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Assessment of Lateral Displacements using Neuro-Fuzzy Group Method of Data Handling Systems

M. Goharriz, S. M. Marandi*

Department of Civil Engineering, Shahid Bahonar University of Kerman, Kerman, Iran

P A P E R I N F O

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A B S T R A C T

Lateral spreading is one of the most destructive effects of liquefaction. Liquefaction is known as one of the major causes of ground failure related to earthquake. This phenomenon is likely to occur when the rate of earthquake-induced excess pore water pressure buildup exceeds the rate of drainage. Estimation of the hazard of lateral spreading requires characterization of subsurface conditions. In this study, neuro-fuzzy group method of data handling (NF-GMDH) is utilized for assessment of lateral displacement in both ground slope and free face conditions. The NF-GMDH approach is improved using particle swarm optimization (PSO) algorithm. The comprehensive database used for the development of the model was obtained from different earthquakes. Contributions of the variables influencing the lateral displacement of soil are evaluated through a sensitivity analysis. Performance of the NF-GMDH-PSO models are compared with those yielded using empirical equations in terms of error indicators parameters and the advantages of the proposed models over the conventional method are discussed.

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1. INTRODUCTION

Lateral spreading, a phenomenon observed after occurrence of liquefaction, has caused extensive damage during many earthquakes (e.g., 1971 San Fernando, 1983 Nihonkai-Cihubu, and 1987 Superstition Hills). Prediction of liquefaction and the resulting lateral displacement is a complex engineering problem due to disparate nature of soils and participation of a large number of factors involved. Because of the participation of a large number of factors, the determination of liquefaction-induced lateral displacement is a complex geotechnical engineering problem. Several methods have been developed to predict lateral ground displacements using analytical [1], laboratory [2, 3], and finite element methods [4]. However, these methods have not been able to estimate lateral displacements caused by liquefaction with a good accuracy.

Assessment of liquefaction potential and determination of liquefaction induced lateral displacement have attracted considerable attention of geotechnical earthquake engineers in the past three decades [5-10]. Empirical models based on case histories have remained the more popular methods. Several researchers [11-15] introduced empirical correlations and multi-linear regression models for the assessment of liquefaction induced lateral displacement.

The progress of advanced computational methods for problems analysis has necessitated the accurate determination and estimation of lateral displacement. In the recent years, new aspects of modeling, optimization, and problem solving have been evolved in light of the pervasive development in computational software and hardware. These aspects of software engineering are referred to as soft computing based methods such as artificial intelligence which is a powerful tool for multivariate and nonlinear modeling. In case of complicated problems, experimentalists prefer these trial approaches rather than analytical optimization. A large number of researchers applied artificial intelligence (AI) models in the various fields of geotechnical engineering such as stress-strain modeling

*Corresponding Author's Email: marandi@uk.ac.ir (S.M. Marandi)

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of soil [16], slope stability [17], shallow foundations [18], and liquefaction [19].

In the past years, the GMDH networks provided successful evaluations in various field of geotechnical engineering sciences such as prediction of the scour depth around hydraulic structures [20-22] and estimation of the S_u-N_{SPT} correlation [23]. Application of the GMDH networks yielded relatively precise estimations than those obtained using empirical equations based regressive models. The main concern of the GMDH network is to present analytical solutions for various problems within a feed forward network in form of quadratic polynomial whose weighting coefficients are obtained using regression method [20, 21, 23].

In the recent decades, structure of the GMDH network has been improved based multi-stage fuzzy decision rule as neuro-fuzzy GMDH to obtained physical insights of problems with high degree of complexity. The NF-GMDH networks have been successfully applied to the different problems such as grinding characteristics, forecasting the unreliable mobile communication [24, 25]. The neuro-fuzzy GMDH has higher flexibility and lower complexity compared to the GMDH network. The Other advantages of the NF-GMDH models were presented in literatures [26-28].

In case of practical contributions, the NF-GMDH model in the field of geotechnical engineering has not been applied yet. In this study, a computer program is coded for the NF-GMDH network with MATLAB. Also, the PSO algorithm is applied in topology design of the NF-GMDH model for prediction of the lateral spread. The performance of the proposed NF-GMDH-PSO is evaluated with empirical equations based regression models.

