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REVIEW ARTICLE

Intelligence Prediction of Some Selected Environmental Issues of Blasting: A Review

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Abstract:

Background:

Blasting is commonly used for loosening hard rock during excavation for generating the desired rock fragmentation required for optimizing the productivity of downstream operations. The environmental impacts resulting from such blasting operations include the generation of flyrock, ground vibrations, air over pressure (AOp) and rock fragmentation.

Objective:

The purpose of this research is to evaluate the suitability of different computational techniques for the prediction of these environmental effects and to determine the key factors which contribute to each of these effects. This paper also identifies future research needs for the prediction of the environmental effects of blasting operations in hard rock.

Methods:

The various computational techniques utilized by the researchers in predicting blasting environmental issues such as artificial neural network (ANN), fuzzy interface system (FIS), imperialist competitive algorithm (ICA), and particle swarm optimization (PSO), were reviewed.

Results:

The results indicated that ANN, FIS and ANN-ICA were the best models for prediction of flyrock distance. FIS model was the best technique for the prediction of AOp and ground vibration. On the other hand, ANN was found to be the best for the assessment of fragmentation.

Conclusion and Recommendation:

It can be concluded that FIS, ANN-PSO, ANN-ICA models perform better than ANN models for the prediction of environmental issues of blasting using the same database. This paper further discusses how some of these techniques can be implemented by mining engineers and blasting team members at operating mines for predicting blast performance.

Keywords: Blasting, Environmental issues, Performance prediction, Computational techniques, Air over pressure (AOp), Rock fragmentation.

1. INTRODUCTION

Blasting is the most effective technique used for several decades for breaking rock in civil engineering projects. When an explosive is detonated inside a drill hole, a large amount of energy is instantaneously released in the form of waves in the

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ground and gases are released in the air [1, 2]. For breaking rock, only 20 to 30% of energy released is used to create fragmentation and to throw the material for further excavation while the rest of the energy is wasted in the form of flyrock, ground vibration, and air over-pressure [3 - 6]. For the civil and mining engineer, it is a challenge to achieve the overall objectives of blasting through optimum powder factor with desired fragmentation and minimizing the environmental impacts due to blasting while optimizing overall mining cost.

Optimum rock fragmentation by blasting is desirable for downstream operation productivity consisting of loading, hauling, crushing and grinding. During 1960s and 80s, various researchers have tried to predict blastability through various empirical equations [7]. However, the predicted performance does not accurately model the actual results. With the advancement of computational power and software programming, it is possible to predict the different blast performance parameters, including blast fragmentation, flyrock distance, ground vibration and air overpressure due to blasting. These techniques involve training and testing of blast data and comparing the results using different computational algorithms. This paper reviews various soft computational techniques for prediction of blast performance.

2. GENERAL DEFINITIONS AND CONCEPTS

2.1. Flyrock

In opencast bench blasting, flyrock, which is the excessive throw of any portion of rock from the blasting face, is not the desired phenomenon [8 - 10]. Identification and demarcation of blasting danger zones are important due to the hazards associated with damage to property and possible serious bodily injuries and fatalities associated with flyrock accidents [11]. The major factors contributing to flyrock are hole diameter, inadequate stemming, inappropriate delays, misfires, and excessive charging due to voids or higher powder factor, misfires, geological structures and rock mass properties [12 - 14]. Accidents due to flyrocks are caused as a result of lack of knowledge and incompetence or higher confidence in judging flyrock distance, inadequate security arrangements to guard any person entering into danger zone of blasting [15 - 17].

2.2. Ground Vibration

Ground vibrations, measured as Peak Particle Velocity (PPV), depend upon a maximum charge per delay and the distance from the blasting face. Many empirical predictor equations have been developed by different researchers on these two parameters [18 - 20]. Fig. (**1**) shows how primary and secondary surface waves due to the blast transmit ground vibrations to a structure.

Peak particle velocity is measured in mm/second. Ground vibration can cause structural damage and different countries have developed their own standards for ground vibration limits. Human beings are highly sensitive to ground vibration. For example, damage criteria for concrete structure are 50 mm/second of ground vibration due to blasting. However, a person can detect ground vibration of 0.5 mm/second. Ground vibration is a major annoyance to nearby human settlements around mines. Attending to complaints related to blast-induced ground vibration can be a challenging task for any mine management.

