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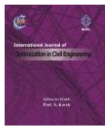

A NEW APPROACH FOR EVALUATION OF SEISMIC SLOPE PERFORMANCE

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ABSTRACT

The evaluation of seismic slope performance during earthquakes is important, because the failure of slope (such as an earth dam, natural slope, or constructed earth embankment) can result in significant financial losses and human. It is important, therefore, to be able to forecast such displacements induced by earthquake. However, the traditional forecasting methods, such as empirical formulae, are inaccurate because most of them do not take into consideration all the relevant factors. In this paper, new intelligence method, namely relevance vector regression (RVR) optimized by dolphin echolocation (DE) and grey wolf optimizer (GWO) algorithms is introduced to forecast the earthquake induced displacements (EID) of slopes. The DE and GWO algorithms is combined with the RVR for determining the optimal value of its user-defined paramee RVR. The performances of the proposed predictive models were examined according to two performance indices, i.e., coefficient of determination (R^2) and mean square error (MSE). The obtained results of this study indicated that the RVR-GWO model is a reliable method to forecast EID with a higher degree of accuracy (MSE= 0.0160 and R^2= 0.9955).

Keywords: Seismic Slope Performance; Relevance Vector Regression; Dolphin Echolocation Algorithm; Grey Wolf Optimizer Algorithm

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1. INTRODUCTION

Earthquake-induced sliding displacements are commonly used to assess the seismic performance of slopes. Earthquakes with magnitudes greater than 4.0 can cause landslides on very susceptible slopes, and earthquakes with magnitudes greater than 6.0 can generate widespread landsliding [1]. Whether a particular slope produces a landslide in an earthquake depends on details of slope configuration, material strength and ground motion [2]. Many

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researchers attempt to find rapid and accurate ways to predict earthquake induced displacements (EID) of slopes. In this paper, the well–known research works are addressed. Lin, Whitman [3] evaluated the earthquake induced displacements of sliding blocks. Saygili, Rathje [4] proposed an empirical predictive models for earthquake-induced sliding displacements of slopes. Carro et al. [5] studied the application of predictive modeling techniques to landslides induced by earthquakes. Refice, Capolongo [6] evaluated the probabilistic modeling of uncertainties in earthquake-induced landslide hazard assessment. Rathje, Saygili [7] evaluated the probabilistic modeling of earthquake-induced sliding displacements of natural slopes. Ambraseys, Srbulov [2] proposed a predictive formulae and graphs for co-seismic and post-seismic permanent displacements for translational movements which allow the assessment of the vulnerability of natural and man-made slopes subjected to earthquakes. Miles, Keefer [8] studied the seismic slope-performance models using a regional case study. In this research compares four permanent displacement models based on Newmark's sliding-block analogy for assessing regional seismic slope-performance. The models vary primarily by the groundmotion descriptor used to correlate with Newmark displacement. Bray, Travasarou [9] suggested a simplified procedure for estimating earthquake-induced deviatoric slope displacements. Jibson [10] evaluated the predicting earthquake-induced landslide displacements using Newmark's sliding block analysis. Ling, Leshchinsky [11] studied seismic performance of simple slopes. This research was concerned with an extension of a rotational limit equilibrium method for determining the permanent displacements of slopes under seismic excitation. In the proposed procedure, the sliding mass treated as a rigid rotating body defined by a log spiral trace. Permanent displacements obtained by double-integration of the equation of motion in a manner similar to Newmark's translational sliding block method. The seismic slope stability analysis is based on the rotational limit equilibrium approach.

Although empirical or semi-empirical formulae is an alternative for forecasting of EID of slopes, most of these do not take all the relevant factors into consideration, resulting in inaccurate predictions. Lately, more intelligent methods, such as artificial neural networks (ANNs) and support vector regression (SVR) are successfully applied in non-linear modeling. However, it is difficult to determine the architecture for ANNs and stochastic events are present during the building of the model (i.e. given the same training set, the different solution is often found). In contrast, solution found based on SVR is global and deterministic. But it still has the trouble to determine the parameters (e.g. insensitivity ε and penalty weight C) and choose appropriate kernel function. Relevance vector regression (RVR) is a good competitor of SVR. It is a probabilistic model similar to the SVR, but where the training takes place in a Bayesian framework. The most impressive feature of this method is that it can offer good generalization performance while the inferred predictors are exceedingly sparse in that they contain relatively few non-zero weights associated with the corresponding basis functions [12]. Unlike in SVR framework where the basis functions must satisfy Mercer's kernel theorem, in the RVR case there is no restriction on the basis functions [12,13]. Also, kernel width σ is the only parameter to be tuned in RVR model. Consequently the sparse RVR model could generalize better with very less computation time than SVR. In this study, the optimized RVR is proposed for indirect prediction of EID. The efficiency of the RVR model is tried to increase through electing the optimal value of its parameters. Optimization algorithms employed for improving RVR are dolphin echolocation

(DE) and grey wolf optimizer (GWO) algorithms. The DE and GWO algorithms are used to select the appropriate kernel parameters of their RVR model. The goodness of each hybrid model was evaluated by using the data available in the literature. Finally, a statistical error analysis has been performed on the modeling results to investigate the effectiveness of the proposed method.

2. THEORY

In this section, first the literature review relevant to the RVR is presented and then, there are some descriptions about the DE and GWO algorithms.