2. DATA COLLECTION

2. 1. Influencing Factors on Lateral Displacement

Liquefaction occurrence and the resulting lateral displacement depend on the physical and mechanical characteristics of the soil layers in the site, the depth of the water table, the intensity and duration of the ground shaking, the distance from the source of the earthquake and the seismic attenuation properties of in situ soil. A thorough understanding of the factors affecting lateral ground displacement is needed in order to obtain accurate displacement predictions. Based on the previous researches e.g., [29], the most important factors that affect the lateral displacement due to liquefaction can be categorized as earthquake (earthquake magnitude, M; the nearest distance of site to the seismic energy source, R), topographical (slope of ground surface, S; free face ratio, W), and soil (the cumulative thickness of saturated cohesion-less layers with corrected blow counts of SPT $(N_1)_{60}$ less than 15, T_{15}; the average fines content for granular materials included within T_{15}, F_{15}; the average mean size for granular materials within T_{15}, $D50_{15}$) factors.

The difference between the two types of ground condition is reflected in the geometry of ground surface at the location of the displacement vectors. As shown in Figure 1, the free face case is characterized by the free face ratio (H/L), where H is the height of the free face (i.e., difference between the crest and toe elevations) and L is the horizontal distance from the toe of free face to the displacement vector.

2. 2. Data Analysis

In this paper, the authors reanalyze those available earthquakes data and an attempt is made to propose a model liquefaction-induced lateral ground displacement. A wide-range database was compiled from previously different earthquakes (1906 San Francisco, 1964 Anchorage, 1964 Niigata, 1971 San Fernando, 1979 Imperial Valley, 1983 Nihonkai-Chubu, 1983 Borah Peak, 1987 Superstition Hills, 1989 Loma Prieta, 1995 Hyogo-Ken Nanbu).

The database was divided into two separate groups denoted as training and testing sets consisting 80 and 20% of data, respectively. Once the training of the model has been successfully accomplished, the performance of the trained model is validated using the validation data, which have not been used as the part of model building process. The data division process was performed so that the main statistical parameters of the training and testing subsets (i.e., maximum, minimum, mean, and standard deviation) become close to each other. For this purpose, a trial selection procedure was carried out and the most possible consistent division was determined [30].

The case histories involving the lateral displacement towards a free face and those corresponding to gently sloping ground, have been analyzed separately. The lateral displacement database includes 426 case histories gathered from the literature. In the collected database, 219 cases are related to sloping ground condition and the 207 cases involve free face ground. Descriptive statistics of these two groups variables used in the model development for both sloping ground and free face conditions are presented in Table 1.

In the model development, the parameters M, R, W, S, T_{15}, F_{15}, and $D50_{15}$ used as inputs parameters and lateral ground displacement (D_h) was the single output variable.

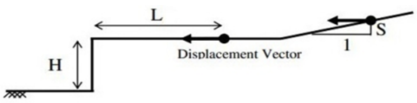

Figure 1. Topography related to free face and sloping ground conditions

3. DESCRIPTIONS OF THE NF-GMDH MODEL

The GMDH network is a learning machine based on the principle of heuristic self-organizing, proposed by Ivakhnenko in the 1960s [31]. Also, it is a series of operations of seeding, rearing, crossbreeding, selection and rejection of seeds correspond to the determination of the input variables, structure and parameters of model, and selection of model by principle of termination [32]. The other descriptions of the GMDH network were presented in literatures [20-22, 33]

In this paper, a neuro-fuzzy GMDH model based PSO algorithm has been proposed for the lateral spread prediction. The structure of neuro-fuzzy GMDH is constructed automatically using heuristic self-organized algorithm [25, 26]. The neuro-fuzzy GMDH network is a very flexible algorithm and it can be hybridized easily by other iterative and evolutionary algorithms. Furthermore, a simplified fuzzy reasoning rule is utilized to improve the GMDH network as follows [34]:

If x_1 is F_{k1} and x_2 is F_{k2}, then, output y is w_k .Gaussian membership function is used in term of F_{kj} which is related to the k^{th} fuzzy rules in the domain of the j^{th} input values x_j.

$$F_{kj}(x_j) = \exp(-(x_j - a_{kj})^2 / b_{kj}) \tag{1}$$

where, a_{kj} and b_{kj} are constant values for each rules. Also, the y parameter is defined as output that has been expressed as follows:

$$y = \sum_{k=1}^{K} u_k w_k \tag{2}$$

$$u_k = \prod_j F_{kj}(x_j) \tag{3}$$

where, w_k is real value for k^{th} fuzzy rules [25, 34].

