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Original Paper

Optimal ELM–Harris Hawks Optimization and ELM–Grasshopper Optimization Models to Forecast Peak Particle Velocity Resulting from Mine Blasting

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Most mining and tunneling projects usually require blasting operations to remove rock mass. Previous studies have mentioned that if the blasting operation is not properly designed, it may lead to several environmental issues, such as ground vibration. This study presents various machine learning (ML) techniques, i.e., hybrid extreme learning machines (ELMs) with the grasshopper optimization algorithm (GOA) and Harris hawks optimization (HHO) for controlling and predicting ground vibrations resulting from mine blasting. Actually, the GOA–ELM and HHO–ELM models are improved versions of a previously developed ELM model, and they are able to provide higher performance capacity. For the proposed ML modeling, a database was established consisting of 166 datasets collected from Malaysian quarries. The efficacy of the proposed ML techniques was observed in the training stage as well as in the testing stage, and the results were evaluated against five parameters constituting the fitness criteria. The results showed that the GOA–ELM model delivered more accurate ground vibration values compared to the HHO–ELM model. The system error values of the GOA–ELM model for the training and testing datasets were 2.0239 and 2.8551, respectively. The coefficients of determination of the GOA-ELM model for the training and testing datasets were 0.9410 and 0.9105, respectively. It was concluded that the new hybrid model is able to forecast ground vibration resulting from mine blasting with high level of accuracy. The capabilities of this hybrid model can be extended further to mitigate other environmental issues caused by mine blasting.

KEY WORDS: Ground vibration, Blasting environmental issues, Extreme learning machine, Harris hawks optimization, Grasshopper optimization algorithm.

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INTRODUCTION

In today's context, an engineer's first choice for fragmenting rock in opencast mines, construction projects and tunneling is blasting. The main reason is that it is economical, as compared to any other method (Raina et al. 2004). The main purpose of blasting is to break in situ rock into pieces of the right sizes to facilitate loading and transportation. However, blasting is associated with some undesirable side effects on the neighborhood and environment, e.g., air overpressure, flyrock and ground vibration (Saadat et al. 2014; Koopialipoor et al. 2018a; Shang et al. 2020 ; Zhou et al. 2019; Nguyen et al. 2019, 2020). To ensure the safety of blasting operations, it is important to forecast all the results of blasting, in particular its undesirable side effects.

Several scientific techniques and forecasting models have been developed over the years for assessing and predicting the negative side effects of blasting. Of all the environmental issues arising out of blasting, the most serious is blast-induced ground vibration (BIGV). That is because it gives rise to a host of other issues—vibration and damage to building structures, slope instability and bench instability in opencast mines, negative effects on groundwater, damage to railways and highways and annoyance to local communities (Verma and Singh 2011; Khandelwal et al. 2011; Mahdiyar et al. 2020). Many neighboring families have complained about the possible risk to their health and safety when they experience blasting in nearby opencast mines and quarries. That is all the more reason for BIGV to be predicted accurately before a blast, so that the undesirable side effects of blasting operations can be controlled or mitigated (Armaghani et al. 2015).

The most important measures of BIGV are frequency and peak particle velocity (PPV). As per the Bureau of Indian Standards (Standard 1973), of these two parameters, PPV is more important and relevant for controlling structural damage (Khandelwal and Singh 2009). Many researchers have gone into the development of empirical formulas for predicting BIGV (Duvall and Fogelson 1962; Langefors and Kihlstrom 1963; Davies et al. 1964; Roy 1993). However, the problem with empirical methods/equations is that they suffer from poor accuracy (Monjezi et al. 2011). One reason for the inaccuracy of empirical equations is that they can handle just two parameters, namely distance from blast site and maximum charge per delay. They ignore other important parameters, like spacing, burden and powder factor, which influence vibration due to blasting (Standard 1973; Armaghani et al. 2015). Another reason for the inaccuracy of empirical methods is that they are usually designed for a specific geological area and are generally not capable of being applied to another location. It has been demonstrated that when applied to other locations, empirical equations became more inaccurate (Monjezi et al. 2013). Other statistical methods with multiple inputs have been tried for BIGV prediction, but like empirical equations, the accuracy of the predictions was not good enough, particularly when new data are used in place of old data.

The availability of artificial intelligence (AI) was used to solve many problems related to science and engineering (Yang et al. 2018a, b; Koopialipoor et al. 2018b, c, d, 2019a; Guo et al. 2019; Xu et al. 2019; Liu et al. 2019; Huang et al. 2019, 2020, 2021a, b; Zhao et al. 2019, 2020a, b; Tang et al. 2020; Armaghani et al. 2020; Asteris et al. 2020; Qi 2020; Pham et al. 2020). Several researchers reported the effective role of AI models in predicting PPV (Khandelwal and Singh 2007; Dindarloo 2015). During the construction of a dam project in Iran, Monjezi et al. (2011) used an artificial neural network (ANN) model. This model used two hidden layers for the prediction of BIGV. The predictions derived from the ANN model were compared with predictions from empirical and statistical models using multiple linear regression methods. It was found that the ANN model was more accurate than all of the other models in the prediction of BIGV. Amiri et al. (2016) combined an ANN with the K-nearest neighbors (KNN) algorithm, called the ANN–KNN model, to predict PPV. They compared the PPV predicted by the ANN–KNN model with that of an ANN model, a few empirical models and a few other models from published sources. They concluded that the ANN–KNN model had the best accuracy for prediction of PPV. Another hybrid AI-based model for predicting PPV was developed by Shahnazar et al. (2017), in which particle swarm optimization (PSO) was used along with the neuro-fuzzy technique called the PSO–ANFIS model. In another study, Zhou et al. (2020a) used a new hybrid gene expression program–Monte Carlo (GEP–MC) technique to introduce a novel method of predicting BIGV. This GEP–MC model showed the probabilities of risk in the surface mine technologies through PPV.

According to several published papers in the field of ground vibration, it seems that the new models based on AI and machine learning (ML) algorithms would be very useful for the prediction of PPV. Therefore, in this study, two combinations of the grasshopper optimization algorithm (GOA) and Harris hawks optimization (HHO) with extreme learning machines (GOA–ELM and HHO–ELM) were used to predict PPV. The PPVs predicted by the GOA–ELM and HHO–ELM were compared with those of the basic ELM model. In the following sections, the background of each of these ML models and the development of these ML techniques are described. The predictions of PPV from each of these models based on the data available are compared and thoroughly evaluated. Finally, the most accurate model is identified and recommended for use in forecasting BIGV.

