Recent Developments in Machine Learning and Flyrock Prediction

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Abstract The blasting techniques are employed in mining and underground works to loosen the rock mass and ease the excavation. The blasting practices are economical and swifter in terms of their engineering application, however, they are of major environmental and safety concerns. The major issues related to blasting are flyrock, air over pressure, and ground vibrations etc. The rock fragments of rockmass are thrown outward after blasting, which can be threat to workers and machineries involved in the work, and sometimes nearby human settlements can be its victim. Therefore, an accurate prediction of the flyrock distance is the needed by mining practitioners. Earlier, experts have developed several empirical methods based on certain known parameters to assess flyrock distance. However, with time they become irrelevant and were easily replaced with advanced machine learning algorithm. The present study reviews some of these latest publications (2019–2021) examining flyrocks through artificial intelligent technique. The study incorporates types of machine learning models employed, input parameters used and number of datasets supporting the models. The input parameters were further classified according to rock-mass properties, blast design at site, and explosives responsible for blasting. Moreover, to compare the reliability of the model coefficient of correlation of the testing data of the all the documented model were evaluated. Rock density, rock mass rating and Shmidt hammer rebound number (SHRN) were found to be uncertain parameters.

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Artificial Neural Network (ANN) and other hybrid models for prediction of flyrock were compared.

Keywords Machine learning · Optimization algorithms · Flyrock prediction · Blasting

1 Introduction

Blasting implies the fragmenting of rocks into smaller sizes. Chemical energy of the explosives is converted into mechanical energy, leading to fragmentation. Therefore, blastability can be defined as the characteristics of blast design, explosive features and legislative constraints, depending on the site particulars, and rockmass conditions [1–4]. Simply put, blastability indicates the ease of blasting a rockmass under a specific set of condition [5–8]. One of the major environmental and safety concerns with blasting in mining is flyrock distance. Flyrocks cause accidents and damage to equipment. Factors governing flyrock can either be controlled attributes viz., charge, burden and spacing or uncontrolled parameters, which is the fabric and strength of the rock mass. Mining engineers' control blasting setup based on their assessment of rock-mass parameters, geometrical analysis and prior experiences on similar site conditions [9–11]. Rock mass structure and parameters are crucial for ascertaining the blast design and blasting operations; hence, rock mass classification is routinely carried out in any mining or civil engineering project. Previously, researchers have correlated hole diameter with burden and spacing, eventually impacting the blast design [12]. The geotechnical engineers hold the major position to decide the blasting parameters and explosives prior to blasting on drilling locations. Moreover, initially the attributes like production capacity, loading equipment and bench height dominates the selection of drilling equipment [13]. Therefore, in order to understand and minimize flyrocks, it's imperative to assess the blasting mechanism and its correlation to flyrocks. Furthermore, myriad new approaches have been developed recently to estimate the flyrock distance based on contributing geotechnical and blasting parameters. The paper attempts to review these novel techniques in terms of viability and accuracy.

Blasting is the conversion of chemical energy into mechanical energy to fragment the rock mass. Geo-engineers and workers have found that explosive charge concentration per unit length is directly proportional to the hole diameter, consequently the extent of hole diameter directly affects the flyrock distance and ground vibrations [14, 15]. At certain blasting venues, different drill sizes can be viable to enhance the feasibility and production. Figure 1 provides details of blast design parameters for production blast such as burden (β), spacing (A), hole diameter (τδ), stemming length (αμ), bench height (ύπ), subdrilling (u) and hole depth (βo).

Burden (β) is the perpendicular distance between blasting face and hole. The relationship between hole diameter (τδ) and burden proposed by many researchers and represented by Eq. (1).