The NF-GMDH model is one of the adaptive learning networks that have hierarchical structure. In this model, each neuron has two input variables and one output. General configuration of the neuro-fuzzy GMDH with two fuzzy rules for each partial description (PD) was presented in Figure 2.

Through Figure 2, output of each neuron in a layer is considered as the input variable in the next layer. The final output is calculated using the average of the outputs from the last layer. From Figure 2, it can be said that the inputs from the m^{th} model and p^{th} layer are the output variables of the $(m\text{-}1)^{th}$ and m^{th} model in the $(p\text{-}1)^{th}$ layer. The mathematical function for calculating y^{pm} is,

$$y^{pm} = f(y^{p-1,m-1}, y^{p-1,m}) = \sum_{k=1}^{K} \mu_k^{pm}.w_k^{pm} \tag{4}$$

$$\mu_k^{pm} = \exp\left\{-\frac{(y^{p-1,m-1} - a_{k,1}^{pm})^2}{b_{k,1}^{pm}} - \frac{(y^{p-1,m} - a_{k,2}^{pm})^2}{b_{k,2}^{pm}}\right\} \tag{5}$$

where, μ_k^{pm} and w_k^{pm} are the k^{th} Gaussian function and its corresponding weight parameter, respectively, that are related to the m^{th} model in the p^{th} layer. In addition, a_k^{pm} and b_k^{pm} are the Gaussian parameters that are utilized for the i^{th} input variable from the m^{th} model and p^{th} layer.

$$y = \frac{1}{M}\sum_{m=1}^{M} y^{pm} \tag{6}$$

Also, the final output is expressed using following function: The learning process of feed forward neuro-fuzzy GMDH network is known as an iterative method to solve the complicated systems. In each iteration, the error parameter for the network can be obtained as follows:

$$E = \frac{1}{2}(y^* - y)^2 \tag{7}$$

which y^* is the predicted value.

4. DEVELOPMENT OF THE NEURO-FUZZY GMDH MODEL

In this section, the NF-GMDH model is developed using PSO algorithm. The basic structure of NF-GMDH has been consisted of partial descriptions (neurons). As mentioned in previous section, grouped parameters in form of Gaussian variables and weights related to the fuzzy rule are unknown in each partial description (PD). PSO algorithm has been applied to optimized grouped-unknown parameters in PDs [25, 26]. Performing the NF-GMDH and PSO models is a parallel action in each PD. Also, two fuzzy rules were used to model the neuro-fuzzy in each PD. The NF-GMDH-PSO model has four inputs and one output. Through modeling the NF-GMDH-PSO model for the lateral spread in free face, 45 partial descriptions (PDs) were produced in the first layer.

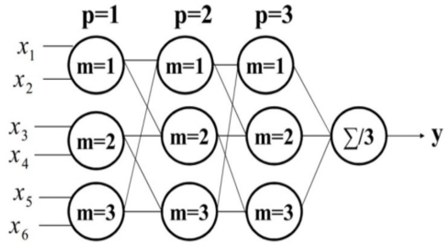

Figure 2. General structure of the NF-GMDH

After that the second layer was generated using 45 PDs from the first layer. This process could be continued until minimum error of training network is obtained [28]. In conclusion, the NF-GMDH-PSO network was modeled with three layers, 45 PDs, and 90 fuzzy rules generated through an optimization process. In addition, for ground status, the proposed NF-GMDH-PSO model has three layers with 30 PDs and 60 fuzzy rules. Figures 3 and 4 illustrated proposed structures of the NF-GMDH-PSO for prediction of lateral spread in free face and ground conditions, respectively. Table 2 indicates the values of the PSO properties for predicting the lateral spread in both conditions. Furthermore, three of partial descriptions (PDs) generated in the first layer of the proposed NF-GMDH-PSO networks were expressed as follows: For free face conditions:

$$(D_h)_1^1 = 0.321\exp[-\frac{(M-0.8152)^2}{1.5}-\frac{(R-0.8152)^2}{1.5}]+ 1.0788\exp[-\frac{(M-0.3917)^2}{0.01}-\frac{(R-0.3917)^2}{0.01}] \tag{8}$$