RESEARCH SIGNIFICANCE

One of the most undesirable side effects of rock blasting is related to ground vibration and PPV. Ground vibrations from blasting, if not controlled, not only lead to major annoyances and inconveniences to the local population, but they also adversely affect nearby structures, property and equipment. In some cases, local populations have caused mines to close. High levels of vibration can damage and choke groundwater bodies and upset the ecological balance in the neighborhood (Khandelwal and Singh 2009). Uncontrolled PPV can give rise to deforestation in nearby forest areas. In mining operations, PPV can damage free faces and generate significant amounts of back-breaks (Duvall and Fogelson 1962), resulting in problems in drilling and the generation of boulders in subsequent blasts. It is therefore important to forecast PPVs accurately and to demarcate accurately blast safety zones, so that blasting engineers are able to forecast, restrict and contain ground vibrations and flyrock arising from blasting operations.

The prediction and control of PPV therefore become a major concern in blasting operations because it is dependent on many complex parameters. The output parameter and predictor variables are highly dynamic and nonlinear. The most elementary simulation models for the prediction of blast vibrations are based on physical parameters (Duvall and Petkof 1959; Edwards and Northwood 1960). Simply put, these physically based models consisted of one equation to take into account all physical phenomena and blasting parameters and predict blast vibration in a simple manner. The major drawback of the physically based model was the requirement to measure the parameters and the complexity of the mathematical formulation necessary to arrive at a simple solution.

ML models are practical and viable options to be adopted when the availability of data is limited, and their simple forecasts are more crucial than an in-depth understanding of the cause-and-effect mechanism. However, if the operators are keen on understanding the relationships between blast geometry and other factors and examining the connection between input variables, more sophisticated versions of ML, such as the basic ELM and its variants (hybrid models), would be needed to simulate, explore and establish empirical relationships between the blasting parameters and PPV.

THEORETICAL BASIS OF THE ML TECHNIQUES

Grasshopper Optimization Algorithm

Based on the herding pattern of grasshoppers, a meta-heuristic algorithm called GOA (grasshopper optimization algorithm) was developed by Saremi et al. (2017). In GOA, there are three kinds of relationships that determine the swarming behavior of grasshoppers; each of these is represented by an equation given below:

$$\text{Social relationships}: SR_i = \sum_{j=1}^{N} s(d_{ij})\hat{d}_{ij} \quad (1)$$

$$\text{Gravity force}: GF_i = -g\text{x} \quad (2)$$

$$\text{Wind advection}: WA_i = u\text{x} \quad (3)$$

M_i is the location of the i^{th} member and it is represented by

$$M_i = r_1 SR_i + r_2 GF_i + r_3 WA_i \quad (4)$$

In the above equations, r_1, r_2, r_3 are random numbers in the range (0,1); s and d_{ij} define the social forces and Euclidean distances between the ith and jth individuals, respectively; g is the gravitational constant; u is a constant drift; $\hat{e}_g$ is the unit vector toward the center of the earth; and $\hat{e}_w$ is the unit vector for the wind direction. The social distance, $s(r)$, is derived from the following relationship:

$$s(r) = fe^{(-r/ak)} - e^{(-r)} \quad (5)$$

where f is the attractive length scale and k is the attraction severity. Mafarja et al. (2019) studied the effects of f and k on grasshopper behavior. They

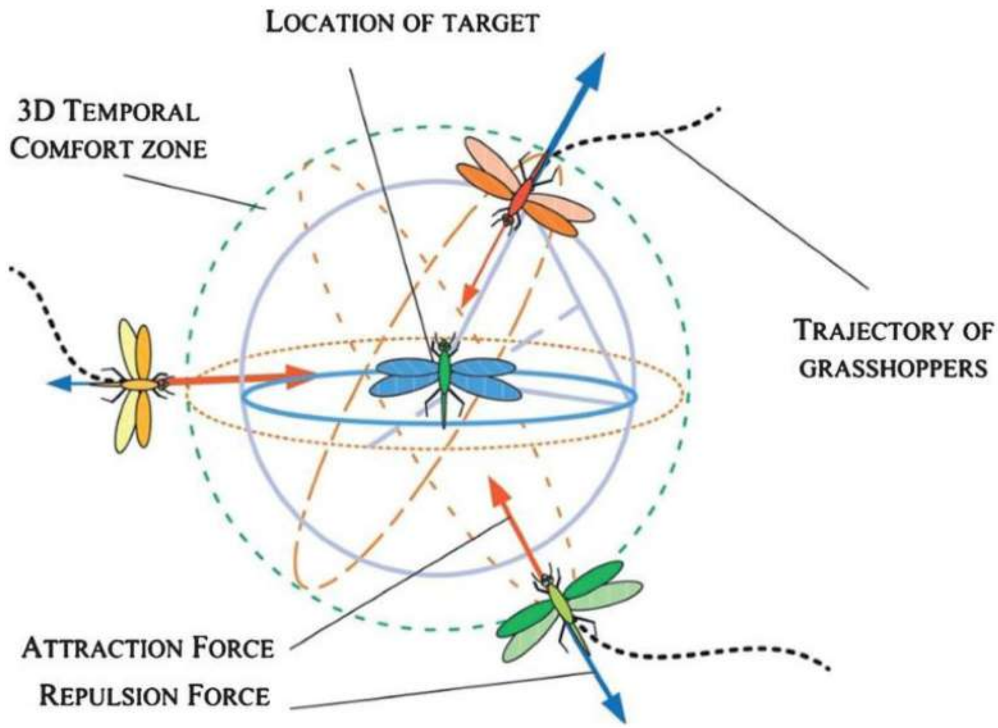


Figure 1. Definition of GOA position (Jia et al. 2019).

observed that there is a strong opposition or repulsion between any two grasshoppers if the physical distance between them falls in the range of 0 and 2.079. If not, the grasshoppers are in a comfort zone (Fig. 1). More information regarding this optimization technique can be found in Saremi et al. (2017).

Harris Hawks Optimization

The cooperative hunting behavior of the HHO has been used to represent various issues for which optimal solutions need to be found (Bui et al. 2019). The HHO algorithm was proposed by Heidari et al. (2019) to solve optimization problems in different areas of science and engineering. As one can see from Fig. 2, there are three phases in HHO—an exploration phase, an exploitation phase and a transition phone in between. In the first phase, a hawk searches and locates a prey animal and its position, *X*rabit. Assigning a random relationship to the prey, *Xrand*, the hawks define their own position in relation to the position of the prey through an iterative process:

$$X(\text{iter}+1) = X_{\text{rand}}(\text{iter}) - r_1 X_{\text{rand}}(\text{iter}) - 2r_2 X(\text{iter}) \text{ if } q \geq 0.5$$
$$X_{\text{rabit}}(\text{iter}) - X_m(\text{iter}) - r_3(LB + r_4(UB - LB)) \text{ if } q < 0.5 \tag{6}$$

where Xm is the average position and r_i is a position based on i, a random number varying from $i = (1,2,3,4,\ldots q)$. The term m is given by:

$$Xm(\text{iter}) = 1/(N)\sum_{(i=1)}^{N} X_i(\text{iter}) \tag{7}$$

where N is the size of the hawk and Xi is the location. The escaping energy of the hunt, Eh, is given by:

$$E_h = 2E_0\left(1 - \frac{\text{iter}}{T}\right) \tag{8}$$

where T is the maximum size of the repetitions and E_0 is the initial energy. It is noted that $E_0 \in (-1, 1)$ and that the decision to start the exploration phase or exploitation phase is dependent on the value of $|E|$. For instance, in the exploitation phase, the value of $|E|$ represents the type of attack made to capture

