A Review of Prediction of Blast Performance using Computational Techniques

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Abstract
In hard rock excavation, drilling and blasting is commonly used for loosening rock. Optimum rock fragmentation due to blasting is desirable for downstream operation productivity. Environmental impacts due to blasting consist of flyrock, ground vibration, air over pressure (AO$_P$). Blast performance depends upon mainly 3 factors consisting of rock mass properties, blast design and explosives system utilised. Mean fragment size is commonly used for rock fragmentation analysis. During 1960-80, blast performance was evaluated using empirical methods. With advancement of computing power during the last two decades, various computentional techniques have been developed for predicting fly rock distance, peak particle velocity, air over pressure with various input paramters based on set of blasts. Technique involves training and testing blast data and comparing results with different computentional algorithm. Various computetntional techniques consisting of Artifical bee algorithm (ABC), Artifical Neural Network (ANN), Fuzzy Interface System (FIS), GA Genetique algorithm (GA), Imperialist Competitive Alorithm (ICA), Particle Swarm Optimization (PSO), Supoort Vector Machine(SVM) for predicting blast performance are reviewed. Presently, various computentional techniques are ustilsed by researchers. This paper further discusses how these techniques can be implemented at operating mines by mining engineers, blasting team for predicting blast performance.

Keywords: Artifical bee algorithm, Artifical Neural Network, Fuzzy Interface System, Genetique algorithm, Imperialist Competitive Alorithm, Particle Swarm Optimization , Supoort Vector Machine

1. Introduction

Blasting is most effective technique used for several decades for breaking rock in civil engineering projects. Whenever any explosives is detonated inside the drill hole, a large amount of energy is instaneously released in the form of waves in the ground and gases are released in the air [1]. For breaking rock only 20 to 30% of energy released is used to create fragmentation, throw for further excavation and rest of energy is wasted in the form of fly rock, ground vibration, air overpressure and dust [2-4]. For the mining engineer, it is challenge to achieve overall objectives of blasting through optimum powder factor with desired fragmentation and minimizing environmental impacts due to blasting and also minimizing overall mining cost. Optimum rock fragmentation due to blasting is desirable for downstream operation productivity consisting of loading, hauling, crushing and grinding. During 1960-80, various researchers have tried to predict blastability which is susceptibility to break rock through various emperical equations [5]. However, the prediction results are far from actual results. With the advancement of computantional power and software progrmming, it is possible to predict various blast performance parameters consisting of blast fragmentation, fly rock, ground vibration and air over pressue due to blasting. Technique involves training and testing blast data and comparing results with different computantional algorithms.This paper reviews various soft computantional techniques for prediction of blast performance.

2. General Defintions and Concepts

2.1 Flyrock

In opencast bench blasting, flyrock is not a desired phenomenon which is excessive throw of any portion of rock from the blasting face [6-8]. Identification and demarcation of danger zone due to blasting is important due to the hazards associated with damage to the property, serious bodily injuries and fatalities due to fly rock accidents. The major factors contributing to fly rock are hole diameter, inadequate stemming, inappropriate delays, misfires, excessive charging due to voids or higher powder factor, misfires, geological structures and rock mass properties. [9-11]. Accidents due to fly rocks are caused as a result of lack of knowledge and incomptency or higher confidence in judging flyrock distance, inadequate security arrangements to guard any person entering into danger zone of blasting [12-14].

2.2 Ground Vibration

It depends upon maximum charge per delay and the distance from the blasting face. Many empirical predictor equations have been developed by many researchers on these two parameters [15-18]. Figure 1 shows how primary and secondary surface waves due to the blast, transmit ground vibrations to the structure.

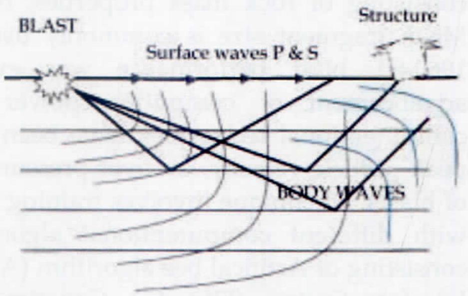

Figure 1 - Ground vibration due to blasting [8]

Ground vibration is measured in mm/ second. Ground vibration can cause structural damage. Various countries have developed their own standards for ground vibration limits. Human can perceive 100 times more as compared to damage criteria due to ground vibration. For example, damage criteria for concrete structure is 50 mm / second of greound vibration due to blasting. Person can detect any ground vibration of 0.5 mm/ second. Ground vibration is a major annoyance to nearby human settlements around mines. For attending any complaint due to blast ground vibration can be challenging task for any mine management.

