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Prediction of blast-induced ground vibrations via genetic programming

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ABSTRACT

Excessive ground vibrations, due to blasting, can cause severe damages to the nearby area. Hence, the blast-induced ground vibration prediction is an essential tool for both evaluating and controlling the adverse consequences of blasting. Since there are several effective variables on ground vibrations that have highly nonlinear interactions, no comprehensive model of the blast-induced vibrations are available. In this study, the genetic expression programming technique was employed for prediction of the frequency of the adjacent ground vibrations. Nine input variables were used for prediction of the vibration frequencies at different distances from the blasting face. A high coefficient of determination with low mean absolute percentage error (MAPE) was achieved that demonstrated the suitability of the algorithm in this case. The proposed model outperformed an artificial neural network model that was proposed by other authors for the same dataset.

1. Introduction

Blasting is one of the most energy/economic-efficient methods of rock fragmentation which is widely used in mining, civil, construction, and environmental projects around the world. However, there are several drawbacks, including but not limited to: nearby residents' complaints, damage to residential structures, damage to adjacent rock masses and slopes, damage to the existing ground water conduits, and the ecology of the nearby area [1–12]. The main source of these undesirable effects is excessive blast-induced ground vibrations. Thus, predicting the adjacent ground vibrations is an essential tool for safe, environment friendly and sustainable blasting operations. Ground vibrations can be defined and measured in terms of peak particle displacement, velocity, acceleration, and frequency. There are three methods of empirical, theoretical, and soft computing in addressing the problem of prediction of the blast-induced ground vibrations which are briefly introduced in the following.

Conventionally, there are several widely used empirical predictors for estimation of the blast-induced ground vibrations. USBM proposed the first ground vibration predictor [13]. In the following years; Langefors and Kihlstrom [14], Ambraseys and Hendron [15], Ghosh and Daemen [16], and Pal Roy [17] proposed other empirical predictors. These methods consider two main input parameters of the maximum charge used per delay and distance between blast face and the monitoring points [14–20]. Despite their simplicity and fast application, several recent studies showed their shortcomings in rendering acceptable predictions [21,22]. Generally, the empirical methods have the two major limitations of the lack of generalizability and limited number of input variables. On the other hand, some researchers tried to propose theoretical models based on the physics of blasting. For instance, Sambuelli [23] tried to propose a theoretical model for prediction of PPV on the basis of some blast design and rock parameters [23]. However, because of the complicated nature of the blasting process and its highly non-linear interaction with the non-homogeneous and non-isotropic ground, proposing a comprehensive closed form mathematical model is almost impossible. Recently, following the rapid growth in soft computing methods, including artificial intelligence, several researchers have tried to benefit from these newly emerging techniques. In this category, the artificial neural networks (ANNs) might be the most widely used methods for prediction of the ground vibrations. ANNs are among the black-box modeling techniques that map some input variables into the output(s). The technique is capable of handling very nonlinear interactions between different variables through assigning and adjusting proper weights. However, no functional relationship will be proposed (Black-box modeling). Khandelwal and Singh [24] used ANNs for prediction of PPV in a large mine in India [24]. Iphar et al. [25] employed an adaptive neural-fuzzy inference system (ANFIS) for prediction of PPV in a mine in Turkey [25]. Monjezi et al. [26] used ANNs to predict blast-induced ground vibrations in an underground project [26]. Bakhshandeh et al. [27] used ANNs to adjust burden, spacing, and total weight of explosive used in order to minimize PPV [27].

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Genetic Programming (GP) is among the recent advances in mathematical modeling, which are based on evolutionary principles. GP is an extension of Genetic Algorithm (GA) which generates thousands of computer programs for solving regression and classification problems. Unlike the conventional GA technique that seeks optimal values for predefined parameters, GP manipulates many programs, based on the Darwinian Evolution Theory, to find both the best models and parameters for a given set of variables. Developed by Ferreira [28], gene expression programming (GEP) is a development of the original GP. In GEP, unlike GP, the entities are encoded as simple strings of fixed length (chromosomes).

Although GP has been emerged recently, there are numerous applications available in the literature. GP has been employed in a range of geological, environmental, and civil problems [29–31]. However, to the best of the author's knowledge, this is the first time that the GEP method is used for prediction of the frequency of blast-induced ground vibrations. Unlike other soft computing techniques, such as ANNs that do not render a functional relationship between the independent variables and the response, GEP constructs a nonlinear relationship. Hence, the technique results in a better understanding of the phenomena. To provide sufficient evidence for the superiority of GEP compared to other available techniques, a benchmark study conducted by Singh et al. [32], using ANNs, was selected [32].