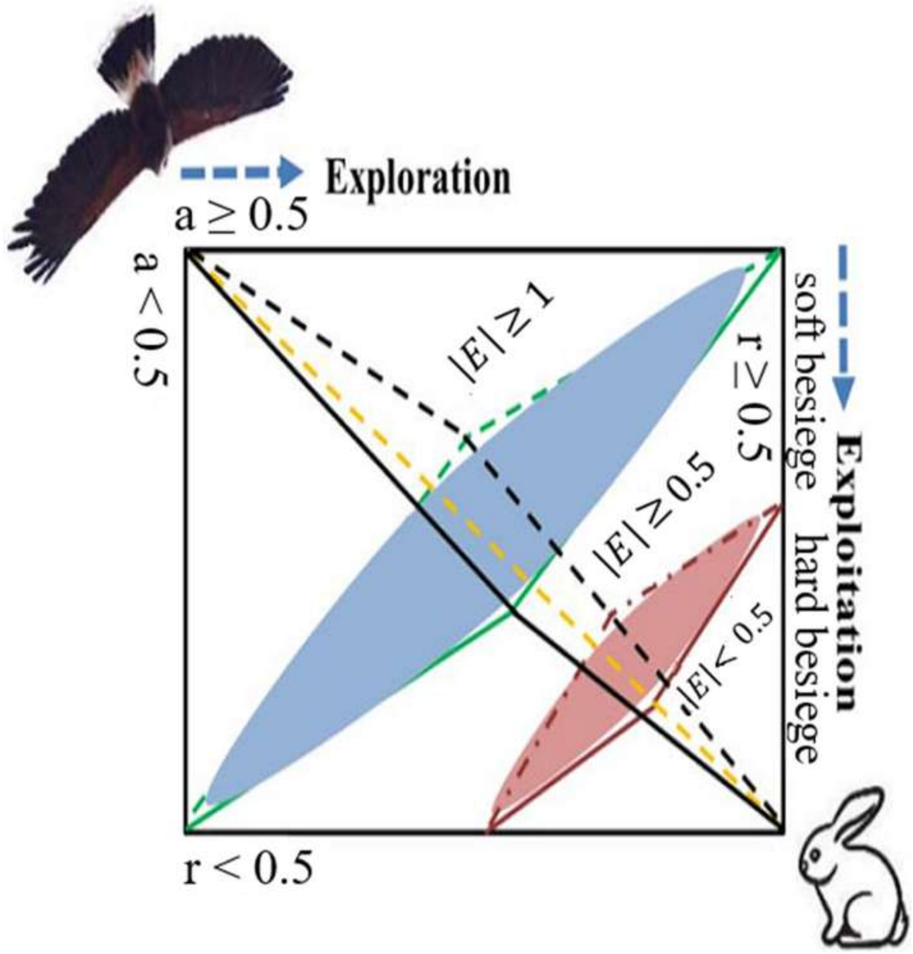


Figure 2. The three phases of HHO algorithm (Aleem et al. 2019).

the rabbit. When $|E| \geq 0.5$, it is said to be an easy catch, whereas when $|E|<0.5$, the catch is said to be difficult (Bao et al. 2019; Du et al. 2019).

Extreme Learning Machine

The ELM is a mechanism containing a single hidden layer and a neural feed-forward network called SLFN, which is useful for solving classification and regression problems (Pal and Deswal 2014). In some cases, such as in a model suggested by Huang et al. (2011), a kernel function is used in place of a hidden layer consisting of many nodes. This technique was further elaborated by Pal and Deswal (2014) and Huan et al. (2011) as follows. In the ELM, the relationship between the training data (N), the hidden neurons (H) and the activation function ($f(x)$ is defined as:

$$ej = \sum_{i=1}^{H} f(w_i, c_i, x_j) j = 1 \ldots N \quad (9)$$

where w_i represents the weight vector of the hidden input layer, α_i represents the weight vector of the hidden output layer, x_j is the input variable, c_i is the bias measure of the ith hidden neuron and ej represents the ELM output for data point j. A continuous probability distribution (Pal and Deswal 2014) gives randomly generated input weights. A simple method of measuring the output weights is:

$$\beta = A^{+} Y \quad (10)$$

where A represents the hidden layer output matrix [see Eq. (11)], A^{+} is the generalized inversion of A as per the Moore–Penrose formula and Y denotes the target values of the ELM. Equation (10) can be rewritten in a compact manner as $A = Y$, where A stands for the hidden layer output matrix of the neural network and Y represents the output of variable vectors. The three matrices can be depicted in a compact manner as follows:

$$A = \begin{bmatrix} h(x_1) \\ \vdots \\ h(x_N) \end{bmatrix} = \begin{bmatrix} f(w_1, c_1, x_1) \ldots f(w_H, c_H, x_1) \\ \cdots \\ f(w_1, c_1, x_j) \ldots f(w_H, c_H, x_j) \end{bmatrix} \tag{11}$$

$$\alpha = \begin{bmatrix} \alpha_1^T \\ \vdots \\ \alpha_H^T \end{bmatrix} \text{ and } Y = \begin{bmatrix} y_1^T \\ \vdots \\ y_N^T \end{bmatrix} \tag{12}$$

where $h(x)$ represents the feature mapping of the hidden layer. Matrix A forms the basis of the output from the ELM algorithm. The ELM is solved using the kernel function (k, xi, xj). In such a case, the feature mapping is done using the kernel matrix calculation given as:

$$k(x_i, x_j) = h(xi).h(x_j). \tag{13}$$

Compared to many conventional neural network models, the ELM has a higher learning rate at higher speeds; its generalization capacity is also higher, and so, its forecasts are more accurate. Some input layer neurons 'n' and some output layer neurons 'm,' along with some hidden layer neurons, are shown in the SLFN (see Fig. 3). For example, if {Xi, Yi} is the training dataset, Xi = [$X1$, $X2$,..., Xn] will be the input data, Yi = [$Y1$, $Y2$, ..., Ym] will be the output data and 'm' will be the number of training samples.