2.3 Airblast Over Pressue or Airblast (ABOP)

It is the air blast over pressure created due to blasts. These shock waves are caused by a combination from one to several factors : release of energy direct from the surface, a relase of inadequately confined gases and a shock from a large free face, gas release pulse due to escaping of gases through rock fractures and pulse from stemming column during ejection of stemming [19-22]. 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) causes concussion. Higher air over pressure is created with methods of blasting such as plaster or pop shooting as secondary blasting, use of detonating cords. Down-the-hole initiation system such as NONEL and electronic detonators reduce air over pressure.

2.4 Fragmentation

It is represented by 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 instaneous energy released during blasting [23-24].

3. Computentional techniques

Various computentional technquies which are commonly used for solving complex engineering and scientific problems are described below:

3.1 Artificial Neural Network (ANN)

Since 1980, ANN has become popular to resolve complex problems. ANN is a part of Artificial Intelligence, 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 function to take 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 analysed by the system to predict outputs [25]. 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 are 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 a direct modelling of the functions of human brain [26]. ANN can be precisely designed for any specific problem to be solved, using three fundamental components [27]:

- 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 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 [28]. 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 are 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. Biases are like weights, but have a constant number of 1. All neurons in the BPNN, except for the Input Layer, are connected to a bias neuron and a transfer function. The transfer function acts like 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. 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. Several extensions of this algorithm are possible. From an abstract point of view, it is just needed target function that depends on the vector. There are multiple degrees of freedom for constructing this function, including some freedom how to penalize, or regularize, different parts of the vector, and some freedom how to use the kernel trick. Finally, the algorithm can be modified using using as primal objective function to get final results [31].

3.3 Artificial Bee Colony (ABC) Algorithm

It is for optimizing complex engineering problems through intelligent exploring behaviour of honey bee swarms which can be simulated [32]. Colony bees are divided to three categories: employed, onlookers and scouts [33]. Initially, scout bees search honey as food source. Continuous onlooker bees are at hive during searching period. Employed bees perform "waggle dance," when a high quality honey is found. Communication among scout bees about the food sources quality occurs in the dancing area and honey as food soruce is selected. In the ABC algorithm, a possible solution of the problem can be optimized by finding the quantity of nector in a food source which corresponds to the quality of the solution [34].

3.4 Genetic Algorithm

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 [35] during 1960s and then developed by Goldberg [36]. 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 segments of them with each other. Newly created chromosomes are known as children. Mutation is another genetic operator that can select chromosomes randomly in the suggested range (e.g., 1 ? 0). This process is repeated until the stopping conditions (the maximum number of generation or desired value for the best solution) are met [35–40].

4. Methodology

Figure 2 illustates ground vibration and air overpressure as target blast performance parameters to be predicted. The input parameters are selected based on literature review from previous research related to ground vibration and airblast. There are nine input parameters selected consisting of hole depth, charge per delay, burden to spacing ratio, stemming length, subdrilling, powder factor, RQD %, distance from blast, and number of holes. ANN structure is designed with one hidden layer.