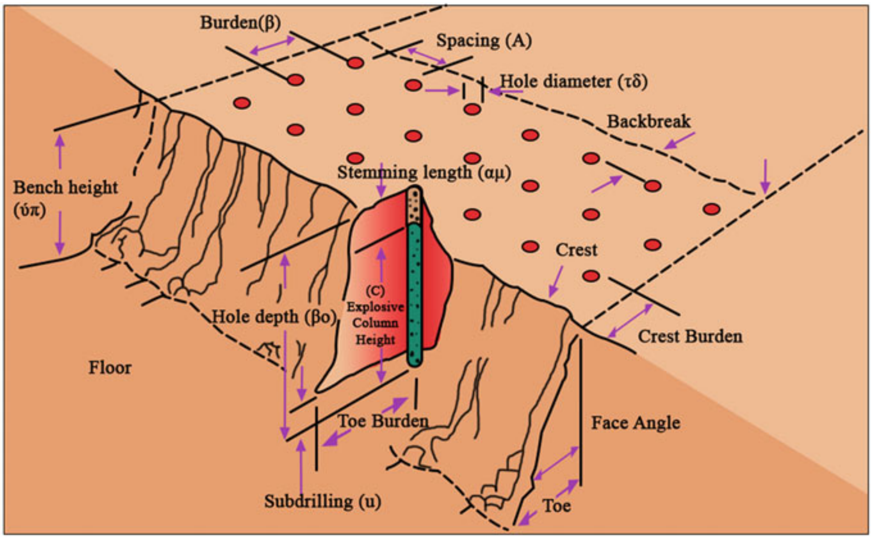

Fig. 1 Blast design and related terminology

$$\beta = C_1 * \tau\delta \tag{1}$$

where, C_1 is constant dependent upon inherent properties of rock mass and explosives. Table 1 highlights the range of C1 values as proposed by several researchers.

Burden is also expressed in terms of bench height and can be expressed with following Eq. (2).

$$\beta = C_2 * \acute{\upsilon}\pi \tag{2}$$

where, C_2 is constant which varies from 0.25 to 0.50 for satisfactory blasts [20].

A vertical distance between toe and crest of bench literally means bench height (ύπ), which is eventually determined considering the hole diameter and loading equipment. Longer bench heights render precariousness to design and favours rock-fall and flyrock. Since blasting occurs with conversion of explosives into gases, stemming technique avoids the chances of blown out shots, such as excessive flyrock and air over-pressure while blasting. Therefore, sufficient stemming lengths prevents

Table 1 Constants for drill hole diameter to burden

Name of researcher	Range of values for constant C_1
Jimeno et al. [16]	25 to 40
Hagan [17], Bhandari [18]	20 to 35
Dick et al. [19]	20 to 40

potential damage to workers, locals and avoids risk to environment [21, 22]. Hole depth in blasting setup can be evaluated as a summation of bench height and subgrade drilling length. To prevent toe formation subgrade drilling becomes essential, and it may vary from 10–20% of bench height. Scientific studies have revealed that the parameters like burden, hole diameter, spacing or bench height simultaneously control blasting operations, moreover, their ratios decide the blast performance [23, 24]. Spacing is related to burden and can vary from 1 to 1.8 times [12]. Many researchers utilize burden to spacing ratio for evaluation of blast performance. Bench height to burden is called stiffness ratio. Various workers have used stiffness ratio for the design of blast [25]. The same ratio is also utilized for prediction of blast fragmentation and flyrock [26].

Blasting phenomenon are associated with enormous energy, which are eventually released to loosen the rockmass and make excavation economical. However, only part of the released energy is involved in loosening the rock mass, and remaining ones create potential threat for the environment. Flyrock is also a result of the extra energy released in the process of blasting (Fig. 2). The flyrock causes severe problems to local inhabitants, and if suitable precautions are not adopted, they can turn into threat for civil workers and engineering machinery. Therefore, the accurate knowledge of flyrock becomes essential for agencies to reduce or mitigate their impact on population and property. In the same line, researchers and industries have worked together to mark critical factors responsible in assessment of flyrock (Fig. 3).

