش‌ها با توسعه مدل‌های صحیح پیش‌بینی کننده ضروری می‌باشد. در این مطالعه استراتژی‌های بهبود یافته‌ای برای پیش‌بینیPPV بر اساس حداکثرخرج ماده منفجره شده در تاخیرات و فاصله بین مرکز انفجار و ایستگاه اندازه‌گیری با استفاده از مفهوم ماشین کمیته هوشمند (ICM) ارائه شده است. از اینرو، علاوه بر روابط تجربی (EPs) و دو روش هوش مصنوعی ANN و ANFIS، چهار نوع مختلف ICM شامل ICM با متوسط‌گیری ساده و وزن (SAICM و WAICM) و ICM چند جمله‌ای مرتبه اول و دوم (FPICM و SPICM) بر اساس خروجی دو مدل ANFIS و ANN برای پیش‌بینی PPV بر اساس داده‌های اندازه‌گیری شده در معدن مس سونگون پیشنهاد شده است. از این‌رو الگوریتم ژنتیک (GA) برای پیدا کردن ضرایب مدل‌های WAICM، FPICM و SPICM استفاده شد. در نهایت عملکرد هفت مدل پیش‌بینی کننده PPV با استفاده از شاخص‌های R^2، RSME وVAF مورد بررسی قرار گرفت. نتایج نشان می‌دهد که روش‌های ICM در پیش‌بینی PPV نسبت به EP ها و مدل‌های هوش مصنوعی برتری دارد. علاوه بر این، عملکرد سه مدل SAICM، WAICM و FPICM نزدیک به یکدیگر هستند، در حالیکه SPICM بهینه شده با GA عملکرد بهتری نسبت به تمام مدل‌های توسعه داده شده در این تحقیق دارد. مقدار R^2 و RSME داده های آموزش و آزمون برای مدل SPICM به ترتیب برابر با ۰/۸۵۷۱، ۰/۸۳۵۲ و ۰/۰٤٥٤ ، ۱۲/۳۰۷٤ است. درنهایت، روش ICM مدل‌های دقیق‌تر و قابل اطمینان‌تری نسبت به مدل‌های هوش مصنوعی ارائه می‌کند.

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