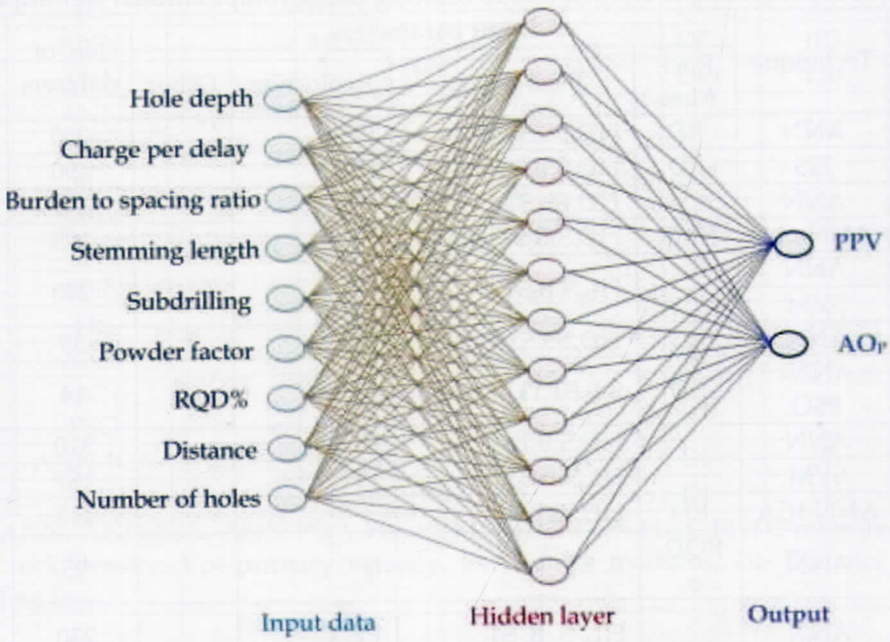

Figure 2 - Example of ANN network predicting PPV and AOp

At least 100 data sets as input data parameters are selected with corresponding output data. One of the algorithm say genetic algorithm (GA) is selected. Random data sets (60% of total data set) are selected for training data and R^2 and RMSE values are determined using designed ANN structure. The same model is selected for testing the data and R^2 and RMSE values are determined. Based on these values suitability of the model is decided. The same process is repeated using another algorithm say artificial bee colony (ABC). Among two models best model is selected for prediction. Similar process is adopted for prediction of other blast performance parameters of flyrock and fragmentation.

5. Discussion on Review of Prediction Results

Many researchers have utilized various computentional techniques for presdiction of blast performance consisting of flyrock, ground vibration, airover pressure and rock fragmentation. These techniques are reviewed in this paper.

5.1 Flyrock Prediction

Table 1 shows prediction of flyrock due to blasting using computational techniques consisting of ANN, ANN-GA, ANN-ICA, ANN-PCO, FIS and SVM. Input rock mass parameters are rock density, rock mass rating and compressive strength. Input blast design parameters are hole diameter, spacing, burden, spacing-burden ratio, stemming length, hole length and hole depth. Input explosives related parameters are powder factor, maximum charge per delay and specific charge per delay. 272 average number of datasets analysed and R^2 value varied from 0.89 to 0.98.

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	Other		
[41]	ANN	RD	HD,BS,ST,SD	PF, C		250	0.98
[42]	FIS	RD	HD,S,B,ST,SD	PF,C		490	0.98
[43]	ANN		HD,BS,ST,D,B,SD	PF,C		192	0.97
[44]	ANN-GA	RMR	HD,S,B,ST,,SD	PF,C		195	0.89
[45]	ANN		HL,S,B,ST,D	PF		245	0.92
	SVM						0.97
[46]	ANN	RD	HD,BS,ST,N,SD	PF,C		39	0.97
[47]	ANN-PSO	RD	S,B,ST,D,N,SD	PF,C		44	0.94
[48]	ANN		HD,S,B,D,	C		310	0.98
[49]	SVM		HL,S,B,ST.SD	PF		187	0.95
[50]	ANN-ICA	RD	HD, BS, ST,			113	0.98
[51]	ANN	RQD, σ_c	B, ST	q		95	0.98
[52]	ANN		HL, S, B, ST	PF, C		230	0.94
	FIS						0.95

ANN- Artifical neural network, FIS- Fuzy interface system, GA- Genetic algorithm, PSO- Particle sworm optimization, ICA- Imperailist competitive algorithm , SVM- Support vector machine, PSO- Particle sworm optimization, 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

5.2 Ground Vibration Prediction

Table 2 illustrates prediction of ground vibration due to blasting using various computentional techniques namely ANN, FIS, SVM, ANN-PSO and ANN-FIS. Rock density, primary velocity, young's modulus are rock mass related properties. Burden, spacing, hole diameter, stemming length, hole length, spacing burdn ratio, spacing diameter ratio are blast design related parameters. Maximum charge per delay, total charge and powder factor are explosives related paremeters. Distance from blast face is important as ground vibration reduces with increase in distance. Average number of data sets used were 80. R^2 value varies from 0.85 to 0.99 for prediction of ground vibration.