Hybridization of ELM

Huang et al. (2006) established that the ELM model is versatile enough to employ many activation functions. It uses general universal approximations and enjoys a capacity for fast learning that makes it an attractive and feasible technique to be applied by many researchers in prediction tasks (Cui et al. 2018). These features of ELM can be strengthened by mixing it with other algorithms, like those inspired by nature (Zhu et al. 2018). For example, Mohapatra et al. (2015) combined the ELM with a 'cuckoo search' algorithm, which is used to classify medical data. In another study, Satapathy et al. (2017) used a 'firefly algorithm' to optimize the ELM and make it amenable to analyzing the photovoltaic interactive microgrid. Li et al. (2019) used a 'whale optimization' algorithm to optimize an ELM for assessing the aging factor in insulated gate bipolar transistors. In these related studies, it was found that the optimized versions of ELM can perform better than the basic ELM in terms of performance prediction capacity. One reason for this could be that the basic ELM uses stochastic initialization of the network input weights. This, along with hidden biases, can increase the probability of solutions getting stuck in local minima (Cao et al. 2012). For this reason, the present study focused on combining ELM with two optimization algorithms, i.e., GOA and HHO, to update the input weights and hidden biases of the ELM model and to get optimal results. These hybrid models can be used to control and predict ground vibration induced by mine blasting.

DESCRIPTION OF THE DATA

A good starting point to evaluate new models for predicting ground vibration is to establish and use a solid database. For this study, Pulau Penang, a granite quarry in Penang, Malaysia (Fig. 4), was chosen, and blasting data were collected accordingly. This quarry consists of two granite plutons: North Penang Pluton and South Penang Pluton. The North Penang Pluton has three units—Granite Tanjung Bunga, Granite Feringgi and microgranite at the top. The South Penang Pluton is comprised of muscovite–biotite granite, containing mostly microcline. The surface of this area is just top soil, measuring about a meter in thickness, consisting of sandy clay with tree roots in most parts.

Blasting here is carried out for the production of granite aggregates for construction projects. The quarry has a capacity to produce about 500,000 to 700,000 tons per year. Generally, blasting is carried out about 2–4 times a week, using blast hole diameters of 76 mm and 89 mm. The number of holes per blast ranges from 18 to 84. The total explosives quantity used in a blast ranges from 856.6 to 9420.5 kg. Data for 166 blasting operations were measured and recorded for critical parameters like, among others, burden-to-spacing ratio, hole diameter, stemming length, maximum charge per delay, total charge and powder factor. For each blast, the PPV was measured and recorded together with distance of PPV monitoring from the free face, which ranged from 285 to 531 m. The database included

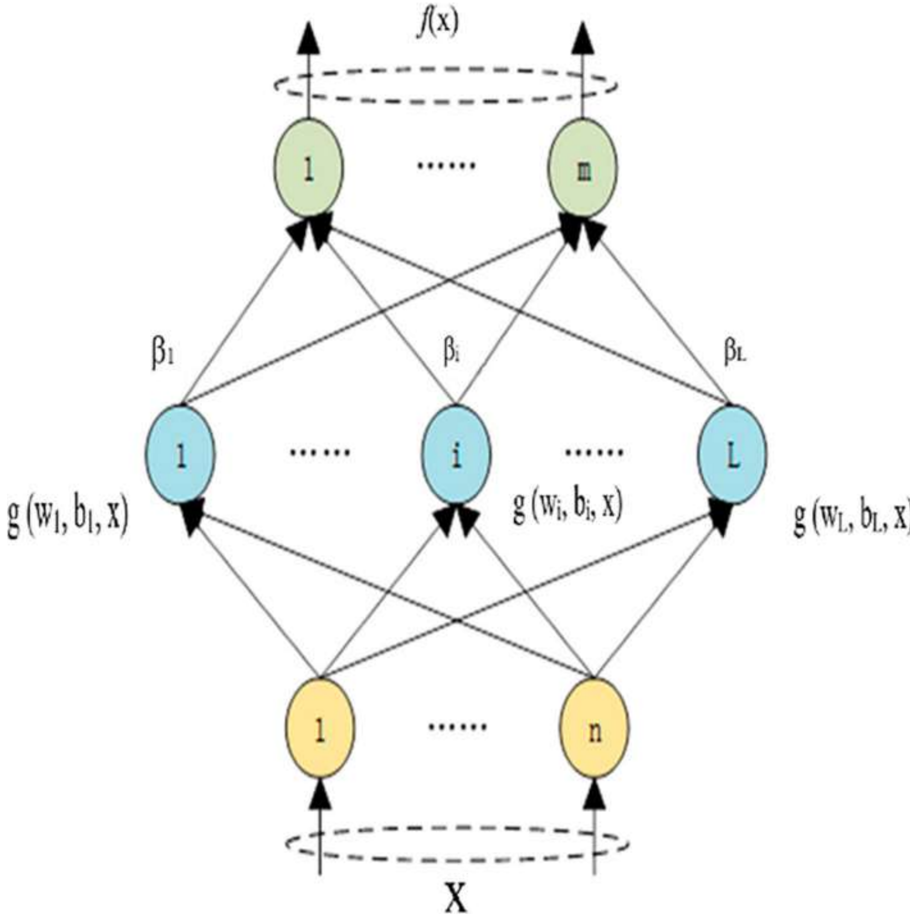


Figure 3. View of the proposed basic ELM.

166 measured operations for the prediction of PPV. This database was used for developing the basic ELM and the optimized ELMs, namely GOA–ELM and HHO–ELM. Figure 5 provides an overview of each input and system output (i.e., PPV) in the database that was used.

PROPOSED MODELS TO PREDICT PPV

In this study, input weights and hidden biases, which constitute the ELM parameters, were calibrated for predicting ground vibration using the GOA–ELM and HHO–ELM hybrid models. The optimal parameters obtained for each of the two of optimization algorithms were applied separately to the ELM to find output weights and predict test data output. Figure 6 shows the process of hybrid ELM models. These models were developed by applying subroutines provided by MATLAB. In the model created as part of this study, PPV was the output (y) and the input matrix was x = (BS, HD, St, PF, MC, and DI).

In the development of models for prediction, the first step is generally determining datasets for training and testing. In this study, for the development of the ELM, GOA–ELM and HHO–ELM models, 80% of datasets were randomly identified and kept aside for training and the remainder for testing (Koopialipoor et al. 2018b, 2019b; Lu et al. 2020). Using a trial-and-error approach, the models were tuned for optimization to give the best PPV estimation. The parameters for value tuning of the models were chosen and varied until the best fit was reached. The models were then evaluated for the highest efficiency on the basis of six indices: coefficient of correlation (R), coefficient of determination (R^2), root-mean-square error (RMSE), mean abso-