And, for ground status: the superscript and subscript of each parameter present the number of pertaining layer and partial description, respectively.

$$(D_h)_2^1 = 0.8656\exp[-\frac{(R-1.5)^2}{0.4856}-\frac{(W-1.5)^2}{0.4856}]+ 0.3689\exp[-\frac{(R-0.5253)^2}{0.6089}-\frac{(W-0.5253)^2}{0.6098}] \tag{9}$$

$$(D_h)_3^1 = 0.8344\exp[-\frac{(W-1.3703)^2}{1.4927}-\frac{(T_{15}-1.3703)^2}{1.4927}]+ 0.3817\exp[-\frac{(W-1.417)^2}{1.1325}-\frac{(T_{15}-1.417)^2}{1.1325}] \tag{10}$$

$$(D_h)_1^1 = 0.5337\exp[-\frac{(R-0.5214)^2}{0.5326}-\frac{(S-0.5214)^2}{0.5326}]+ 0.7945\exp[-\frac{(R-1.0933)^2}{1.4429}-\frac{(S-1.0933)^2}{1.4429}] \tag{11}$$

$$(D_h)_2^1 = 0.5242\exp[-\frac{(S-0.5384)^2}{1.0855}-\frac{(T_{15}-0.5384)^2}{1.0855}]+ 1.1171\exp[-\frac{(S-1.3952)^2}{0.1}-\frac{(T_{15}-1.3952)^2}{0.1}] \tag{12}$$

$$(D_h)_3^1 = 0.2207\exp[-\frac{(T_{15}-0.1)^2}{0.9413}-\frac{(F_{15}-0.1)^2}{0.9413}]+ 0.5294\exp[-\frac{(T_{15}-0.8705)^2}{1.3274}-\frac{(F_{15}-0.8705)^2}{1.3274}] \tag{13}$$

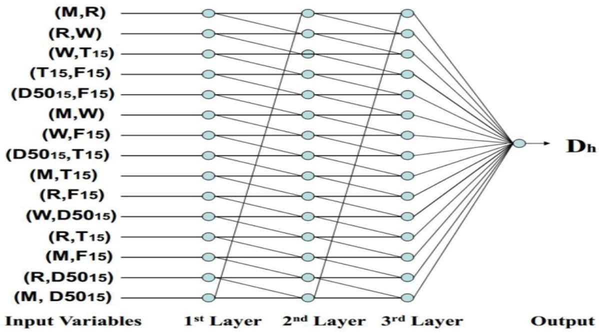

Figure 3. Proposed structure of the NF-GMDH-PSO model for prediction of the lateral spread in free face conditions

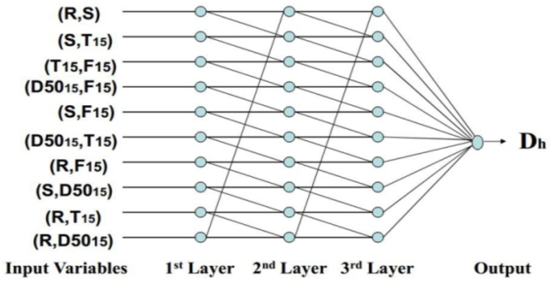

Figure 4. Proposed structure of the NF-GMDH-PSO model for prediction of the lateral spread in sloping ground conditions