2.3. Air Overpressure (AOp) or Airblast

This is the air overpressure or airblast created due to blasting. These shock waves are caused by a combination of several factors: release of energy direct from the surface, release of inadequately confined gases, a shock from a large free face, gas release pulse due to gases escaping through rock fractures, and pulse from stemming column during ejection of stemming [21 - 24]. Air overpressure from blasting consists of a wide range of frequencies, some of which are sensed by the people as noise, while the low frequency component (< 20 Hz) can cause concussion. Higher air overpressure is created with methods of blasting such as plaster or pop shooting (often used for secondary blasting), and the use of detonating cords. Down-the-hole initiation systems such as NONEL and electronic detonators reduce air overpressure.
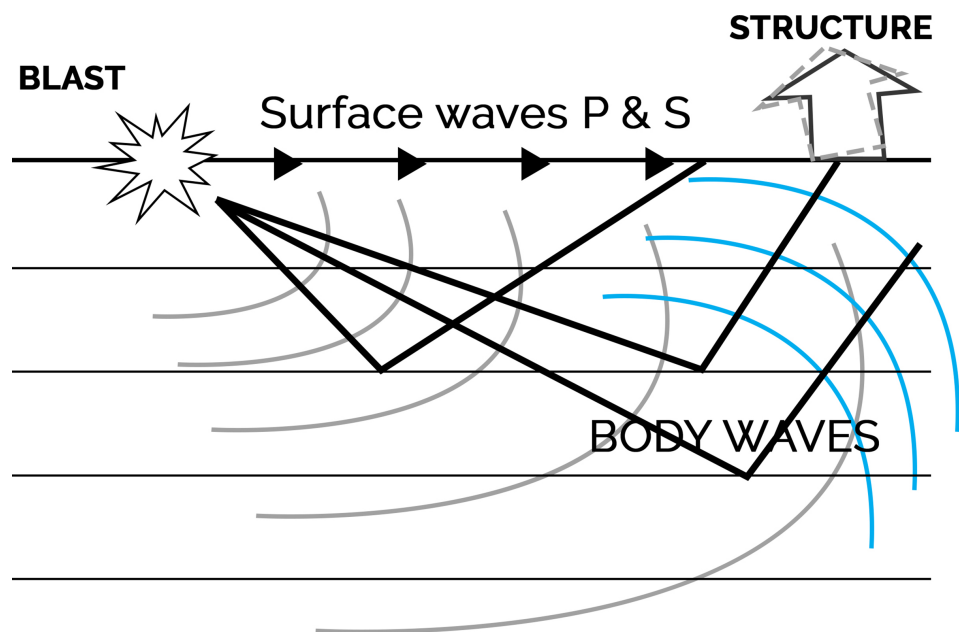

Fig. (1). Ground vibration due to blasting [10].

2.4. Fragmentation

Fragmentation is represented by the mean fragment size or 80% of maximum fragment size. Fragment size is important as it affects downstream productivity of loading, hauling and crushing operations. Fragmentation is affected mainly by rock mass properties, blast design and instantaneous energy released during blasting [25].

3. COMPUTATIONAL TECHNIQUES

Various computational techniques have been commonly used for solving complex engineering and scientific problems [26 - 67]. Some of the most important soft computational techniques in the field of blasting are described as follows:

3.1. Artificial Neural Network (ANN)

Since 1980, ANN has become popular to resolve complex problems. ANN is a part of Artificial Intelligence (AI), along with Case Based Reasoning, Expert Systems and Genetic Algorithms. Classical statistical theories – Fuzzy Logic and Chaos theory are related fields. This methodology is inspired by how human brain functions to make appropriate decisions. This is considered to be an 'intelligent tool', in which the network 'learns' to establish patterns from old, established data. Based on the previous learning, new input data is analyzed by the system to predict outputs [68 - 71]. Basically, the ANN is an information processing system that is similar to the human brain in structure and functions. During the process of studying, memorizing and reasoning, the human brain, creates a complex network that is connected together for processing various tasks. Human brain performs by interconnecting a large number of simple processing units called Neurons, into a pattern, capable of performing data processing and knowledge representations. Similarly, the ANN attempts direct modelling of the functions of human brain [72]. ANN can be precisely designed for any specific problem to be solved, using three fundamental components [73]:

- Transfer Function
- Network Architecture
- Learning Law

In order to interpret new data, the neural network needs to be trained in pattern recognition first. There are a number of methods and algorithms available for training neural networks.