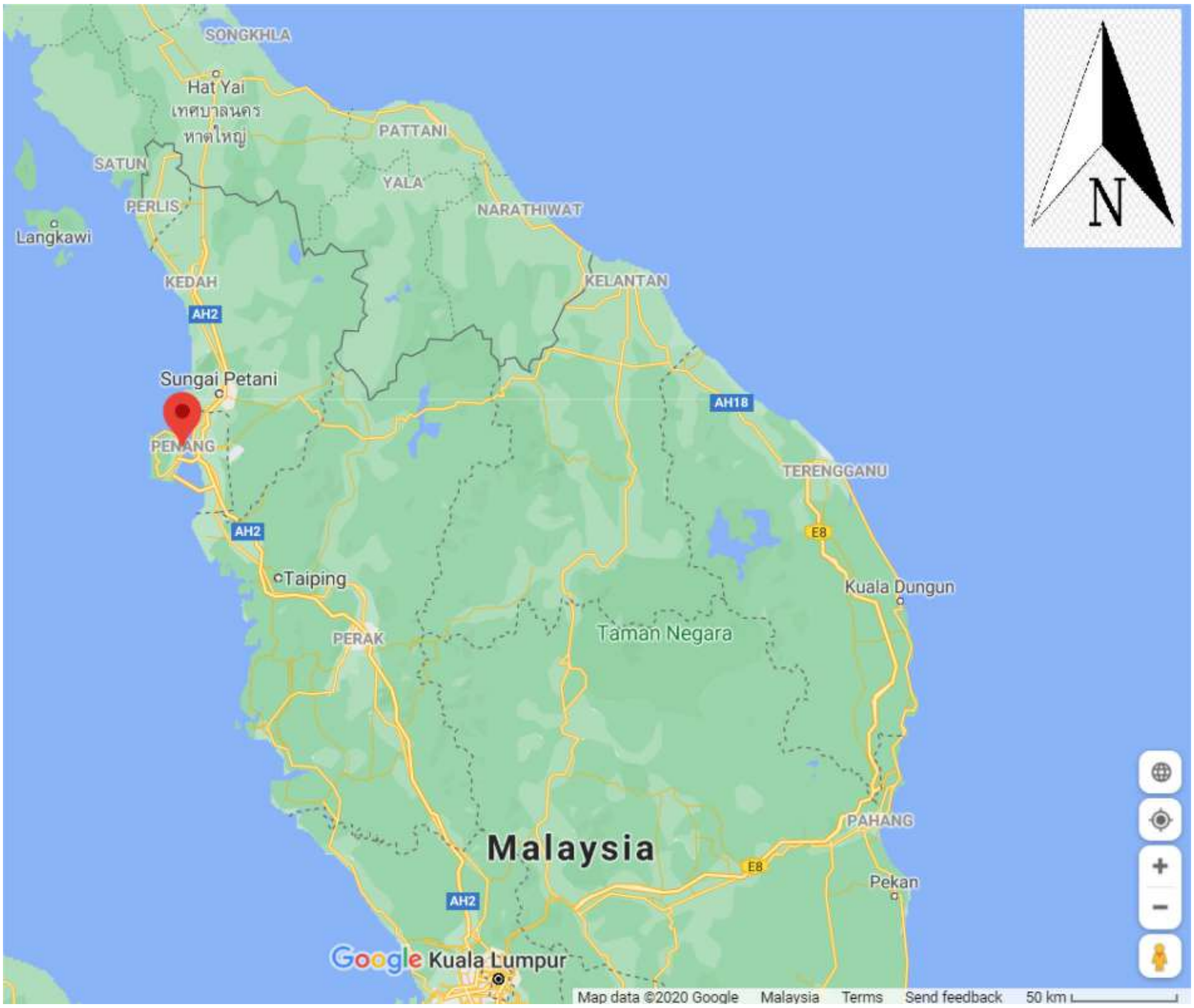


Figure 4. Location of the study area.

lute error (MAE), mean absolute percentage error (MAPE) and Nash–Sutcliffe efficiency coefficient (NSE). These indices have been used to assess the performance prediction capacities of many published researches (Koopialipoor et al. 2019c, d; Sun et al. 2019; Cai et al. 2020; Ye et al. 2020; Zhou et al. 2020b, c). Their formulas are given below:

$$R = \left[\frac{\sum_{i=1}^{k} \left(PPV_{E_i} - PPV_{\overline{E}_i}\right)\left(PPV_{O_i} - PPV_{\overline{O}_i}\right)}{\sqrt{\sum_{i=1}^{k} \left(PPV_{E_i} - PPV_{\overline{E}_i}\right)^2 \sum_{i=1}^{n} \left(PPV_{O_i} - PPV_{\overline{O}_i}\right)^2}} \right] \tag{14}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{k} (PPV_i - PPVO_i)^2}{k}} \tag{15}$$

$$\mathrm{MAE} = \left(\frac{1}{k} \sum_{i=1}^{k} \left| PPV_{O_i} - PPV_{E_i} \right| \right) \tag{16}$$

$$\mathrm{MAPE} = \left(\frac{100}{k} \sum_{i=1}^{k} \left| \frac{PPV_{O_i} - PPV_{E_i}}{PPV_{O_i}} \right| \right) \tag{17}$$