Table 2 - Prediction of ground vibration due to blasting due to computational techniques

Ref.	Technique	Input parameters				No. of datasets	R^2
		Rock Mass	Blast design	Explosives	Other		
[53]	ANN				DI	44	0.98
[54]	FIS		ST,N	C	DI	29	0.99
[55]	ANN		HD,ST	C	DI	182	0.95
[56]	ANN			C	DI	130	0.92
[57]	ANN			C	DI	162	0.94
	FIS						0.90
[58]	FIS			C	DI	33	0.92
[59]	SVM			C	DI	32	0.89
[44]	SVM			C	DI	37	0.89
	ANN						0.85
[60]	FIS		B, S, ST, N	C	DI	120	0.95
[61]	ANN			C, TC	DI	20	0.93
[47]	ANN-PSO	RD	B, S, ST, D, SD	C, PF	DI	44	0.94
[62]	ANN-ICA	V_p, E	BS, ST,	C, PF	DI	95	0.98
[63]	ANN		HL, BS, ST,	C	DI	115	0.98

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

5.3 Air Over Pressure (Air Blast) Prediction due to Blasting

A NN, ANN-PSO FIS and SVM are computentional techniques used for prediction of air over pressure. RQD is rock mass parameter which can affect AOp. Spacing, burden, hole diameter, hole depth, stemming length and number of rows are blast design parameters. Maximum charge per delay, powder factor are explosives related parameters.

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

Ref.	Technique	Input parameters				No. of datasets	R^2
		Rock Mass	Blast design	Explosives	Other		
[64]	ANN			C	DI	56	0.96
[65]	ANN			C	DI	162	0.92
	FIS						0.86
[66]	SVM			C	DI	75	0.85
[67]	ANN		HD, S, B, N, D, ST	PF		38	0.93
[68]	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.

5.4 Prediction of Rock Fragmentation due to Blasting

ANN, ANN-ICA,FIS and MVRA are computentional techniques deployed for prediction of rock fragmentation. Rock density, blastability index, RQD, GSI, mean block size are rock mass parameters. Various ratios consisting of burden to spacing ratio, stemming to burden ratio, burden to diameter ratio, bench height to diameter ratio in addition and individual parameters are blast design parameters. Maximum charge per delay, powder factor are explosives related parameters. Average number of data sets are 233 and R^2 value varied from 0.845 to 0.98. MVRA showed least R^2 value was least of 0.674.

Table 4 - Prediction of rock fragmentation due to blasting due to computational techniques

Ref.	Technique	Input parameters				No. of datasets	R^2
		Rock Mass	Blast design	Explosives	Other		
[29]	FIS	RD	B,S,ST,N,SD,HD			415	0.96
[30]	ANN		D,HD,BS,ST,N,	C,PF		250	0.98
[31]	ANN	BI	D,B,S,ST,SD,	C,PF		220	0.97
[32]	ANN		B,S,HD,SD,	SC		103	0.85
[33]	ANN-ICA	RQD, X_B	BS,B/D,H/B,ST/B	C		102	0.949
	ANN						0.941
[34]	ANN	GSI, RQD, X_B	BS,B/D,H/B,ST/B	C, PF		78	0.845
	MVRA						0.674

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

6. Conclusions

Environmental impact due to blasting flyrock, ground vibration, air over pressure need to be predicted in advance. Rock fragementation is important performance indicator of blasting for improving productivity in mining operation, Based on various researchers in put parameters. ANN decides structure consisting of input layers, hidden layers and output. Processing of data is done with various algorithms, Best predicted value is selected for future predictions. Most of the computentaional techniques provide good value of prediction with R^2 in the range of 0.9 to 0.98. Thus practicing mining engineers can collect input data for individual blast for 100 datasets and utilze one of the computational techniques for prediction of target parameter with very good accuracy.

It is concluded that ANN technique is most suitable for predicting all four blast performance parameters. ANN-ICA, FIS are additional techniques which are also best suitable for predicting flyrock, ground vibration and air over pressure. SVM technique is best suitable for predicting flyrock.

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