TABLE 1. Descriptive Statistics of the Variables Used In the Models Development

Model	Variables		All data				Training stage				Testing stage			
			Max.[a]	Min.[b]	Mean	S.D.[c]	Max.	Min.	Mean	SD	Max.	Min.	Mean	SD
Free face	Inputs	M	9.2	6.4	7.19	0.54	9.2	6.4	7.17	0.55	9.2	6.4	7.27	0.53
		R (km)	100	0.5	18.12	16.03	100	0.5	17.38	15.5	95	0.5	21.13	19.1
		W (%)	56.8	1.64	11.21	9.19	56.8	1.64	11.31	9.38	41.38	2.27	10.83	8.45
		T_{15} (m)	16.7	0.2	8.36	4.87	16	0.2	8.2	4.87	16.7	0.5	9.02	4.86
		F_{15} (%)	70	1	17.86	13.54	70	1	18.13	13.92	47	3	16.78	11.94
		$D50_{15}$ (mm)	1.98	0.04	0.36	0.42	1.98	0.04	0.37	0.44	1.98	0.07	0.33	0.33
	Output	D_h (m)	10.16	0.01	251	2.29	10.16	0.01	2.61	2.36	8.39	0.01	2.1	1.95
Sloping ground	Inputs	M	9.2	6.4	7.53	0.37	9.2	6.4	7.55	0.33	7.7	6.4	7.43	0.34
		R (km)	100	0.2	24.26	12.62	100	0.2	24.91	13.1	65	0.2	21.69	10.35
		S (%)	11	0.05	1.05	1.62	11	0.05	0.92	1.2	11	0.21	1.54	2.68
		T_{15} (m)	19.7	0.01	6.49	3.94	19.7	0.01	6.63	3.94	11.6	0.7	5.95	3.95
		F_{15} (%)	68	0	9.53	11.53	59	0	9	10.41	68	0	11.66	15.16
		$D50_{15}$ (mm)	12	0.06	0.44	1.06	10	0.06	0.38	0.74	12	0.06	0.7	1.84
	Output	D_h (m)	3036	0.01	1.89	1.02	3.36	0.01	1.92	1.03	3.55	0.01	1.77	1.01

TABLE 2. Values of the PSO Properties for Predicting the D_h Parameter

Parameter	Range
Omega	0.04-0.09
Number of Particles	40
Number of Variables	6
Maximum Iteration	100
error	0.00001
C_1 and C_2	2.5
Weighting Coefficients	0-1.5

5. MODEL PERFORMANCE

In order to examine the robustness of the proposed models, the coefficient of determination (R^2), mean absolute error (MAE), and root mean squared error (RMSE) between the measured and predicted lateral displacement (D_h) were obtained according to the following equations:

$$R^2 = \frac{\sum_{i=1}^{n}\left(x_i^m\right)^2 - \sum_{i=1}^{n}\left(x_i^m - x_i^p\right)^2}{\sum_{i=1}^{n}\left(x_i^m\right)^2} \tag{14}$$

$$MAE = \frac{\sum_{i=1}^{n}\left|\left(x_i^m - x_i^p\right)\right|}{n} \tag{15}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(x_i^m - x_i^p\right)^2}{n}} \tag{16}$$

where, N is the number of data, x_i^m and x_i^p is measured and predicted values, respectively.

6. RESULTS

Numerous runs were performed with various initial settings and the performance of the developed model was analyzed for each run. Consequently, the best model was selected according to statistical criteria such as R^2, MAE and RMSE. In addition, a comprehensive parametric study was performed to monitor the behavior of each model versus variations of input variables. Proposed NF-GMDH based model that selected as most appropriate model, was constituted by six input parameters (M, R, W or S, T_{15}, F_{15}, $D50_{15}$) and one output (D_h).

Precision of the proposed model is examined by plotting the observed versus predicted values of the lateral displacement (D_h) for training, testing, and all data as shown in Figsures 5-10, respectively.

The results shown in Figures 5–7 indicate reasonable good performance of NF-GMDH based model for assessment of lateral displacement of free face cases because the predicted values are satisfactorily distributed between two lines illustrating 0.6 and 1.4 times of observed values. In the free face condition, the values of R^2, MAE, and RMSE are equal to 0.916, 0.462, and 0.664, respectively, for training sets (Figure 5) and 0.897, 0.545, and 0.742, respectively, for testing sets (Figure 6). Figures 8-10 depicts good accuracy of NF-GMDH based model for predicting D_h of sloping ground cases because the predicted values are distributed between two lines illustrating 0.7 and 1.3 times of observed values. Figures 8 and 9 illustrate the observed and predicted lateral displacement values of sloping ground cases for training (R^2=0.907, MAE=0.252, RMSE=0.312) and testing (R^2=0.892, MAE=0.270, RMSE=0.331), respectively.