2. Materials and methods

In this section, first the case study, which is entirely taken from Ref. [32], is presented as a benchmark for the current study. The GP and GEP are briefly introduced in Sections 2.2 and 2.3. Since the fundamental theories and applications of the methods are widely covered elsewhere, we will not present a detailed review in this section. Rather, the interested readers are referred to many available publications, particularly the original references, i.e. [28,33,34].

2.1. Dataset

Table 1 shows the dataset used by Ref. [32] for construction of their predictive ANNs model. Nine parameters of blast hole diameter (mm), No. of holes, hole depth (m), burden (m), spacing (m), stemming (m), maximum charge per delay (kg), horizontal distance (m), and radial distance (m) were assumed as the effective independent variables on the frequency of ground vibrations as the response (dependent) variables.

The authors presented a multiple regression model for the same dataset. They obtained better results from the ANNs in terms of prediction errors. Mean absolute percentage error (MAPE) of 9.3%, and coefficient of determination (R^2) of 81% were obtained from the best ANNs.

2.2. Genetic programming

Developed by Koza [33], GP is an extension of the traditional GA in which the structures undergoing adaptation are hierarchical computer programs of dynamically varying size and shape [33]. In GA, the optimization task is to find (near) optimal values for a set of given variables. However, in GP both the structure of the solution (e.g., type of the fitness function for a regression problem) and the optimal values of its associated parameters are derived together. In GP, thousands of solutions (computer programs) are generated and evolved consecutively based on the Darwinian principle of survival. Search for the solution starts with a population of completely randomly generated programs (solutions) from a predefined set of available functions (e.g., arithmetic functions) and terminals (independent variables). All programs will be measured against a fitness function (e.g., root mean square error in a regression problem) and the best ones survive and will bred to the next generation. GP can be represented as a hierarchically structured tree comprising functions and terminals. Fig. 1 illustrates a simple representation of a GP tree for the function $y = z^2(\sin x + C_1)$. The tree reads from left to right and from bottom to top. Mimicking the Darwinian principle of survival, the fittest solutions (smallest error) will be chosen to generate a population of new offspring programs for the next generation. In the next step, some genetic operations, namely mutation and crossover, will generate new offspring from the fittest programs of the previous generation. The operator selects a random node in a tree and replace it with another node or subtree. The new offspring will be evaluated with the error or fitness function. The process continues until reaching a predefined threshold in terms of the best fit or error.

2.3. Gene expression programming

Proposed by Ferreira [28], GEP is a development of the conventional GP [28]. Like GP, in GEP the main steps include: the function set, terminal set, fitness function, control parameters, and stop criteria. The fundamental difference between the three algorithms, GA, GP, and GEP, resides in the nature of the individuals: in GA the individuals are symbolic strings of fixed length (chromosomes); in GP the individuals are nonlinear entities of different

Table 1
Dataset used in this study (Adapted from [10]).

Hole dia. (mm)	No. of holes	Hole depth (m)	Burden (m)	Spacing (m)	Stemming (m)	Max. charge/delay (kg)	Horizontal distance (m)	Radial distance (m)	Ground vibration (Hz)
160	28	12.0	4.0	4.0	6.00	220	172	219	47
250	6	19.0	6.0	7.0	4.50	250	70	151	64
160	13	12.5	3.0	3.5	3.80	280	175	221	40
150	25	12.0	4.0	3.5	2.00	125	118	95	27
250	5	18.2	6.0	6.0	4.75	170	68	148	64
250	11	10.0	2.6	2.8	3.00	250	42	138	30
160	28	12.0	4.0	4.0	6.00	220	96	166	54
160	17	12.5	3.0	3.5	3.80	280	132	190	47
250	7	18.0	6.5	6.5	4.50	180	245	278	64
150	6	14.5	3.0	3.5	3.50	125	149	172	51
160	17	12.5	3.0	3.5	3.80	280	165	214	43
160	10	7.0	3.0	3.5	4.50	90	109	180	76
160	40	7.5	4.0	4.0	3.50	150	98	164	54
250	6	19.0	3.5	5.0	4.50	250	42	138	54
250	33	5.0	3.0	3.0	4.00	94	555	573	65