Back Propagation Neural Network (BPNN) is most commonly used and consists of 3 layers: input, hidden and output [74 - 76]. In the process, the neurons in the Hidden Layer undergo certain changes. These changes depend on the problem to be solved and the number of neurons that change is the same as the number of input and output variables in the problem. A 'Transfer Function' determines the changes taking place in the neurons and the extent of the changes are determined by 'biases' that are introduced in each of the layers. Weights are coefficients for resolving an equation. Positive weights increase the output of an equation. Bias is a constant value added to the product of the inputs and the outputs. Bias is added to offset the result in either the positive side or the negative side. All neurons in the BPNN, except for the Input Layer, are connected to a bias neuron and a transfer function. The transfer function acts as a filter for the summation of the signals received from the different neurons. The transfer function is designed to map the output received from a set of neurons or layer of neurons to the pre-recorded actual output and establish a pattern.

3.2. Support Vector Machine (SVM)

These are supervised learning machine models that analyze data used for classification and regression analysis using learning algorithms. SVM training algorithm builds a non-probabilistic binary linear classifier. The support vector clustering algorithm applies the statistics of support vectors to classify unlabeled data [8]. In pattern recognition, the SVM algorithm constructs nonlinear decision functions by training a classifier to perform a linear separation in some high dimensional space that is nonlinearly related to input space. To generalize the SVM algorithm for regression analysis, an analog of the margin is constructed in the space of the target values [77]. Several extensions of this algorithm are possible. From an abstract point of view, it just needs target function that depends on the vector. There are multiple degrees of freedom for constructing this function, including some freedom on how to penalize, or regularize, different parts of the vector, and some freedom on how to use the kernel trick. Finally, the algorithm can be modified using as primal objective function to get final results [8].

3.3. Artificial Bee Colony (ABC)

It is for optimizing complex engineering problems through intelligent exploring behavior of honey bee swarms which can be simulated [78]. Colony bees are divided into three categories: employed, onlookers and scouts [79]. Initially, scout bees search honey as a food source. Continuous onlooker bees are at hive during searching period. Employed bees perform "waggle dance," when high-quality honey is found. Communication among scout bees about the food source quality occurs in the dancing area and honey as food source is selected. In the ABC algorithm, a possible solution of the problem can be optimized by finding the quantity of nectar in a food source which corresponds to the quality of the solution [80].

3.4. Genetic Algorithm (GA)

Genetic algorithm (GA) is a branch of AI and evolutionary algorithms and is one of the modern approaches of numerical optimization that is based on Charles Darwin's theory of "survival of the fittest" and "natural selection". This method was first developed by Holland [81] during the 1960s and then developed by Goldberg [82]. The process of GA algorithm starts with a random generation of chromosomes. Then, the fitness of individual chromosomes in the generation will be evaluated. The selection operator similar to Darwin's natural selection that gives more chance to better solutions and less chance to worse solutions in the next generation, will be applied on the individuals. In the following, by applying genetic operators (mutation and crossover) on the remaining chromosomes, the next generation of chromosomes is created. Crossover is the main operator that selects two parent

chromosomes randomly and swaps a segment of them with each other at the chosen cross-site(s) randomly along the string length. Newly created chromosomes are known as children. Mutation is another genetic operator that can select chromosomes randomly in the suggested range (*e.g.*, 0 to 1 or vice versa) with a small mutation probability. This process is repeated until the stopping conditions (the maximum number of generation or desired value for the best solution) are met [83 - 85].

4. DISCUSSION ON REVIEW OF PREDICTION MODELS

Many researchers have utilized various computational techniques for prediction of blast performance consisting of flyrock, ground vibration, air over-pressure and rock fragmentation. These techniques are reviewed in this paper.