The values of statistical parameters of neuro-fuzzy group method of data handling (NF-GMDH) based model for training, testing, and all data set are presented in Table 3.

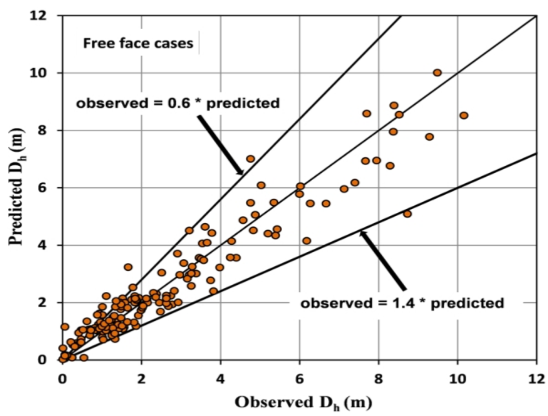

Figure 5. Measured versus predicted values of D_h for free face cases - training data set

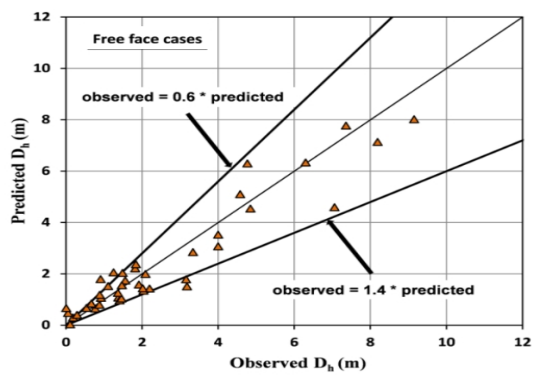

Figure 6. Measured versus predicted values of D_h for free face cases - testing data set

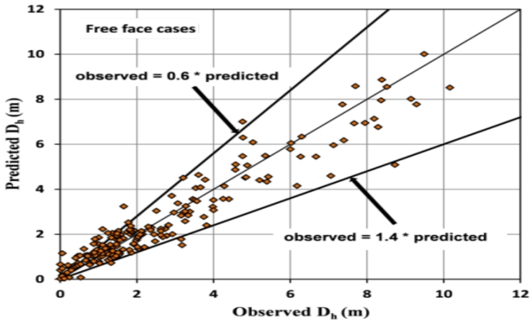

Figure 7. Measured versus predicted values of D_h for free face cases - all data

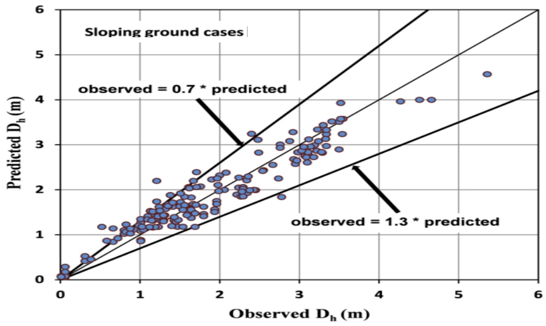

Figure 8. Measured versus predicted values of D_h for sloping ground cases - training data set

TABLE 3. Target Statistical Parameters of NF-GMDH Based Models

Group	Performance					
	Free face			Sloping ground		
	R^2	MAE	RMSE	R^2	MAE	RMSE
Training	0.916	0.462	0.664	0.907	0.252	0.312
Testing	0.897	0.545	0.742	0.892	0.270	0.331
All data	0.911	0.481	0.680	0.905	0.256	0.315

7. MODELS ACCURACY

Difference between the observed D_h to the values predicted by the NF-GMDH based model for free face conditions as relative error, with respect to the free face ratio, *W*, and T_{15} for all data set is shown in Figures 9 (a, b). As the scattering increases in this figure, the accuracy of the model consequently decreases. It is observed that the developed model can predict the D_h of free face cases with reasonable accuracy because the relative error is satisfactorily distributed between two lines illustrating $\pm 1m$ relative error.