2.1 Relevance vector regression (RVR)

The RVR, presented by Tipping [12] is actually a special case of a Gaussian process. Unlike the SVR, the uncertainty of the output estimation value can be characterized. Also, the RVR has better sparseness than the SVR, which can reduce online prediction complexity. In addition, the RVR does not need to estimate the error/margin tradeoff parameter C, which can reduce the computational time and the kernel function, does not need to satisfy the Mercer condition. For those advantages of the RVR approach compared with the SVR, RVR received great attention and is successfully employed in regression problems of estimation [14,15].

In RVR approach, supposing the system is multiple-input-single-output, given a dataset of *N* input vectors with *N* corresponding scalar-valued target $\{x_n, t_n\}_{n=1}^{N}$, the output $t = (t_1, ..., t_N)^T$ can be expressed as the sum of an approximation vector $y = (y(x_1), ..., y(x_N))^T$ The targets are from the model with additive noise:
.

$$t_n = y(x_n, w) + e \tag{1}$$

where *w* is the weight vector and *e* is the random noise. The function *y(x)* is defined as follows:

$$y(x, w) = \sum_{i=1}^{N} w_i K(x, x_i) + w_0 = \sum_{i=1}^{N} w_i \Phi(x) \tag{2}$$

$\Phi(x)$; here, it is given as $\Phi(x) = [1, K(x, x_1), K(x, x_2), ..., K(x, x_N)]$.

The targets can be given as $p(t_n | x_n) = N(t | y(x_n), \sigma^2)$. The likelihood of the complete dataset can be written as:

$$p(t | w, \sigma^2) = \frac{1}{2\pi\sigma^2} \exp\left\{-\frac{1}{2\sigma^2} \| t - \Phi(x) w \|\right\} \tag{3}$$

where $w=(w_0,w_1,...,w_N)$, $t=(t_1,t_2,...,t_N)$ and Φ is the $N\times(N+1)$ design matrix. Here, RVR approach adopts a Bayesian perspective and constrains w and σ^2 by defining a prior probability distribution over the weights:

$$p(w|\alpha)=\prod_{i=1}^{N} N\left(w_i\,|0,\alpha_i^{-1}\right)=\frac{1}{2\pi^{(N+1)/2}}\prod_{i=1}^{N}\alpha_i^{1/2}\exp\left(-\frac{\alpha_i w_i^2}{2}\right) \tag{4}$$

$$p(\alpha)=\prod_{i=1}^{N} gamma\left(\alpha_i\,|a,b\right) \tag{5}$$

$$p(\beta)=gamma\left(\beta|a,b\right) \tag{6}$$

where b=σ^2, *a* is an N+1 hyper-parameter, and gamma $(\alpha|a,b)$ is defined as

$$gamma\left(\alpha|a,b\right)=1\Gamma(a)^{-1}b^{a}\alpha^{a-1}e^{-b\alpha}\Gamma(a)=\int_0^\infty t^{a-1}e^{-t}dt \tag{7}$$

Also, the posterior over weights can be considered through the Bayesian rule:

$$p(w\,|t,\alpha,\sigma^2)=\frac{p(t\,|w,\sigma^2)p(w\,|\alpha)}{p(t\,|\alpha,\sigma^2)}=\frac{1}{2\pi^{(N+1)/2}}\left|\sum\right|^{-1/2}\exp\left\{-\frac{1}{2}(w-\mu)^T\sum{}^{-1}(w-\mu)\right\} \tag{8}$$

where the posterior covariance and mean are defined as follows:

$$\sum=\left(\sigma^{-2}2\Phi^T\,2\Phi+A\right)^{-1} \tag{9}$$

$$\mu=\sigma^{-2}\sum\Phi^T t \tag{10}$$

where $A=diag\left(\alpha_1,\alpha_2,...,\alpha_N\right)$. The likelihood distribution over the training targets given by Tipping [12]:

$$p\left(t\,|\alpha,\sigma^2\right)=\int p(t\,|w,\sigma^2)p(w\,|\alpha)dw=(2\pi)^{-N/2}|C|^{-1/2}\exp\left\{\frac{1}{2}t^T C^{-1}t\right\} \tag{11}$$

where the covariance is given by $C=\sigma^{-2}I+\Phi A^{-1}\Phi^T$. A detailed explanation of the RVR approach can be found in [12,16].

2.2 GWO algorithm

GWO is a new population based algorithm which is proposed by Mirjalili et al. [17]. The GWO inspired by grey wolves. For simulating the leadership hierarchy in GWO, four groups are defined: delta, omega, alpha and beta. Also, the three main steps of hunting, attacking prey, encircling prey and searching for prey are simulated. This algorithm requires a factors number to be set, namely, beta, delta, initialize alpha, search agents number, maximum iterations number, the stopping criterion and sites selected number for neighborhood search. A detailed description of the GWO algorithm can be found in [17,18]. The flow chart of the GWO is illustrated in Fig. 1. In this study, the kernel parameter of Gaussian RBF kernel ($K_{RBF}(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{\gamma^2}\right)$) is selected by GWO algorithm.