4.1. Flyrock Prediction

Table **1** shows the prediction of flyrock distance due to blasting in 11 data sets analyzed using ANN, ANN-GA, ANN-imperialism competitive algorithm (ICA), ANN-particle swarm optimization (PSO), fuzzy inference system (FIS) and SVM. The input rock mass parameters are rock density, rock mass rating and compressive strength. 42% of data set has rock density as an input parameter. Rock density plays an important role in the estimation of flyrock distance. The lighter the rock, the greater is the distance covered by flyrock. The input blast design parameters are hole diameter, spacing, burden, spacing-burden ratio, stemming length, hole length and hole depth. Burden and burden spacing ratio are used as input parameters by all data sets. Flyrock distance is inversely proportional to burden and hence burden plays an important role in prediction of flyrock distance. Stemming length and hole depth/ hole length have been used as input parameters by 92% and 87% of data sets, respectively. Flyrock distance is inversely proportional to stemming length. Flyrock distance increases with the increase in hole depth/ hole length. The parameters related to the explosives used are powder factor, maximum charge per delay and specific charge. Maximum charge per delay and powder factor as input parameters have been used by 75% and 67% of data sets, respectively. Maximum charge per delay represents the maximum explosive energy release. On the other hand, powder factor shows overall explosives energy release per unit volume of rock. Both factors play a crucial role

in the assessment of flyrock distance. An average of 197 datasets were analyzed for the assessments and the. R^2 value varied from 0.89 to 0.98.

4.2. Ground Vibration Prediction

Table **2** illustrates prediction of ground vibration due to blasting analyzed with 12 data sets using various computational techniques namely ANN, FIS, SVM, ANN-PSO and ANFIS. Rock density, primary velocity, Young's modulus are rock mass related properties. However, these parameters have been used in only one data set each and hence are not expected to affect ground vibration. Burden, spacing, hole diameter, stemming length, hole length, spacing burden ratio, and ratio are blast design related parameters. Stemming length is used by 46% of the data sets. Optimizing the stemming length helps minimize ground vibrations, hence stemming length is critical parameter. Maximum charge per delay, total charge and powder factor are explosives related parameters. Distance from blast face is important as ground vibration reduces with an increase of distance from the blast face. Maximum charge per delay and distance of monitoring point from the blast face are used by all data sets. Hence, both these parameters are crucial for the prediction of ground vibration. Average number of 86 data sets were analyzed and the R^2 value varied from 0.85 to 0.99 for the prediction of ground vibration.

4.3. Air Over Pressure Prediction Due to Blasting

Table **3** shows the prediction of air overpressure due to blasting analyzed with seven data sets using several computational techniques, namely ANN, ANN-PSO, GA-ANN, FIS and SVM. RQD is rock mass parameter which can affect AOp. However, as it has been used for only one data set, RQD is not considered to be a significant parameter. Spacing, burden, hole diameter, hole depth, stemming length and number of rows are blast design parameters. Hole depth, spacing, burden and stemming length have been used in 40% of data sets, hence these are important input parameters for the prediction of Air over pressure. Input parameters such as the maximum charge per delay and powder factor are explosives related input parameters. Maximum charge per delay and distance between monitoring point and blasting face are crucial. An average number of 96 blasts per data set was analyzed and the R^2 value varied from 0.85 to 0.99.

Table 1. Prediction of flyrock due to blasting using computational techniques.

Ref.	Technique	Input parameters			No. of datasets	R^2
		Rock Mass	Blast design	Explosives		
Monjezi *et al.* [86]	ANN	RD	HD, BS, ST, SD	PF, C	250	0.98
Rezaei *et al.* [4]	FIS	RD	HD, S, B, ST, SD	PF, C	490	0.98
Monjezi *et al.* [87]	ANN		HD, BS, ST, D, B, SD	PF, C	192	0.97
Monjezi *et al.* [88]	ANN-GA	RMR	HD, S, B, ST, SD	PF, C	195	0.89
Amini *et al.* [8]	ANN		HL, S, B, ST, D	PF	245	0.92
	SVM					0.97
Mohamad *et al.* [89]	ANN	RD	HD, BS, ST, N, SD	PF, C	39	0.97
Armaghani *et al.* [2]	ANN-PSO	RD	S, B, ST, D, N, SD	PF, C	44	0.94
Monjezi *et al.* [90]	ANN		HD, S, B, D,	C	310	0.98

(Table 1) contd.....