Moreover, a few potential parameters impacting the distance of flyrock at any blasting site had been categorised in the three main classes, namely, rock-mass of the area, blast design setup, and explosives involved. The rock density (RD) and rock mass rating (RMR) are assimilated in the present study to define the rock-mass. Burden (β), spacing (A), hole diameter (τδ), stemming length (αμ), bench height (ύπ), subdrilling (u) and hole depth (βo) are some of the attributes of blast design mentioned in the present work on flyrock. Besides, the values like Maximum Charge per Delay (C), Capacity of the explosive charge (W), Charge Length (CL), powder

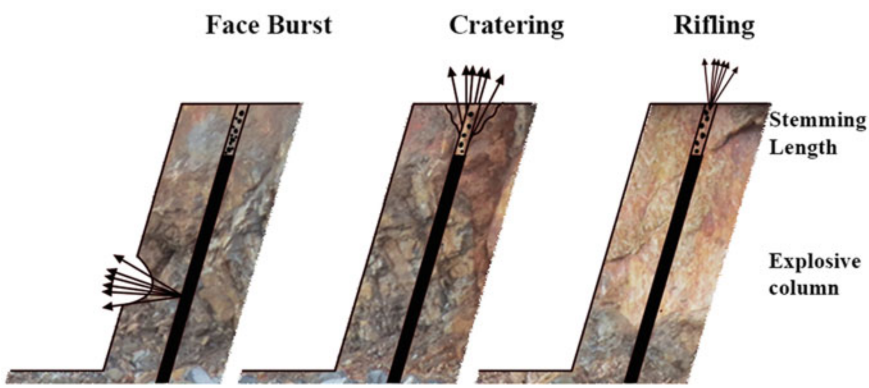

Fig. 2 Schematic diagram of flyrock (modified after Little [27])

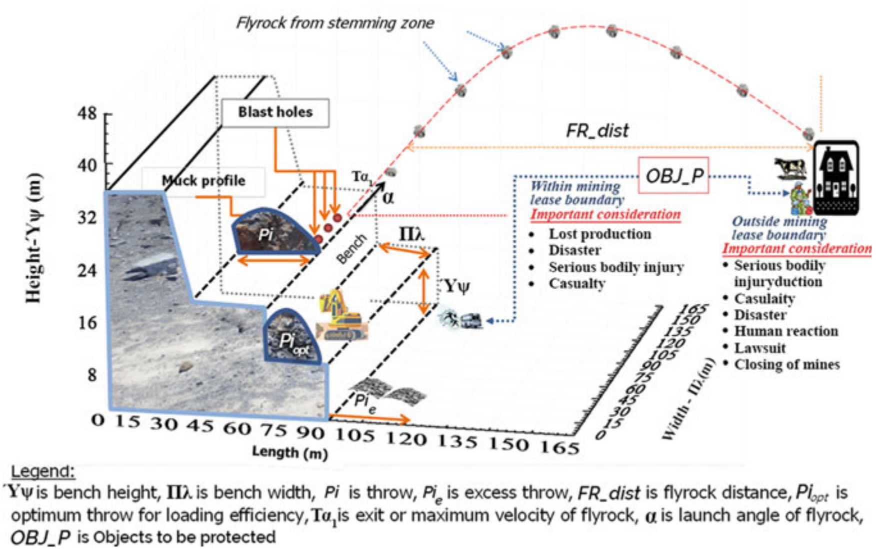

Fig. 3 Schematic diagram showing blasting site of granite quarry, throw, optimum throw, excess throw, flyrock