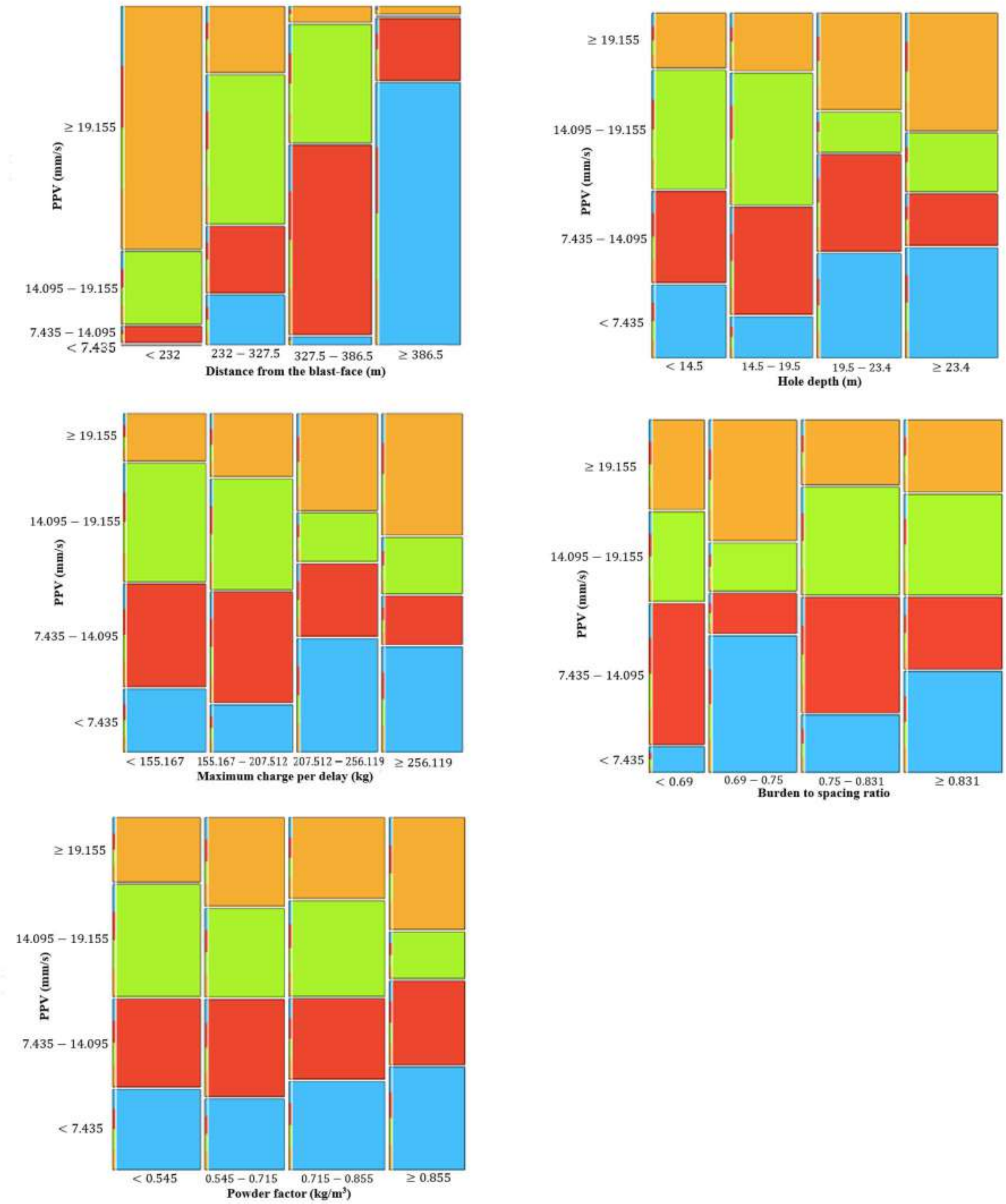


Figure 5. Mosaic display of all data.

$$\mathrm{NSE} = \left[1 - \frac{\sum_{i=1}^{k}(PPV_{E_i} - PPV_{O_i})^2}{\sum_{i=1}^{n}\left(PPV_{O_i} - PPV_{\overline{O}_i}\right)^2}\right] \quad (18)$$

where PPV_{E_i} is the ith estimated PPV ; PPV_{O_i} is the ith observed PPV; PPV_{-E_i} is the average of estimated PPV; PPV_{-O_i} is the average of observed PPV and k is the number of observations.

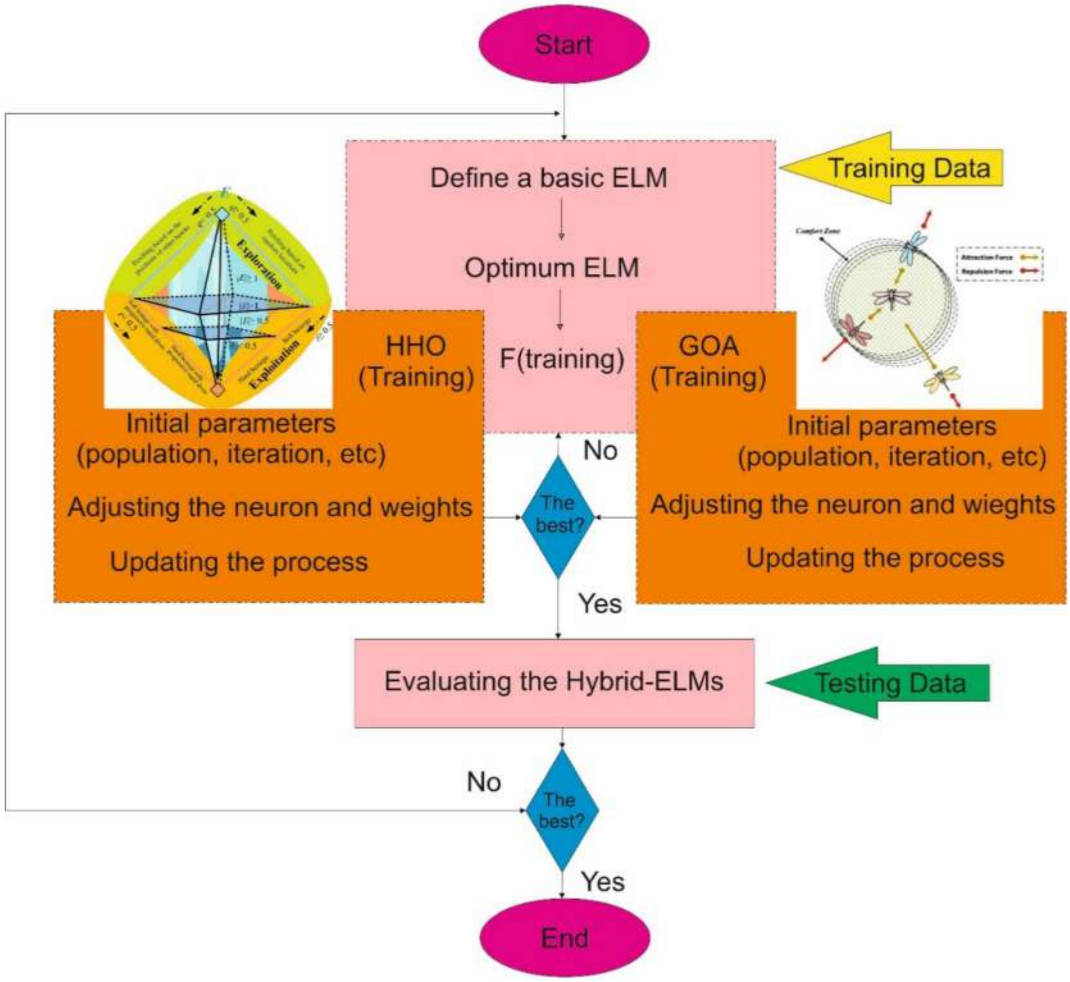


Figure 6. The proposed process of hybrid ELMs.

Table 1. Results of developed models based on various indices

Indices	R	MAE	MAPE	RMSE	NSE	R^2
Training						
ELM	0.9449	2.2896	26.0361	2.7961	0.8927	0.8928
GOA-ELM	0.9701	1.353	15.1388	2.0239	0.9410	0.9410
HHO-ELM	0.9663	1.6514	19.7654	2.1687	0.9337	0.9337
Testing						
ELM	0.9220	2.6151	39.0075	3.4667	0.8364	0.8501
GOA-ELM	0.9542	2.3417	31.3342	2.8551	0.9083	0.9105
HHO-ELM	0.9487	2.6071	33.9205	3.0467	0.8883	0.9001