Ref.	Technique	Input parameters			No. of datasets	R²
		Rock Mass	**Blast design**	**Explosives**		
Khandelwal and Monjezi [1]	SVM		HL, S, B, ST, SD	PF	187	0.95
	MVRA					0.44
Marto *et al*. [91]	ANN-ICA	RD	HD, BS, ST		113	0.98
Trivedi *et al*. [92]	ANN	RQD, σ_c	B, ST	Q	95	0.98
Ghasemi *et al*. [93]	ANN		HL, S, B, ST	PF, C	230	0.94
	FIS					0.95
Armaghani *et al*. [74]	ANN		BS, ST	PF, C	166	0.83
	ANFIS					0.97

ANN- Artificial neural network, FIS- Fuzzy interface system, GA- Genetic algorithm, PSO- Particle swarm optimization, ICA- Imperialist competitive algorithm, SVM- Support vector machine, RD- Rock density, RMR- Rock mass rating, RQD- Rock quality designation, σ_c- Compressive strength, HD-Hole depth, HL- Hole length, S- Spacing, B- Burden, D -Hole diameter, BS- Spacing to burden ratio, ST- Stemming length, SD- Specific drilling, N- Number of rows, PF- Powder factor, C- Maximum charge per delay, q - specific charge, ANFIS- Adaptive neuro-fuzzy inference system.

Table 2. Prediction of ground vibration due to blasting using computational techniques.

Ref.	Technique	Input Parameters				No. of datasets	R²
		Rock Mass	**Blast Design**	**Explosives**	**Other**		
Iphar *et al*. [94]	ANN	-	-	C	DI	44	0.98
Amnieh *et al*. [95]	FIS	-	ST,N	C	DI	29	0.99
Armaghani *et al*. [74]	ANN	-	BS, ST	C, PF	DI	166	0.77
	ANFIS						0.94
Fisne *et al*. [96]	FIS	-	-	C	DI	33	0.92
Li *et al*. [97]	SVM	-	-	C	DI	32	0.89
Monjezi *et al*. [88]	SVM	-	-	C	DI	37	0.89
	ANN						0.85
Ghasemi *et al*. [98]	FIS	-	B, S, ST, N	C	DI	120	0.95
Khandelwal *et al*. [99]	-	-	-	C	DI	170	0.96
Monjezi *et al*. [100]	ANN	-	-	C, TC	DI	20	0.93
Armaghani *et al*. [2]	ANN-PSO	RD	B, S, ST, D, SD	C, PF	DI	44	0.94
Hajihassani *et al*. [101]	ANN-ICA	V_p, E	BS, ST,	C, PF	DI	95	0.98
Ghoraba *et al*. [102]	ANN	-	HL, BS, ST,	C	DI	115	0.98
Mohamed [103]	ANN	-	-	C	DI	162	0.97
	FIS						0.99

For ANN, ANN-ICA, ANN PSO, FIS, SVM, B,S,ST, D, BS,HL,C,PF,TC refer Table 1. RD- rock density, Vp- p-wave velocity, E- Young's modulus, DI- Distance from blasting face.

Table 3. Prediction of air over pressure due to blasting using computational techniques.

Ref.	Technique	Input parameters				No. of datasets	R²
		Rock Mass	**Blast design**	**Explosives**	**Other**		
Khandelwal and Kankar [77]	ANN			C	DI	75	0.92
	MVRA						0.587
Armaghani *et al*. [74]	ANN		BS, ST	C, PF	DT	166	0.86
	ANFIS						0.95
Khandelwal and Singh [104]	ANN			C	DI	56	0.96
Mohamed [103]	ANN			C	DI	162	0.96
	FIS						0.99
Khandelwal *et al*. [105]	SVM			C	DI	75	0.85
Mohamad *et al*. [106]	GA-ANN		HD, S, B,, ST	PF	DI	76	0.97
	ANN						0.90
	MVRA						0.78
Hajihassani *et al*. [5]	ANN-PSO	RQD	HD, S, B, ST	C, PF	DI	62	0.86

(For ANN, ANN-FIS, ANN-PSO, SVM, B, S, ST, HD, D, C, PF refer Table 1 & Table 2.) RQD-Rock quality designation, GA-genetic algorithm.