factor (PF), and amount of explosive used per blast (Wa) are the employed characteristics of explosive entrained in the present research. There is no prevalent engineering technique to simulates flyrock; however, based on the past events of flyrock, machine learning models can be a key player in discerning flyrock distances with greater accuracies [28–35]. Linear multivariate regression (LMR) and gene expression programming (GEP) methods were explored by Monjezi et al. [36] to simulate the flyrock prediction based on the certain blast design parameters and properties of explosives used. Ye et al. [37] examined the effectiveness of the techniques like genetic programming and random forest involving attributes like τδ, αμ, βo, β/A, PF and C, moreover, coefficient of determination in the both the cases resulted approximately 0.90. Support vector regression, and Lasso and elastic-net generalized linear model (GLMNET) with parameters like β, A, αμ, and PF turned out to be valuable models in flyrock's prediction [38]. Koopialipoor et al. [39] studied the role of imperialist competitive algorithm, genetic algorithm, and particle swarm optimization (PSO) over the artificial neural network (ANN) and compared their performance in flyrock prediction. A seventy-two dataset were incorporated β, A, αμ, and C as input to devise flyrock prediction models like, recurrent fuzzy neural network (RFNN) optimized with PSO, adaptive neuro-fuzzy inference system (ANFIS), and a nonlinear regression model [40]. Zhou et al. [37]. investigated attributes like β, A, αμ, βo, C, and PF to examine an ANN model for flyrock prediction, earning coefficient of determination equal to 0.906. Armaghani et al. [42] modelled and compared three different machine learning techniques using 262 datasets implementing β/A, τδ, αμ, βo, C, and PF as means of input parameters and flyrock distance as output parameter. Correlation equations and the method used have been given in Tables 2 and 3.

2 Empirical Flyrock Estimation

The several workers in the past were curious to estimate the flyrock distances following the blasting events, and managed to establish the certain empirical relations based on their observations. This involves identification of factors influencing the flyrock distance, moreover collecting these data for further mathematical operations. Their scrupulous works (Table 2) earned significant results, and motivated several others to carry out research on flyrocks. Indeed, the results were founding stone for the present development in the blasting activities, that equipped the hands of agencies to minimize the flyrock distance. However, the complexities induced in these empirical relationships made the calculation of flyrock distance a tedious and time-consuming task. Furthermore, the present era of soft computing shows quite promising results in the last few decades in various other domains of scientific world. Therefore, the geotechnical engineers cannot keep themselves away from these modern developments for longer time and soon new discoveries replace the earlier ones.

3 Deep Learning Models for Flyrock

In the light of earlier mathematical works and advent of modern computational techniques people were excited to know whether machines can perform the human tasks. Scientists and engineers worked together to accomplish these tasks to bring the present shape of artificial intelligence (AI) and machine learning (ML). In the modern world, access to latest technologies made the availability of enormous data in very short span of time to the researcher. In the present study, one will gain insights of the some of key deep learning techniques used for the estimation of flyrock phenomenon.

The work discusses the application of techniques like Extreme Learning Machine (ELM), Outlier Robust ELM (ORLEM), Artificial Neural Network (ANN), Multiple Linear Regression (MLR), Artificial Neural Network with Particle Swarm Optimization (ANN-PSO), Artificial Neural Network coupled with Harmony Search (ANN-HS), Artificial Neural Network coupled with Advanced Dynamical Harmony Search (ANN-ADHS), Adaptive Neuro-Fuzzy Inference System in combination with Grasshopper Optimization Algorithm (ANFIS-GOA), Adaptive Neuro-Fuzzy Inference System in combination with Cultural Algorithm (ANFIS-CA), Imperialist Competitive Algorithm with ANN (ICA-ANN), Particle Swarm Optimization with ANN (PSO-ANN), Artificial Bee Colonization with ANN (ABC-ANN), Firefly Algorithm with ANN (FA-ANN), Genetic Algorithm with ANN (GA-ANN) (Table 3). These discussed works encapsulate several factors affecting the flyrock