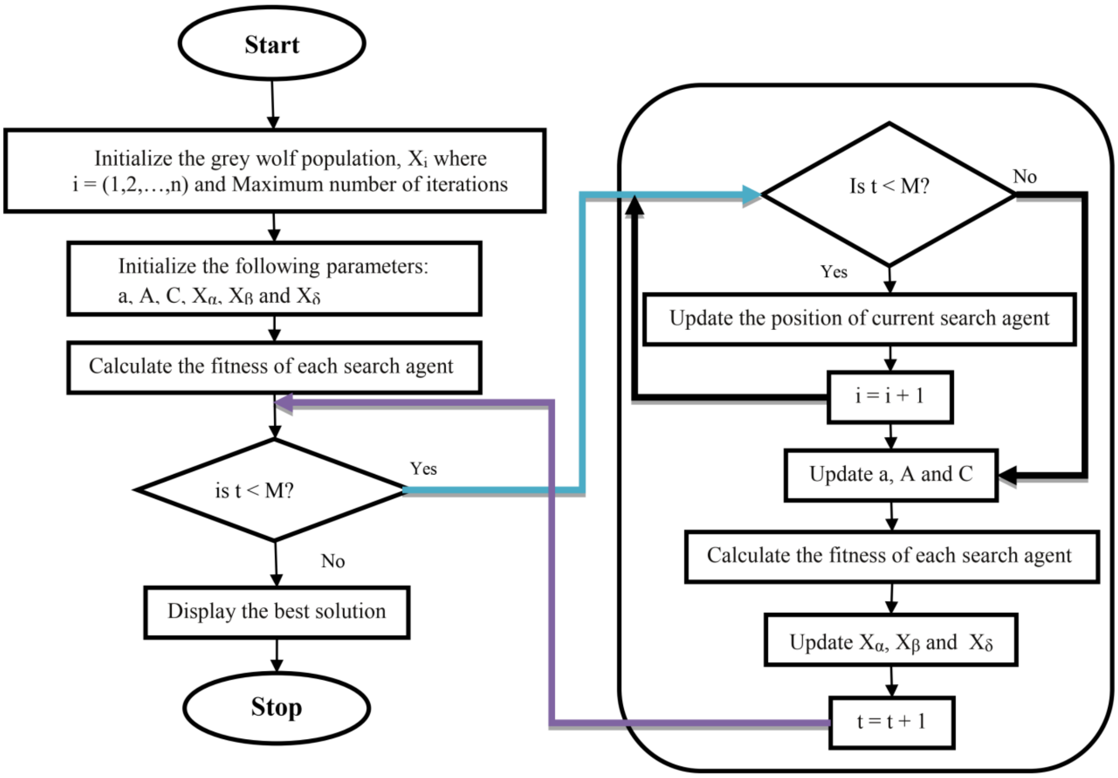


Figure 1. Flow chart of the GWO algorithm.

2.3 DE algorithm

DE mimics strategies utilized by dolphins for their hunting process. Dolphins produce a kind of voice called sonar to locate the target, doing this dolphin change sonar to modify the target and its location. This fact is mimicked here as the main feature of the new optimization method [19]. The DE algorithm [20], simulate the dolphin's echolocation and limiting the search related by distance from the target. For defined this process more clearly, two phases are introduced: In the first phase, the algorithm evaluate all space search to form that to a general search space, so it should be looking for unexplored areas. This task is done by create a series of random locations in the search space. In the second phase concentrate to evaluate the best places from the first phase. A detailed description of the DE algorithm can be found in [20]. Fig. 2 presents the flow chart of the DE algorithm. In this study, the kernel parameter of Gaussian RBF kernel ($K_{RBF}(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{\gamma^2}\right)$) is selected by DE algorithm.