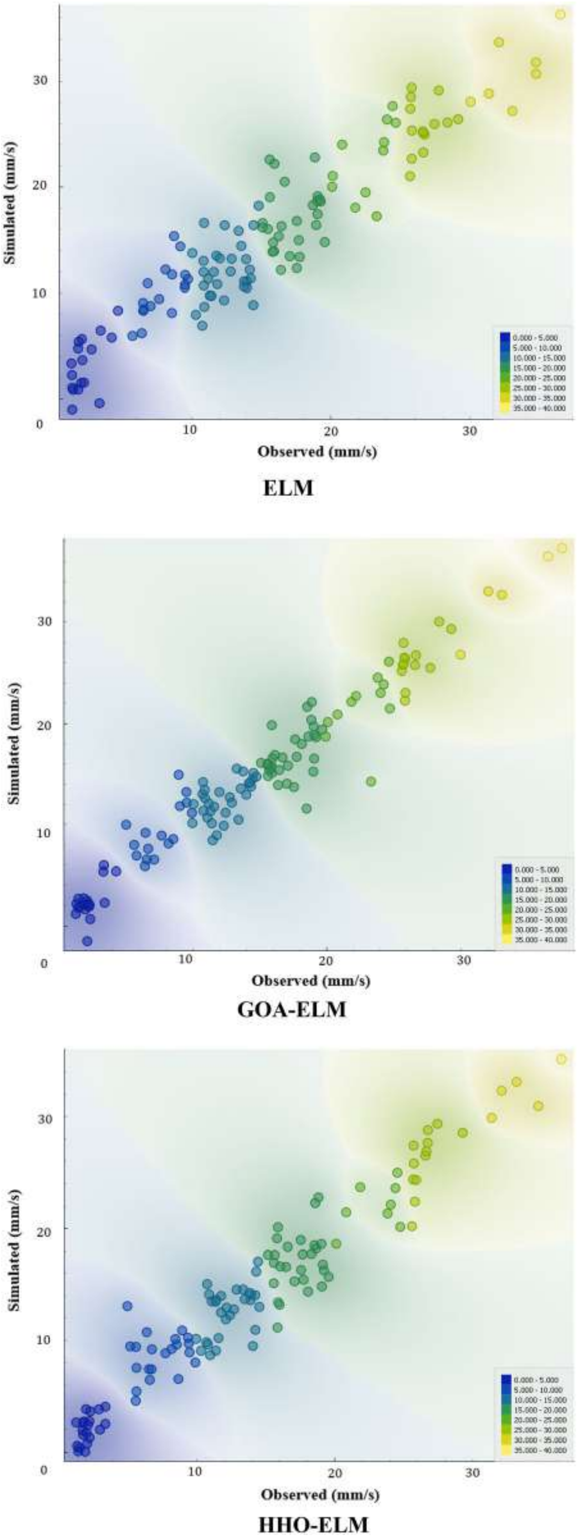


Figure 7. Colorful zoning of results for training data.

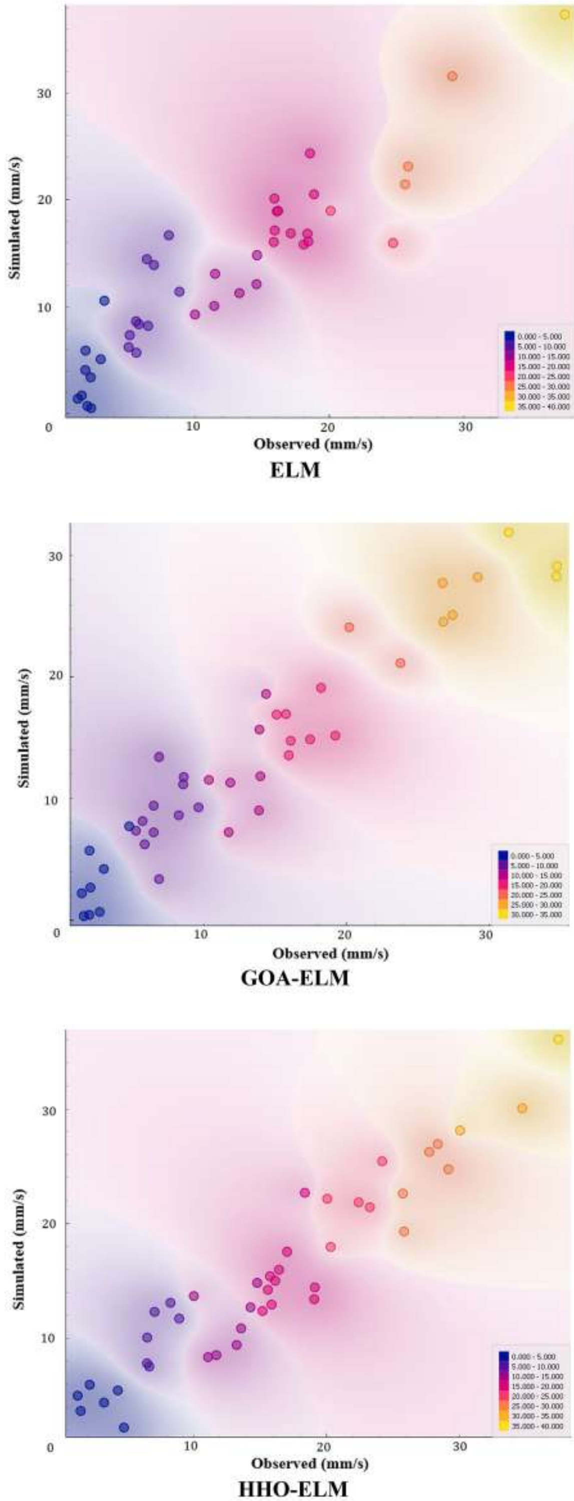
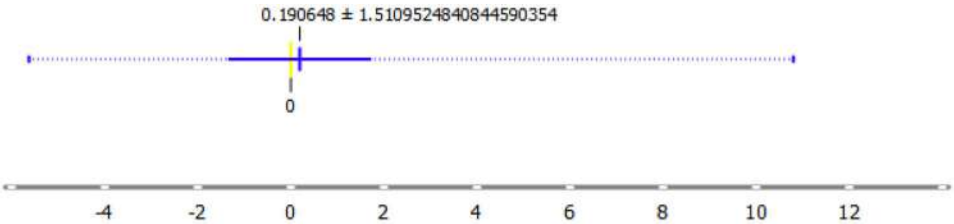
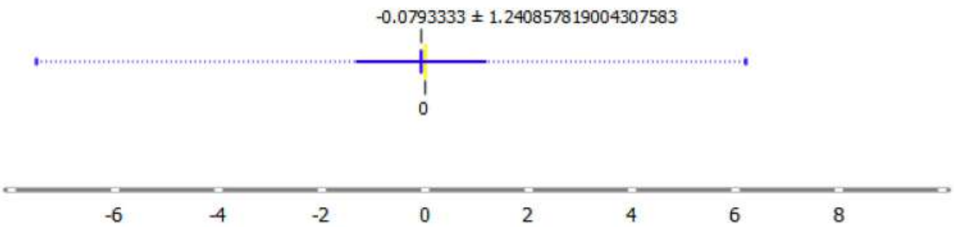


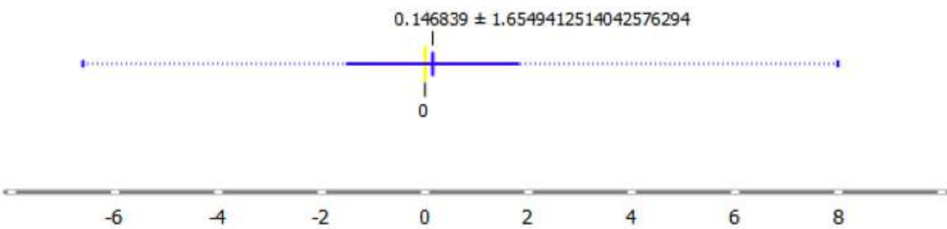
Figure 8. Colorful zoning of results for testing data.