4.4. Prediction of Rock Fragmentation Due to Blasting

Table **4** shows prediction of fragmentation due to blasting analyzed with four data sets using various computational techniques, namely ANN, ANN-ICA, FIS and MVRA. Rock density, blastability index, RQD, geological strength index (GSI), and mean block size are rock mass parameters and since each parameter has been used only once within the data sets, these parameters may be expected to impact fragmentation based on site condition. Various ratios including burden-to-spacing ratio, stemming-to-burden ratio, burden-to-diameter ratio, bench height-to-hole diameter ratio, in addition to the individual parameters, are blast design parameters. Burden/spacing has been used in all data sets. Stemming length and hole depth/bench height are used for 80% of data sets, Hole diameter and specific drilling are used for 60% of data sets. All these blast design parameters contribute Maximum charge per delay, powder factor are explosives related parameters. Maximum charge per delay and powder factor have been used for 60% and 40% of data sets, respectively. Both factors are important and directly contribute to fragmentation. An average of 218, data sets were analyzed and the R^2 value varied from 0.85 to 0.98. MVRA showed the least R^2 value of 0.674.

Table 4. Prediction of rock fragmentation due to blasting using computational techniques.

Ref.	Technique	Input Parameters				No. of Datasets	R^2
		Rock Mass	Blast Design	Explosives	Other		
Monjezi *et al.* [107]	FIS	RD	B,S,ST,N,SD,HD	-	-	415	0.96
Monjezi *et al.* [108]	ANN		D,HD,BS,ST,N,	C,PF		250	0.98
Bahrami *et al.* [109]	ANN	BI	D,B,S,ST,SD,	C,PF		220	0.97
Sayadi *et al.* [110]	ANN		B,S,HD,SD,	SC		103	0.85
Bhatawdekar *et al.* [25]	ANN-ICA	RQD, X_B	BS,B/D,H/B,ST/B	C		102	0.95
	ANN						0.94
	MVRA						0.67

(For ANN, ANN-ICA, RD, RQD, B, S, BS, ST, N, BS, C, PF refer Table **1**, Table **2** and Table **3**). SC is specific charge in explosives charge per meter. MVRA-Multivariable regression analysis, BI- Blastability index, X_B- Mean block size, GSI- Geological strength index.

Table 5. Comparison of algorithms for prediction of environmental effect due to blasting.

Algorithm	The principles of Algorithms	Effects of different algorithms and analysis
ANN	ANN is known as a universal approximator, *i.e.* a flexible functional form that may approximate any random function by arbitrarily specified adequate units of hidden-layer and appropriately adjusted network weights and biases. The key advantage of ANN is its ability to provide flexible mapping between inputs and outputs. The arrangement of hidden units into a multilayer framework generates a map between input and output which is compatible with any underlying functional relationship irrespective of its factual functional form. The gradient descent algorithms (most popular backpropagation (BP) algorithm) are used to tune the learning parameters in network by propagating the output error in backward direction. Several transfer functions are used in hidden and output units for adequate prediction capability of ANN.	R^2 values varied from 0.85 to 0.99.
SVM	SVR finds appropriate hyperplane to fit the data with some acceptable error. Here, the objective function is minimizing the coefficients rather than squared error. The error term is handled in constraints. Where the absolute error <= the maximum error (ε) and slack variable (deviation from the error margin). SVR has two hyperparameters to tune (i) ε and (ii) C for slack variable. We try to find best value of C for that the percentage of data within ε is maximized.	R^2 values varied from 0.85 to 0.97.
FIS	FIS is used to interpret human reasoning in the form of IF-THEN rules. The output of FIS is a fuzzy set which is transformed to crisp value (defuzzification). This inference system is Mamdani type. In Takagi-Sugeno FIS the output is crisp value.	R^2 values varied from 0.94 to 0.99.
ANFIS	ANFIS is hybridization of connectionist strength of ANN and human reasoning-based FIS model. The inference system is based on the Mamdani or Takagi-Sugeno FIS. FIS is consisting of fuzzy IF-THEN rules which are assisted by human expertise. The main advantage of this technique is the interpretability of human knowledge in the form of antecedent and consequent part. The network is adaptive, because fuzzy assignments (degree of membership functions) are adjustable. Where, premise parameters are tuned using BP algorithm in backward direction and in forward direction least square method is used to set consequent parameters.	R^2 value is 0.95
GA-ANN	GA is the most frequently used population-based metaheuristic algorithm and commonly used for several optimization tasks. The chromosomes are the populations. The crossover and mutation are the main operators of GA. During each run, two parents (from population) with best fitness are selected for crossover to create an offspring. For diverse solution, they are mutated with some probability. Finally, the best solution is retained. In GA-ANN. GA is used to tune learning parameters (weights and biases) of ANN rather than gradient approaches.	R^2 value is 0.89.