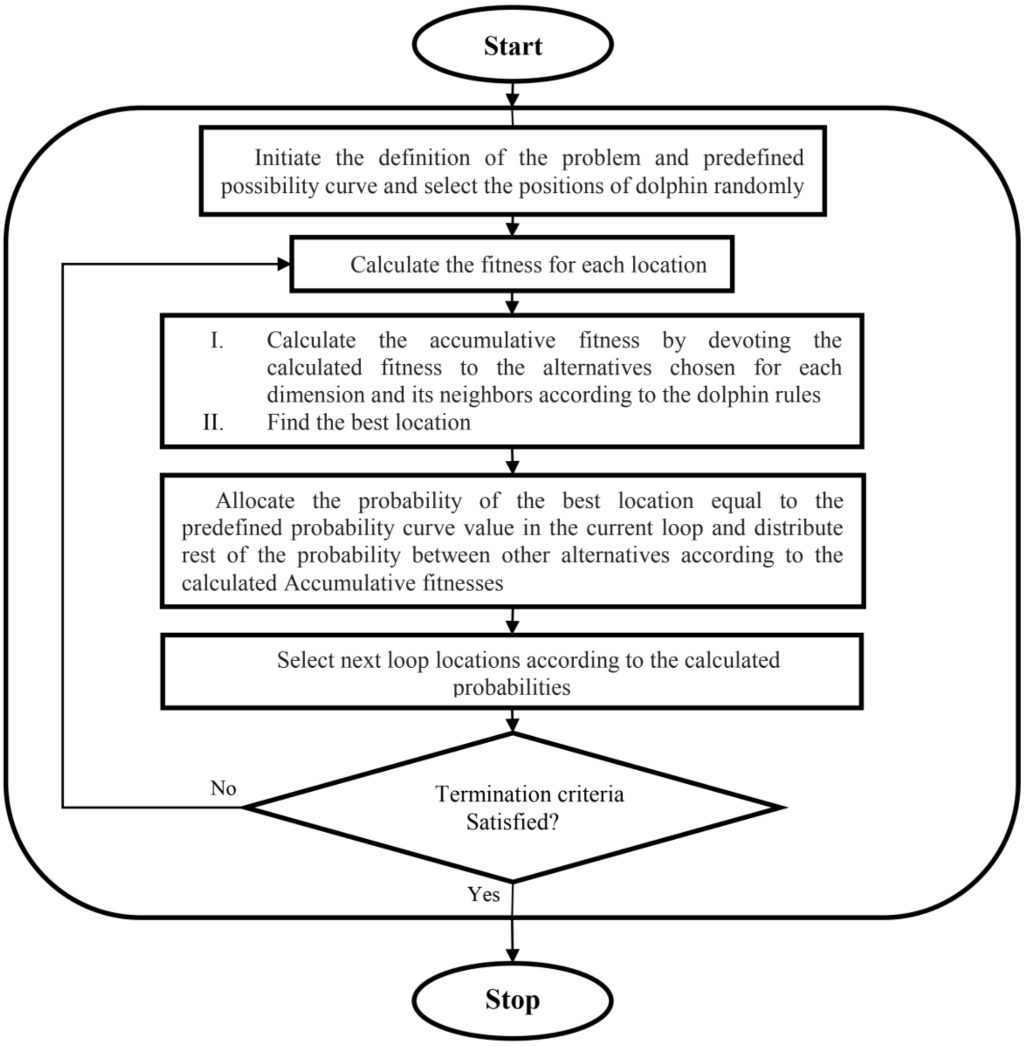


Figure 2. Flow chart of the DE algorithm.

2.4 RVR Optimized by GWO and DE Algorithms

In the RVR, the GWO and DE algorithms are applied as an optimizer for the hyper-parameters of RVR. Usually, the RVR is hybridized with the GWO and DE algorithms, where here, the prediction results achieved by RVR acts as a fitness function evaluation. The optimized value of RVR hyper-parameters can be obtained after a maximum iteration number has been reached. In this paper, the objective function is served by root mean squared error (RMSE), where the lower the RMSE, the better the estimation accuracy. The procedure of optimizing the RVR variables with the GWO and DE algorithms is presented in Fig 3.

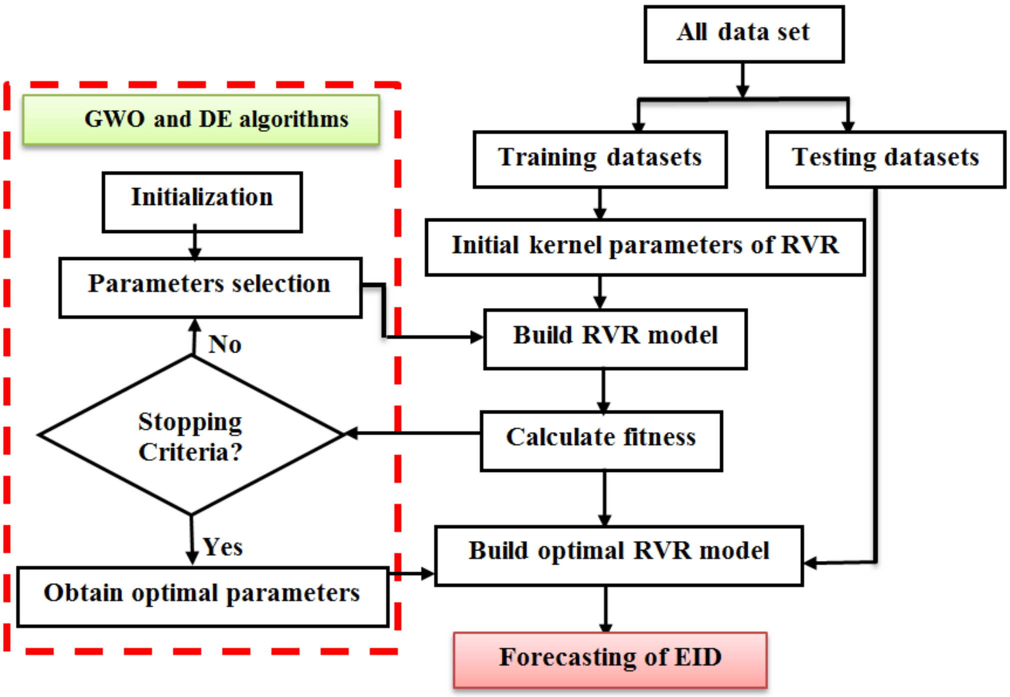


Figure 3. Flowchart of the RVR- DE and RVR-GWO models for forecasting of EID.

3. FORECASTING OF EID USING RVR-GWO AND RVR-DE MODELS

To forecasting of EID, all relevant parameters should be determined, due to the fact that RVR-GWO and RVR-DE work based on given data and do not have previous knowledge about the subject of prediction. Following sections describe the inputs and output parameters and prediction of EID using RVR-GWO and RVR-DE models.

3.1 Database information

The main scope of this study is to implement the above methodology in the problem of the earthquake induced displacements prediction for slopes. Dataset applied in this study for determining the relationship among the set of input and output variables are gathered from open source literature [21]. A dataset that includes 45 case studies was employed in current study, while 36 cases (80%) were utilized for constructing the models and the remainder data points (9 cases) were utilized for models performance evaluation. The partial datasets in Table 1 contains data for 5 slopes, were *u* (displacement) was calculated through the use of Eqs. (12) to (14). The formulation of the problem in the current example case refers to the mapping of the parameters: height (H), unit specific weight (γ), cohesion (C), angle of internal friction (φ), significant duration of shaking ($D_{5\text{–}95}$), maximum horizontal acceleration (k_{max}) to displacement (u). Partial dataset used in this study are presents in Table 1.