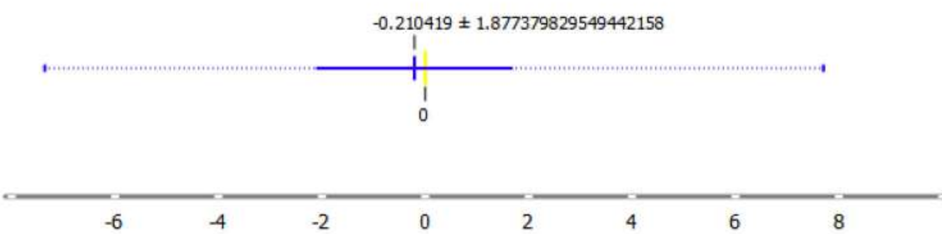
(a) Covariance estimator



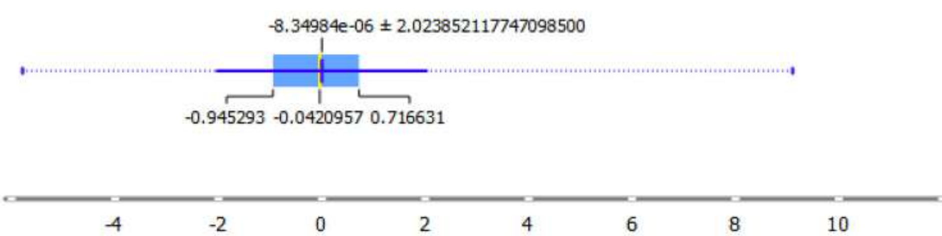
(b) Isolation forest



(c) Local outlier factor



(d) One class SVM



(e) None

◀**Figure 9.** Distributions of errors for the developed GOA–ELM model based on four filters.

RESULTS AND DISCUSSION

Development of Models

The ELM, GOA–ELM and HHO–ELM models were tried out on various fitness parameters with the objective of finding the best ML technique. Table 1 and Figures 7 and 8 show the fitness measures and the observed and predicted PPVs, considering various computing methods, for the training datasets and testing datasets. In the case of the ELM model, during the training phase, there was a good correlation between observed and predicted PPVs; however, during the testing phase, it significantly failed to achieve a good correlation. On the other hand, the hybrid ELM groups were consistent in both the training and testing stages. The GOA–ELM showed the best results in the prediction of PPV induced by blasting, followed by HHO–ELM and ELM.

During the training and testing phases for the hybrid ELM groups, GOA–ELM showed the minimum deviation (R of 0.9701 and 0.9542, MAE of 1.353 and 2.3417, MAPE of 15.1388 and 31.3342, RMSE of 2.0239 and 2.8551, NSE of 0.9410 and 0.9083 and R^2 of 0.9410 and 0.9105). Therefore, this model outperformed the other developed models, and it is introduced as a new, powerful and applicable hybrid technique in the field of ground vibration prediction and generally in solving environmental issues caused by blasting.

In an earlier study, Faradonbeh et al. (2016) developed a GEP equation for the prediction of PPV in blasting, using the same database. For the training and testing datasets, this model was able to achieve R^2 values of 0.914 and 0.874, respectively. In the present study, the authors used the same datasets with a new hybrid prediction model, i.e., GOA–ELM, to predict PPVs produced by blasting. The R^2 values from this hybrid GOA–ELM model for training and testing were 0.9410 and 0.9105, respectively, which are better than the GEP model results by Faradonbeh et al. (2016). Besides, further improved versions of the hybrid ELM models showed results superior to the GEP model in the training and testing phases. It has also been seen that the performance of the hybrid models presented in this research is superior to many other models reported in the literature (Monjezi et al. 2013; Armaghani et al. 2014; Amiri et al. 2016; Sheykhi et al. 2018). In summary, the GOA–ELM is a hybrid model enjoying the advantages of both the GOA and ELM algorithms, which give it a higher performance compared to other models. It can be used reliably to solve environmental issues caused by blasting.

Outlier Effect on the Models

One of the interesting ideas in this research was to design the developed models based on appropriate criteria for the detection of effective data. Because, in different models, data quality has a direct impact on the results, four types of features were used to select the appropriate data. Here, we implemented filters for the data by rating them based on their quality. The four best criteria for selecting valuable data were the one-class SVM, covariance estimator, local outlier factor and isolation forest. This process was used for all datasets. Then, the output data were randomly divided into training and testing data for the developed models. The results of the models are shown in Figure 9. As shown in the figure, the error distributions of the new models based on the four filters are shown. Upon closer inspection, it can be concluded that the error distributions were concentrated close to zero, and the range of large errors was reduced by these filters. Of these four techniques, the model that used the isolation forest filter can be used as an optimized model. This process is applicable to a variety of data and can provide better recognition than more valuable data. This model, built with the isolation forest filter, can be used to evaluate more accurately the PPVs resulting from mine blasting.

CONCLUSIONS

Safety in blasting operations and the reduction in damage to the environment require an accurate prediction of PPV arising out of ground vibration. In this research, PPVs were predicted by different hybrid ML models: ELM, GOA–ELM and HHO–ELM. The prediction performances of these models were then evaluated using different fitness indices. It was found that the GOA–ELM model was the best among all models in terms of accuracy in both the training and testing phases. The fitness indices for the training and testing phases of the ELM, GOA–ELM and HHO–ELM models, respectively, were obtained as follows:

1. RMSE values for training = 2.7961, 2.0559 and 2.0616; and for testing = 3.4667, 2.8541 and 3.0467
2. R^2 values for training = 0.8928, 0.9410 and 0.9337; and for testing = 0.8501, 0.9105 and 0.9001

The above results showed that the hybrid GOA–ELM model had higher performance ratings for predicting PPVs. In addition, it was established that the GOA–ELM model is better than some techniques from other published studies. In conclusion, the hybrid GOA–ELM model is recommended for use not only to predict PPVs but also to resolve other environmental issues caused by blasting (e.g., flyrock and air overpressure) and to determine the blast safety zone. It is further recommended to apply the model within specified ranges over repeated conditions of input parameters to achieve a higher accuracy level. Finally, four types of filters were used to improve the prediction quality of the GOA–ELM model. The results of these filters indicated that by scoring the data, more valuable data should be available to increase the accuracy of the models made to predict PPV.

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