(Table 5) contd.....

Algorithm	The principles of Algorithms	Effects of different algorithms and analysis
ICA-ANN	ICA is a well-known population-based metaheuristic algorithm used for optimization tasks. Here the countries are considered as the populations just like chromosomes in GA. The power of a country is determined by the cost function. Initially some best countries (solutions) become imperialists that control others (colonies) and form empires. The main operators are assimilation and revolution. In assimilation state, the countries are getting closure to imperialist state within the search space. At the time of revolution some of the solutions face random change in positions. Finally, the best country is chosen as the best candidate solution. In ICA-ANN. ICA is used to tune learning parameters of ANN.	R^2 values varied from 0.949 to 0.98.
PSO-ANN	PSO is most popularly used algorithm in optimization tasks. The basic principle of PSO is the global best solution is followed by other local solutions. During each run solutions are updated based on their position and velocity. The main advantage of this approach is its simplicity and easy to implement. The global best solution is retained as the best candidate for optimization tasks. PSO can be used to optimize ANN learning parameter and creates a hybrid model of PSO-ANN.	R^2 values varied from 0.86 to 0.94.

5. DISCUSSION

In this section, the accuracy of collection of different input and output parameters, various computational techniques, uncertainties in blasting, and multi-criteria approaches are reviewed.

5.1. Review of Methodology of Collection of Input and Output Data

Various rock mass properties such as rock density (RD), uniaxial compressive strength (σ_c), and Young's modulus (E) are tested at the laboratory. Rock mass properties such as RQD, average block size (X_B), blastability index (BI) and p-wave velocity are determined in field tests conducted at the blasting face of the individual quarry (Table **4**). Blast design parameters are measured with tape or by systematic survey. All parameters are average values for a given blast. All the values are taken on average basis and hence there is minimum error. Accurate records exist for the explosives consumed per hole and the total explosives per blast. Thus, the calculated values of maximum charge per delay, powder factor and charge per meter are accurate for a given blast. Flyrock distance is measured using tape from blasting face for a given blast and also verified by GPS coordinates. Thus, there is good accuracy of the measured value for the flyrock distance for every blast. Air over pressure and ground vibration are measured with seismograph and hence these outputs are accurate. Fragmentation is measured by taking photographs of the muckpile and analyzed using image analysis software. Thus, there is good accuracy on fragmentation results.

5.2. Review of Computational Techniques

During initial stage of development of computational techniques, the ANN model was used for prediction of blasting performance as correlations with input parameters can be evaluated without much effort. Various researchers have widely used ANN models for the prediction of blasting performance (*e.g.*, [25, 68 - 71, 74, 111]). However, there is a limitation that specific models cannot be developed for each prediction and it depends upon range of data. Hence, many researchers utilize MVRA technique as the benchmark technique to compare results of other computational techniques [1, 25]. On the other hand, various techniques such as SVM-based and FIS-based have higher rate of learning. Prediction

accuracy of these models is higher as compared to ANN. The development of hybrid computational techniques such as PSO-ANN or ICA-ANN have shown highest accuracy as compared to other computational techniques. (Table **5**) shows the comparison of the different algorithms for the prediction of environmental effects due to blasting.