Table 2 Empirical equations for prediction of flyrock

References	Equations	Descriptions
Lundborg et al. [43]	$L_{max} = 260(\tau\delta)^{2/3}$	L_{max} = maximum ejection distance (m); $\tau\delta$ = hole diameter (inch)
Olofsson [44]	$L_{max} = K\varphi.(\tau\delta)$	$K\varphi$ = factor of safety [45]; $\tau\delta$ = hole diameter (cm)
Richards and More [46]	$Faceburst L_{max} = \frac{k^2}{g}\frac{\sqrt{m2.6}}{\beta}$ $Cratering L_{max} = \frac{k^2}{g}\frac{\sqrt{m2.6}}{\alpha\mu}$ $Rifling Lmax = \frac{k^2}{g}\frac{\sqrt{m2.6}}{\beta} sin2\theta_0$	where, θ_0 = drill hole angle; L_{max} = maximum throw (m); β = burden (m); $\alpha\mu$ = stemming length (m); m = charge per meter (Kg/m); g = gravitational constant; k = site constant
Little [27]	$Faceburst L_{max} = \frac{k^2}{g}$ $Cratering L_{max} = \frac{k^2}{g}$ $Rifling L_{max} = \frac{k^2}{g}$	where, L_{max} = maximum throw (m); g = gravitational constant; k = site constant
Ghasemi et al. [47]	$F_d = 6946.547\ [\beta^{-0.796}\ A^{0.783}\ (\alpha\mu)^{1.994}\ (\beta o)^{1.649}\ d^{1.766}(PF/Q)^{-1.465}]$	$R^2 = 0.83$ F_d = flyrock distance (m); Q = mean charge per blast-hole (kg); PF = powder factor (t/kg)
Trivedi et al. [48]	$Flyrock = \frac{10^{5.1} q_1^{0.51} q^{0.14}}{\beta^{0.93}(\alpha\mu)^{0.64}\sigma_c^{0.75} RQD^{0.93}}$	$R^2 = 0.815$; q_1 = linear charge concentration; q = specific charge; σ_c = unconfined compressive strength; RQD = rock quality designation (%)
Armaghani et al. [49]	Flyrock = 177.81 − (3.33 × βo) − (2.55 × A) − (3.49 × β) − (13.93 × (αμ)) + (0.47 × PF) + (1 × MC) − (2.58 × RMR)	PF = powder factor, MC = Maximum Charge per Delay, RMR = Rock Mass Rating

Table 3 Prediction of fly-rock distance in blasting

References	Techniques	Input parameters			No. of datasets	R2
		Rockmass properties	Blasting setup	Explosives		
Lu et al. [50]	ELM	RD	β, A, αμ	PF	82	0.955
	ORELM					0.958
	ANN					0.912
	MLR					0.883
Hasanipanah et al. [51]	ANN	RD	β, A, αμ	PF	82	0.8319
	ANN-PSO					0.8328
	ANN-HS					0.8715
	ANN-ADHS					0.9299
Fattahi and Hasanipanah [52]	ANFIS-GOA	RD	β, A, αμ	PF	80	0.974
	ANFIS-CA					0.953
Li et al. [53]	ICA-ANN	RD, Rn	β/A, βo, αμ	C, PF	113	0.9598
	PSO-ANN					0.9608
	ABC-ANN					0.9666
	FA-ANN					0.9719
	GA-ANN					0.9466
Wu et al. [54]	ICA-Linear	RMR	β, A, αμ	Weight charge	78	0.954
	ICA-Power					0.928
	ICA-Quadratic					0.952
	ANN					0.841

phenomenon in any blasting activity, like Burden (β), spacing (A), stemming length (αμ), hole depth (βo), Powder Factor (PF), Rock Density (RD), Maximum Charge per delay (C), Rock mass rating (RMR) etc. The working principle behind these deep learning techniques have been detailed in the sections below.