Besides, Figures 10 (*a*, *b*) presented the relative errors values of NF-GMDH based models for prediction of lateral displacement (D_h) in sloping ground conditions with respect to variation of slope of ground surface, *S*, and T_{15}. These figures indicate that the proposed model has high accuracy in evaluation of lateral displacement in both free face and sloping ground cases.

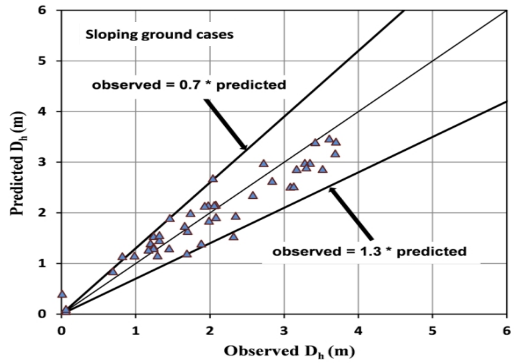

Figure 9. Measured versus predicted values of D_h for sloping ground cases - testing data set

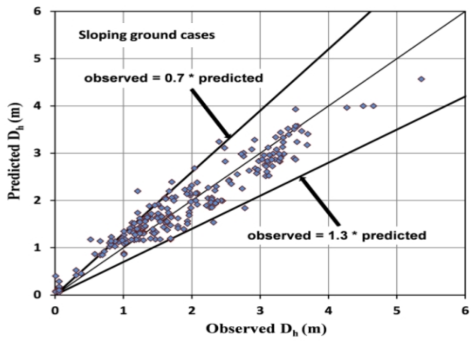

Figure 10. Measured versus predicted values of D_h for sloping ground cases - all element tests data

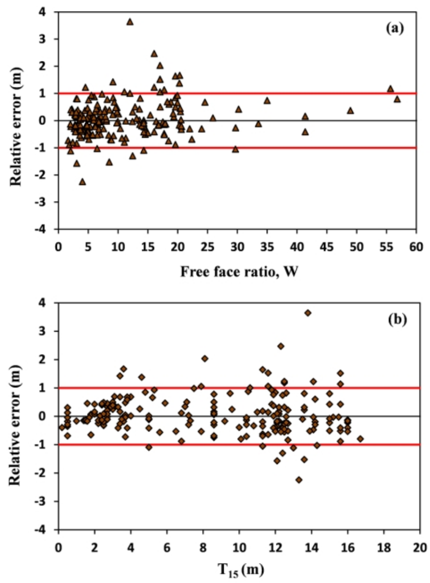

Figure 11. Variation of relative error of NF-GMDH based model for free face cases, *a*) with respect to W, *b*) with respect to T_{15}

8. COMPARISON WITH PREVIOUS STUDIES

Predictions of some previously published empirical relations for evaluation of lateral displacement are compared with the D_h values predicted by the proposed neuro-fuzzy group method of data handling (NF-GMDH) model. Table 4 presents these equations. Due to complexities of the liquefaction-induced lateral displacement phenomenon, the aforementioned constitutive models as well as simplified analytical methods have failed to capture the full effect. Thus, empirical models based on case histories have remained as a popular method in the past decades. Bardet et al. (1999), Youd et al. (2002), and Kanibir (2003) introduced empirical correlations and multi-linear regression (MLR) models for the assessment of lateral displacement (D_h). Table 5 presents the values of R^2, MAE, and RMSE for the proposed NF-GMDH based model, and the values estimated by empirical relations (Table 4) for lateral displacement (D_h) in free face and sloping ground cases. The results presented in this table confirm higher precision of the proposed NF-GMDH based model with respect to the previously equations.

The developed NF-GMDH model is proposed as an applicable and more reliable tool for predicting liquefaction induced lateral displacement because it was developed using a comprehensive database of the previously documented results.

9. SUMMARY AND CONCLUSIONS

Determination of liquefaction induced lateral spreading is complex geotechnical engineering problem. A robust neuro-fuzzy group method of data handling (NF-GMDH) based model was developed for assessment of liquefaction induced lateral displacement using a large data. A wide-range database of case histories consisting of 426 data of liquefaction-induced lateral displacement for free face and sloping ground conditions from ten earthquakes were compiled and analyzed.