5.3. Review of Certain Uncertainties Reported by Researchers on Prediction Blasting Performance

Uncertainty of prediction of flyrock distance [93] and ground vibration [98] is minimized using the fuzzy techniques. Azami *et al.* [112] reported that there are extensive procedures for judging blastability. This uncertainty is due to rock mass classification system where two classes may have overlapping properties. Sometimes, uncertainty arises from the fixed numerical score rating on each input parameter for a given rock class interval. A fuzzy logic based blastability designation predictor model helps the blasting engineer to judge and arrive at a final rating which reduces uncertainty [112]. As per study by Hasanipanah and Amnieh [113], the uncertainty of risk assessment and prediction of flyrock distance was eliminated by utilizing fuzzy rule techniques. Monjezi *et al.* [87] reported that ANN supported uncertainty in the prediction of flyrock distance and flyrock could be controlled. Thus, computational techniques are enabling the elimination of uncertainty in the prediction of blasting performance.

5.4. Review of Multi-Criteria Approaches

There are a number of studies where researchers have achieved two or more objectives on blasting performance. Prediction of AOp, PPV and flyrock distance was achieved through a single study with suitable input parameters [74]. Many researchers have predicted two blast performance outputs. Flyrock distance and PPV [2], fragmentation and flyrock distance [86], flyrock distance and backbreak [88, 110], fragmentation and backbreak [80] have been predicted successfully with various computational techniques.

5.5. Review of Blasting Software

Mine excellence software can maintain a good database of every blast at a given mine site. Such historical databases are useful for future planning and prediction of blasts in the same mine site. With emerging technologies such as mobile phone, Unmanned Aerial vehicles (UAV) and cloud computing, it is

possible to carry out face survey, view the data seamlessly, and design the blast with cloud computing to help obtain good fragmentation using the Pit O Blast Software [114].

6. FUTURE SCOPE OF RESEARCH

[1] Rock mass properties are site specific and contribute to the environmental effects of blasting. The procedure for selecting rock mass properties for each site needs to be identified. The information on rock mass properties can be developed from the exploration stage like the Building Information Model. This will be useful for prediction of blasting performance [115].

[2] Mine Excellence is a database management software for design of blasts based on cloud computing. On the other hand, Pit O Blasts connects emerging technology platforms such as digital camera, UAV, Mobile, Laptop with cloud computing. It is necessary to create a large database of blasts and quickly identify exceptional blasting conditions for design of blasts. Thus, future research should be focused on the development and analysis of large database of blasts, based on digitally captured input and output data, and the prediction of blast performance with AI/ML techniques [114, 115].

[3] Various physical parameters for blast design are based on average values. However, it is important to know the correct burden – toe to crest for every meter of bench height for the first row of the blast. Future research can be done based on capturing the correct blast design data instead of the present practice of using averaged data for the complete blast.

CONCLUSION

Environmental impacts due to blasting in excavations in hard rock, *i.e.*, flyrock, ground vibration, and air over pressure need to be predicted in advance. Processing of data was done with various algorithms and the best predicted value was selected for future predictions. Most of the computational techniques provided good values of prediction with R^2 in the range of 0.9 to 0.99.

ANN, ANFIS and ANN-ICA were found to be the best models for the prediction of flyrock distance (R^2=0.98). FIS model was the best technique for the prediction of AOp and PPV (R^2=0.99). ANN was the best model for the prediction of fragmentation (R^2=0.99).

Rock fragmentation is important performance indicator of blasting for improving productivity in mining operation based on the input parameters used by various researchers. The ANN model was found the best model for prediction of rock fragmentation (R^2=0.99). Thus, practicing mining engineers can collect input data for individual blast for 100 datasets and utilize one of the computational techniques for the prediction of target parameters with good accuracy.

Future research can be based on emerging technologies such as UAV, Mobile platform, GPS Technology, Cloud based databases for capturing blast design data for better design of blasts for achieving desired blasting results.

CONFLICT OF INTEREST

The author declares no conflict of interest, financial or otherwise.

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