3.1 ANN, ELM, ORLEM, MLR, ANN-PSO, ANN-HS, & ANN-ADHS

Artificial Neural Network (ANN) performs several complex operations using arrays of nodes in different layers based on past learning. The ANN model learns the way human brain does, moreover, the model performs better with rise in the number of training data. The most characteristic task of neural network is to perceive the inherent pattern in the data, and solve the complex problems with significant accuracies and swiftly. The structure of ANN has three layers, viz., input, hidden, and output layer;

the input and output layers have nodes equal to the number of input and output parameters assimilated in the study. Whereas, there is no defined number of nodes in the hidden layer, moreover, they can have further sub-layers to obtain best performing model. The best performing model can be engendered either on hit-and-trial basis or tunning through any optimization techniques.

Extreme Learning Machine (ELM) technique was devised to overcome the sluggish learning rate faced by conventional feedforward neural networks (FFNNs). The conventional FFNNs adopts gradient-based learning methods that are too slow, moreover, iterative tunning of each involved parameters is embodied making them further slow. The ELM adopts linear mapping to train the model, with tunning of the parameters numerically equal to the hidden layer nodes, therefore processing time and probability of overfitting is significantly reduced in these models. ELM improves learning speed, however have difficulty in dealing with outliers in data and may render inappropriate results. Therefore, the Outlier Robust Extreme Learning Machine (ORELM) method uses scanty data distribution pattern of outliers and applies the ℓ_1—norm loss function to empower the ELM model capability.

Simple linear regression evaluates and expresses the dependency of one variable over another mathematically. However, there are times when a single parameter is not enough to sufficiently determine the relationship with another parameter, instead one needs to access several variables to find the best relationship numerically. This need is served in the establishing best relationship between multiple input and output parameters through multi-linear regression (MLR) analysis.

The optimization algorithms are involved in the machine learning models, to boost their performances by tunning their hyperparameters. The hyperparameters differ based on the type of machine learning technique involved in the research, moreover the selection of optimization algorithms depends on the direction of the work, speed and memory requirements. In PSO, the workability of any ANN model is enhanced by monitoring the collective direction of particles and tracking their earlier best performances of each particle and their neighbors [55, 56]. One can infer that this optimization algorithms evaluates the best personal and global performances of particles' swarm with successive iteration, eventually the best hyperparameters contribute the best model [39].

The service of harmony search (HS) algorithm is employed to optimize the network of ANN model, and determines the best performing model after a given number of iterations. The impetus behind the HS algorithm is the extemporization mechanism of musicians, implementing the best performing model with stochastic metaheuristic process [57]. The Adjusted Dynamical Harmony Search optimization techniques empowers the ANN to tune the best model structure supplanted with metaheuristic, and the algorithm is based on iterative learning as the enthused-music-search. The preferred harmony component is worked out using two key approaches in the ADHS, viz., harmony memory considering rate, and pitch adjusting rate. Both the approaches are magnified mathematically to update new variable in the harmony memory, after evaluation of maximum and minimum elements. Therefore, the ADHS, an advanced optimization technique augments the power of ANN in minimizing the error between the predicted outcomes of the model and original one [51].

3.2 *ANFIS-GOA, ANFIS-CA, ICA-Linear, ICA-Power and ICA-Quadratic*

Adoptive Neuro-Fuzzy Inference System (ANFIS) finds its application in enumeration of non-linear problems. The ANFIS benefits from fuzzy logic of human's qualitative reasoning (if–then rule) as well as neural learning approaches. In other words, the adoptive network is powered by neuro inference scheme, moreover neuro-fuzzy along with neural network render a sophisticated and robust machine learning technique by diminishing each other's drawbacks [58, 59]. However, again in search of best model structure certain optimization algorithms are needed according to the available datasets in different studies. Moreover, the grasshopper optimization algorithm (GOA) plays a vital role in tunning the hyperparameters of the ANFIS model, that promotes the viability of the model with significant rise in their robustness and accuracies. The motivation behind the GOA is the collective behavior of swarming grasshoppers, and is a type swarm intelligence working on the population-based optimization technique. In GOA, the researchers have established the mathematical relationship to determine the position of i^{th} grasshopper in the swarm as the summation of social interaction between them, the influence of wind advection and gravity on this [60].