$$\log_{10}\left(\frac{u}{k_{\max}D_{5-95}}\right)=1.87-3.477\frac{k_y}{k_{\max}} \tag{12}$$

where D_{5-95}: significant duration of shaking, i.e., 5–95% normalized Arias intensity (sec), $K_{\max}=\frac{MHEA}{g}$ (*MHEA*: maximum horizontal equivalent acceleration, characterizes the amplitude of shaking within the sliding mass) and k_y: yield acceleration of the slope [21].

$$\ln\left(D_{5-95}\right)_{med}=\ln\left[\frac{\left(\frac{\exp\left[5.204+0851(M-6)\right]}{10^{1.5M+16.05}}\right)^{-\frac{1}{3}}}{15.7\times10^{6}}+0.0063\left(r-10\right)\right]+0.8664, \tag{13}$$

$$For\ r\succ 10km$$

$$\ln\left(D_{5-95}\right)_{med}=\ln\left[\frac{\left(\frac{\exp\left[5.204+0851(M-6)\right]}{10^{1.5M+16.05}}\right)^{-\frac{1}{3}}}{15.7\times10^{6}}\right]+0.8664,\ For\ r\prec 10km \tag{14}$$

where M: earthquake magnitude and r: distance in km [21].

Table 1: Partial dataset were used for training and testing model [21].

Input parameters						Output parameter
H (m)	ɣ (KN/m^3)	C (KPa)	Φ (^{o})	D_{5-95}	k_{max}	u (cm)
12	22	8	35	7.9	0.24	0.25
8	22	6	36	17.65	0.24	0.2
6	21	5	35	7.9	0.24	0.07
10	21	5	36	17.65	0.24	1.24
8	22	6	36	7.9	0.24	0.094

3.2 Performance Criterion

In this paper, the difference between the output of the model and the real output is considered as the error and represented in two ways, including mean squared error (MSE) and squared correlation coefficient (R^2) were chosen to be the measure of accuracy [22-24]. Let t_k be the actual value and $\hat{t}_k$ be the predicted value of the k^{th} observation and n be the number of observations, then MSE and R^2 could be defined, respectively, as follows:

$$MSE = \frac{1}{n}\sum_{k=1}^{n}(t_k - \hat{t}_k)^2 \tag{15}$$

$$R^2 = 1 - \frac{\sum_{k=1}^{n}(t_k - \hat{t}_k)^2}{\sum_{k=1}^{n} t_k^2 - \frac{\sum_{i=1}^{n}\hat{t}_k^2}{n}} \tag{16}$$

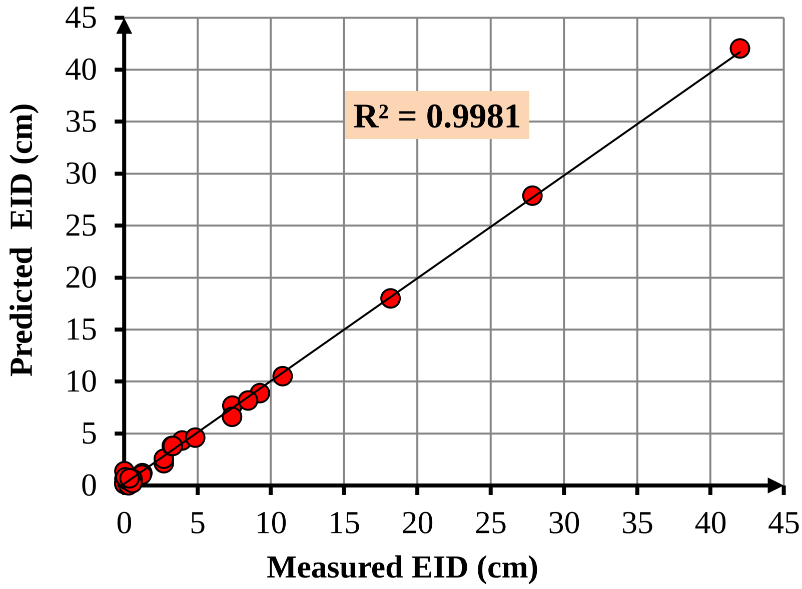
3.3 Algorithms Configuration

In the proposed RVR-GWO and RVR-DE, many parameters need to be set carefully. In the DE algorithm, maximum iterations number=80, population number (number of locations)=25, effective radius=5, power: the degree of the curve=2.88 and PP1: the convergence factor of the first loop=0.095. Also in the GWO algorithm, maximum iterations number=50 and population number (search agent)=25. To obtain a good performance of the RVR model, the parameter is set differently in each operation process. At last, the one much better than the mean value is chosen in this paper.