The cultural algorithm (CA) boosts the ANFIS performing capabilities, as the method attains the inspiration from the evolution of human culture [61]. The algorithm sets to resolve non-linear problems and enables complex computation in search of best ANFIS structure. The algorithm simulates civic sense, reasoning and knowledge acquired in growth of human population with time by means of transfer of information from one generation to another [52].

ICA is acronym for Imperialist Competitive Algorithm, which is a powerful computing optimization technique inspired by socio-political evolution mechanism of colonies and imperialists [62]. History demonstrates the competition among several weaker and powerful kingdoms to gain the control on each other. The mightiest one is termed as imperialist, that governs number of colonies, and invade other countries to take control over them and expand their territories by competing with other rival imperialists. Finally, the strongest empire (colonies along with their imperialist) will hold control over the weaker ones. Atashpaz-Gargari and Lucas [63] coined the idea of ICA with the intention of identifying the dominating imperialist based on their economic, political, and military resources. The governing operations of ICA are to monitor three aspects, viz., assimilation policy, revolution, and competition [54]. The optimization power of ICA can be emplaced over several machine learning models to enhance their performance. Moreover, various multiple regression models (MRMs) benefit from the ICA to enhance their prediction results. In the same line ICA-Linear, ICA-Quadratic, and ICA-Power models can be developed on applying ICA optimization over linear, quadrating, and power MRMs respectively [64]. Similarly, neural network models like ANN can yield better outcomes and significantly reduce their cost/loss function on using optimizing capacity of ICA.

3.3 ABC-ANN, FA-ANN, GA-ANN

The acronym ABC stands for artificial bee colony optimization; the algorithm mimics the nectar collection traits of honey bees. Karaboga [65] introduced the technique to the scientific community, and highlighted its applicability in optimizing the prediction power of well-known machine learning tools. Group of bees organize themselves in three different groups to accomplish the nectar gathering task. The first set of bee group lookouts for the probable source of flower's nectar, and they randomly search for this. On locating a reasonable source, they communicate this information with other members once they return to hive. Afterwards, a few other members (second group) follow the scout bees for further exploitation of located nectar resource. Meanwhile, the third group of bees keep eyes on the hive, and exchange the relevant information with member bees. To transfer information related to the nectar collection bees perform waggle dance. The chain of data transfer will facilitate the selection of most appropriate nectar source and its exploration.

Firefly algorithm (FA) is a kind of metaheuristic algorithm that imitate attractiveness traits of fireflies among themselves. The attractiveness of fireflies relies on the brightness, means the intensity of light emitted by the individual firefly determines their attractiveness strength [66]. In other words, they hold proportional relationship. Moreover, the brighter one will attract the less-brighter one, despite of their sex as these are unisexual species. Furthermore, it has been noted that the objective of the fireflies determines their brightness level. However, the brightness also decreases with the mutual distance among two individual species. If in case any firefly is far away from their swarm, they will perform random movement. The fireflies rely on their bioluminescence behavior to talk, arrange food, and find mates [53]. This swarm-intelligence inspired by fireflies resulted in a valuable optimization algorithm, and aided in enumeration of complex mathematical operation with greater accuracies.

The Genetic algorithm (GA) engenders its working principles from Darwin's evolution theory of natural selection. The theory enunciates that the survival of any species depends in their capabilities to cope with different set of changing environmental and climatic conditions, as well as their instinct to adopt and response the changes. The theory further highlights the survival of fittest creature with dominant genes over the weaker ones. The GA simulates these in the arithmetic operations to assess the fittest organism, on examining the processes of selection, crossover, and mutation in the individual's population [67]. The advent of GA introduced the features of solving linear and non-linear lucidly in different scenarios and simulates real life challenges to boost the performances of known machine learning techniques.

The amalgamation of ANN with the optimization algorithms like ABC, FA, and GA resulted into models like ABC-ANN, FA-ANN, and GA-ANN respectively. Moreover, they improve the performance of the ANN models, after these techniques were employed in the existing ANN models.

4 Results and Discussion

The assessment of several ways of ascertaining the flyrock distance in advance can aid the mining engineers and planner to device the blasting setup. Proper design reduces the number of casualties and losses owing to flyrock associated to blasting. The detailed examination of previous literature suggests that machine learning models will be a swifter, economic, and intelligible tool for flyrock prediction, given that adequate number of datasets are available fro training. Furthermore, these soft computing techniques offer better performance than empirical methods.

The present article examines several research works in between years 2019 to 2021 on machine learning based prediction of flyrock distance. Lu et al., developed a four deep learning models for flyrock estimation taking 82 datasets, and involved parameters like RD, β, A, αμ, and PF. The best result is shown by ORLEM earning a coefficient of determination value of 0.958 [50]. ELM is quite close to ORLEM with the R^2 of 0.955. Besides, two other models like ANN and MLR were developed from the same datasets and same parameters, however their outcomes were not as reliable as ORLEM and ELM.

Another work, taking similar parameters as in previous discussed work developed ANN, ANN-PSO, ANN-HS, and ANN-ADHS [51]. The work shows that implementation of PSO, HS, and ADHS certainly enhanced the capability of neural network model in flyrock prediction. Moreover, the greatest performance (in terms of R^2) was noticed in ANN-ADHS (0.9299) model, followed by ANN-HS (0.8715), ANN-PSO (0.8328), and ANN (0.8319).

In the work of Fattahi & Hasanipanah two ANFIS models blended with GOA and CA optimization algorithms are compiled and their outcomes were assessed with real outcomes [52]. In this work, the authors have taken 80 datasets to account these models based on attributes like RD, β, A, αμ, and PF. In terms of coefficient of determination, the ANFIS-GOA (0.974) beats the ANFIS-CA (0.953). In the year 2021, Li et al. [53] tried to access the effect of different optimization algorithms over ANN in flyrock prediction. Their work incorporated parameters namely, RD, Rn, β/A, βo, αμ, C, and PF over 113 datasets. The research outcomes dictate the performance of models in terms of R^2 such as ICA-ANN (0.9598), PSO-ANN (0.9608), ABC-ANN (0.9666), FA-ANN (0.9719), and GA-ANN (0.9466). In the same line, Wu et al. [54] designed ICA-Linear, ICA-Power, ICA-Quadratic, and ANN taking RMR, β, A, αμ, and weight charge in the account. Seventy-Eight datasets were taken in the development of the model, and ICA-Linear have the best outcome and worst result were shown by ANN.

5 Conclusion

The present article details the mechanism of blasting and the associated catastrophic hazard of flyrock phenomenon. The fundamental attributes like spacing, burden, hole depth, hole diameter, rock quality designation, rock density, stemming length, explosive characteristics etc., have major control on the flyrock distance. Therefore, a careful examination of these properties and a judicious planning can inhibit the risks related to blasting. A number of advanced deep learning computational models have been assessed and compared to ascertain viability of flyrock estimation model. Techniques b = developed between the year 2019–2021 have been considered in the present work, and their performance have been compared using a well-recognized statistical approach- coefficient of determination (R^2). Moreover, a few empirical equations governing the flyrock pattern owing to blasting have been accounted in the present work. The study finds that empirical methods lag behind the deep learning methods in precise estimation of flyrock distances in several aspects. The machine learning models namely, ANN, ELM, ORLEM, MLR, ANN-PSO, ANN-HS, ANN-ADHS, ANFIS-GOA, ANFIS-CA, ICA-Linear, ICA-Power, ICA-quadratic, ABC-ANN, FA-ANN, and GA-ANN models were addressed in detail. Beside, these models were evaluated in terms of number of datasets and type of input parameters involved in the structure of models.

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