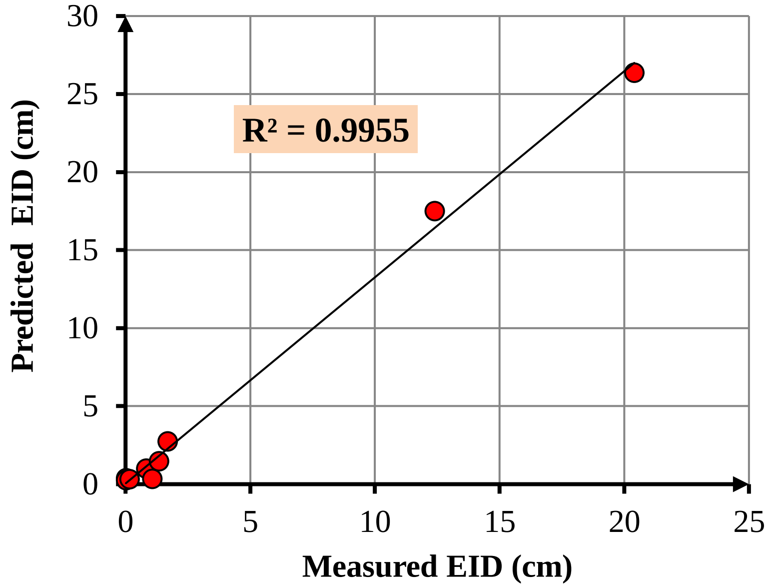
4. RESULTS AND DISCUSSIONS

In this study, RVR-GWO and RVR-DE models were utilized to build a prediction model for the forecasting of EID from available data, using MATLAB environment. All data (45 cases) were randomly divided into two subsets: 80% of the total data was allotted to training data of model construction and 20% of the total data was allocated for test data used to assess the reliability of the developed model. In these models, : H, γ, C, φ, $D_{5\text{–}95}$ and k_{max} were utilized as the input parameters, while the EID was the output parameter.

In data-driven system modeling methods, some pre-processing steps are commonly implemented prior to any calculations, to eliminate any outliers, missing values or bad data. This step ensures that the raw data retrieved from database is perfectly suitable for modeling. In order to softening the training procedure and improving the accuracy of prediction, all data samples are normalized to adapt to the interval [-1, 1] according to a linear mapping function. After modeling, a correlation between estimated values of EID by the RVR-GWO and RVR-DE models and measured values for training and testing phases is shown in Figs. 4 and 5. As shown in Figs. 4 and 5, the results of the RVR-GWO model in comparison with actual data show a good precision of the RVR-GWO model.

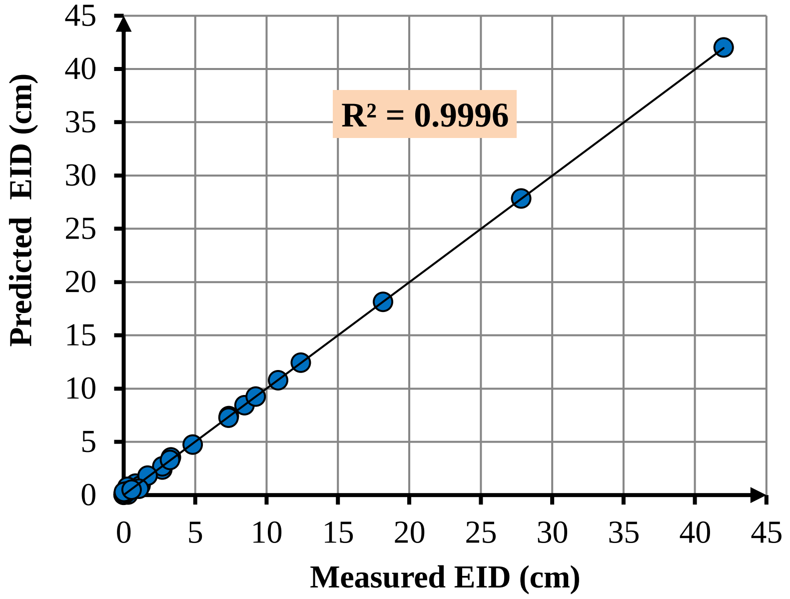


(a)

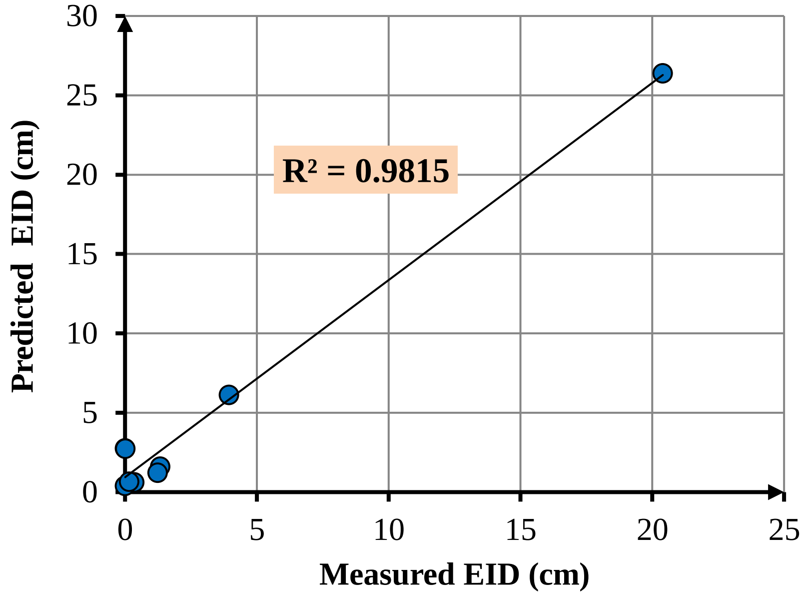


(b)

Figure 4: Correlation between measured and estimated EID using RVR-GWO model for (a) training datasets, (b) testing datasets.



(a)



(b)

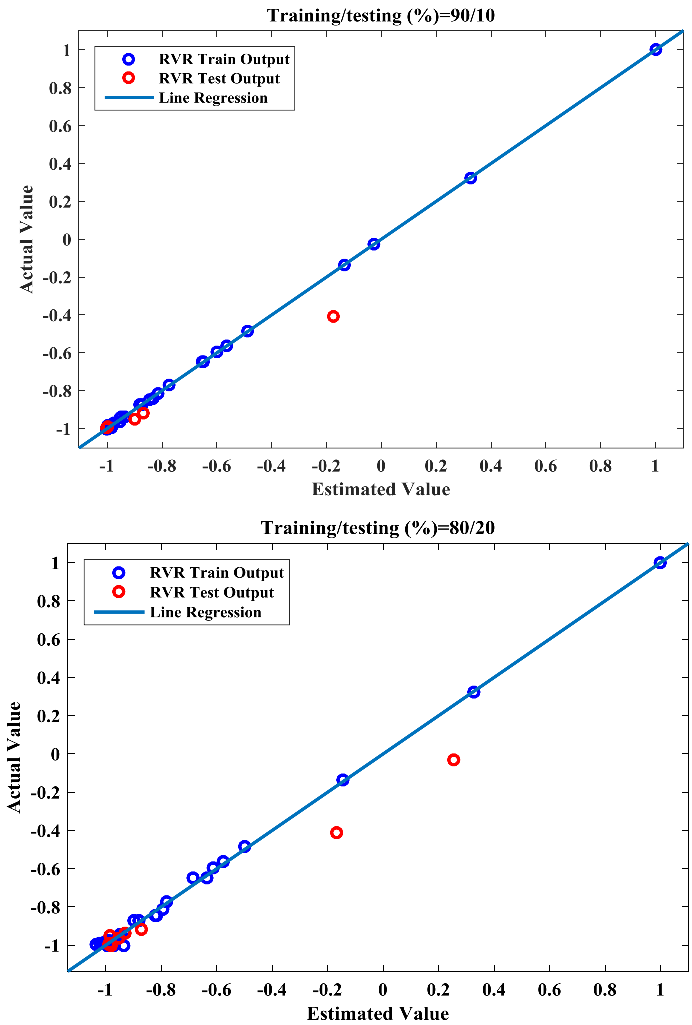
Figure 5: Correlation between measured and estimated EID using RVR-DE model for a) training datasets b) testing datasets

Also, performance analysis of the RVR-GWO and RVR-DE models for predicting EID is shown in Table 2. As presented in Table 2, the RVR-GWO model with MSE= 0.0160 and R^2= 0.9955 is found to be the best predictive model.

Table 2. Performance analysis of the RVR-GWO and RVR-DE models for forecasting of EID

Description		MSE	R^2
RVR-GWO model	Training	0.00044	0.9981
	Testing	0.01609	0.9955
RVR-GWO model	Training	0.00066	0.9996
	Testing	0.01578	0.9815

As it was mentioned, it seems that RVR-GWO model is a more accurate method in forecasting of EID during testing and training steps. However, this strong statement needs more approvals. As a matter of fact, there is one question which is yet required to be answered in this section: whether different fractions of training and testing data may change the performance of the models? This question would require many attempts with different fractions of data to show how the performance of the models may change with different numbers of training and testing data .



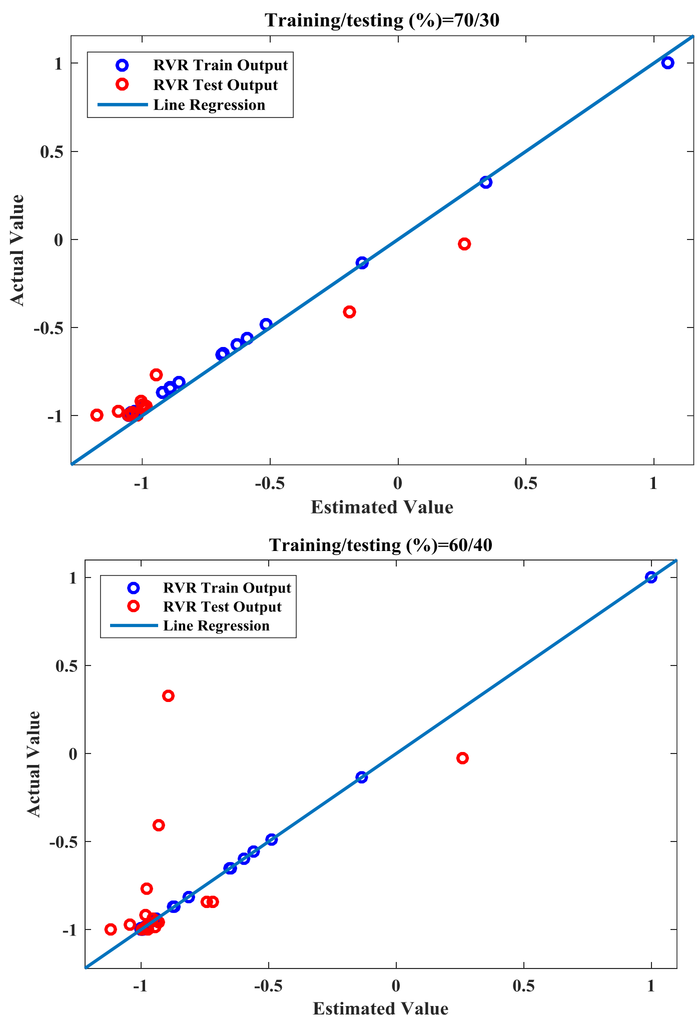


Figure 6. Comparing the performance of RVR-GWO model with different fractions of training and testing data.

Table 3 Comparing the performance of RVR-GWO model with different fractions of training and testing data.

Training/testing (%)	**Model**	**MSE (Train)**	**MSE (Test)**	**R^2 (Train)**	**R^2 (Test)**
90/10	RVR-GWO	0.00063	0.0249	0.9699	0.9826
80/20	RVR- GWO	0.00044	0.0160	0.9981	0.9955
70/30	RVR- GWO	0.00088	0.0182	0.9799	0.9777
60/40	RVR- GWO	0.00114	0.0198	0.9699	0.9684

According to Fig. 6 and Table 3, the MSE and R^2 of RVR-GWO model (for training/testing=80/20) is less than that of the other models in almost all of the cases indicating that it can be a better choice for prediction process. It is worth mentioning that the presented model was developed based upon the limited sets of data and cannot be generalized for all the slopes. However, it is open for more development if more data are available.

5. CONCLUSION

Displacements induced by earthquake are important, because displacements can be very large and result in severe damage to earth and earth supported structures. In this paper, a new approach namely RVR optimized by GWO and DE algorithms is proposed for predicting the EID. In our methodology, GWO and DE algorithms were applied as optimization tool for determining the optimal value of user defined parameters existing in formulation of RVR. The optimization implementation increases the performance of RVR model. The following conclusions were obtained:

The RVR-GWO with MSE= 0.0160 and R^2= 0.9955 is a reliable system modeling technique for forecasting of the EID with highly acceptable degree of accuracy and robustness.

Application of evolutionary algorithms significantly increases the speed and accuracy of finding optimal values of kernel parameters.

Implementation of the optimized RVR combined with evolutionary techniques can be applied as a powerful tool for modeling of non-linear problems encountered in civil and mining engineering.

REFERENCES

1. Keefer DK. Landslides caused by earthquakes, *Geol Soc Am Bull* 1984; **95**(4): 406-21.
2. Ambraseys N, Srbulov M. Earthquake induced displacements of slopes, *Soil Dyn Earthq Eng* 1995; **14**(1): 59-71.
3. Lin, J-S, Whitman, RV. Earthquake induced displacements of sliding blocks, *J Geotech Eng* 1986; **112**(1): 44-59.
4. Saygili G, Rathje EM. Empirical predictive models for earthquake-induced sliding displacements of slopes, *J Geotech Geoenviron* 2008; **134**(6): 790-803.
5. Carro M, De Amicis M, Luzi L, Marzorati S. The application of predictive modeling techniques to landslides induced by earthquakes: the case study of the 26 September 1997 Umbria–Marche earthquake (Italy), *Eng Geol* 2003; **69**(1-2): 139-59.
6. Refice A, Capolongo D. Probabilistic modeling of uncertainties in earthquake-induced landslide hazard assessment, *Comput Geosci* 2002; **28**(6): 735-49.
7. Rathje EM, Saygili G. Probabilistic assessment of earthquake-induced sliding displacements of natural slopes, *Bull New Zealand Soc Earthq Eng* 2009; **42**(1): 18-27.
8. Miles, SB, Keefer, DK. Evaluation of seismic slope-performance models using a regional case study, *Environ Eng Geo* 2000; **6**(1): 25-39.
9. Bray JD, Travasarou T. Simplified procedure for estimating earthquake-induced deviatoric slope displacements, *J Geotech Geoenviron* 2007; **133**(4): 381-92.
10. Jibson RW. Predicting earthquake-induced landslide displacements using Newmark's sliding block analysis, *Transport Res Rec* 1993; **1411**: 9-17.

11. Ling HI, Leshchinsky D. Seismic performance of simple slopes, *Soils Founda* 1995; **35**(2): 85-94.
12. Tipping, ME. Sparse Bayesian learning and the relevance vector machine, *J Mach Learn Res* 2001; **1**(June): 211-44.
13. Nisha MG, Pillai G. Nonlinear model predictive control with relevance vector regression and particle swarm optimization, *J Control Theory App* 2013; **11**(4): 563-9.
14. Gholami R, Moradzadeh A, Maleki S, Amiri S, Hanachi J. Applications of artificial intelligence methods in prediction of permeability in hydrocarbon reservoirs, *J Pet Sci Eng* 2014; **122**: 643-56.
15. Lou, J, Jiang, Y, Shen, Q, Wang, R. Failure prediction by relevance vector regression with improved quantum-inspired gravitational search, *J Network Comput Applic* 2018; **103**: 171-7.
16. Tipping ME. The relevance vector machine. In: Advances in neural information processing systems 2000, pp. 652-8
17. Mirjalili, S, Mirjalili, SM, Lewis, A. Grey wolf optimizer, *Adv Eng Softw* 2014; **69**: 46-61.
18. Mirjalili S, Saremi S, Mirjalili SM, Coelho LDS. Multi-objective grey wolf optimizer: a novel algorithm for multi-criterion optimization, *Expert Syst Appl* 2016; **47**: 106-19.
19. Kaveh A, Jafari L, Farhoudi N. Truss optimization with natural frequency constraints using a dolphin echolocation algorithm, *Asian J Civil Eng* 2015; **16**(1): 29-46.
20. Kaveh A, Farhoudi N. A new optimization method: Dolphin echolocation, *Adv Eng Softw* 2013; **59**: 53-70.
21. Ferentinou, M, Sakellariou, M. Computational intelligence tools for the prediction of slope performance, *Comput Geotech* 2007; **34**(5): 362-84.
22. Fattahi H. Application of improved support vector regression model for prediction of deformation modulus of a rock mass, *Eng Comput* 2016; **32**(4): 567-80.
23. Fattahi H, Moradi A. Risk assessment and estimation of TBM penetration rate using RES-based model, *Geotech Geol Eng* 2017; **35**(1): 365-76.
24. Fattahi H. Adaptive neuro fuzzy inference system based on fuzzy c–means clustering algorithm, a technique for estimation of TBM penetration rate, *Int J Optim Civil Eng* 2016; **6**(2): 159-71.