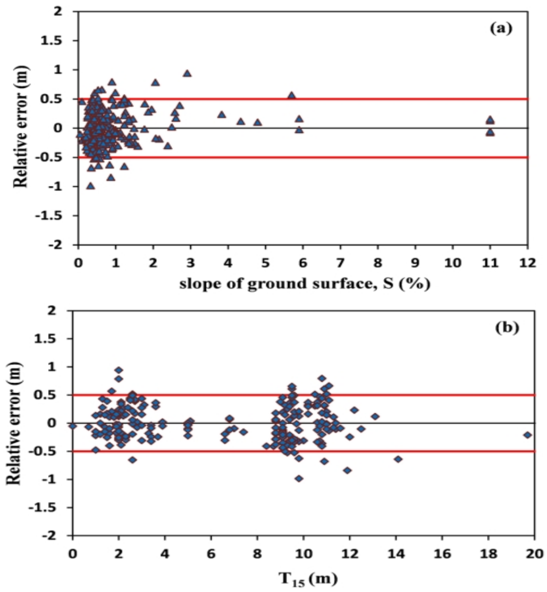

Figure 12. Variation of relative error of NF-GMDH based model for sloping ground cases, *a*) with respect to S, *b*) with respect to T_{15}

TABLE 4. Some Empirical Relations for Prediction of the Lateral Displacement

Reference	Subset	Model
Kanibir (2003)	**Free face**	$\log D_k = -20.71 + 25.32\log M - 1.39\log\left(10^{(0.89M-5.64)} + R\right) - 0.009R + 1.15\log W + 0.19T_{15}0.5 - 0.02F_{15} - 0.84\log\left(D50_{15} + 0.1mm\right)$
	Sloping ground	$\log D_k = -7.52 + 8.44\log M + 0.001\left(10^{(0.89M-5.64)} + R\right) - 0.23R + 0.115 + 0.6\log T_{15} - 0.22F_{15} - 0.89\log D50_{15}$
Youd et al. (2002)	**Free face**	$\log D_k = -16.713 + 1.532M - 1.406\log\left(10^{(0.89M-5.64)} + R\right) - 0.012R + 0.592\log W + 0.540\log T_{15} + 3.413\log\left(100 - F_{15}\right) - 0.795\log\left(D50_{15} + 0.1mm\right)$
	Sloping ground	$\log D_k = -16.213 + 1.532M - 1.406\log\left(10^{(0.89M-5.64)} + R\right) - 0.012R + 0.338\log S + 0.540\log T_{15} + 3.413 \log\left(100 - F_{15}\right) - 0.795\log\left(D50_{15} + 0.1mm\right)$
Bardet et al. (1999)	**Free face**	$\log\left(D_k + 0.01\right) = -17.372 + 1.248M - 0.923\log R - 0.014R + 0.685\log W + 0.3\log T_{15} + 4.826\log\left(100 - F_{15}\right) - 1.091D50_{15}$
	Sloping ground	$\log\left(D_k + 0.01\right) = -14.152 + 0.988M - 1.049\log R - 0.011R + 0.318\log S + 0.619\log T_{15} + 4.287\log\left(100 - F_{15}\right) - 0.705D50_{15}$

TABLE 5. Comparison between Statistical Parameters for NF-GMDH Based Model and Previous Models

Model	Performance					
	Free face			Sloping ground		
	R^2	MAE	RMSE	R^2	MAE	RMSE
NF-GMDH model (this study)	0.911	0.481	0.680	0.905	0.256	0.315
Kanibir (2003)	0.681	0.600	0.654	0.628	0.514	0.612
Youd et al. (2002)	0.791	2.335	3.061	0.517	1.728	1.915
Bardet et al. (1999)	0.698	0.832	1.257	0.574	0.509	0.667

Based on data analysis and the previous researches liquefaction phenomena, the most important factors that affect the lateral displacement (D_h) due to liquefaction categorized as seismological (M, R), topographical (S, W), and geotechnical (T_{15}, F_{15}, $D50_{15}$) parameters.

It was shown that in both free face and sloping ground cases the NF-GMDH based models are able to learn, with a very high accuracy, the complex relationship between liquefaction and its contributing factors in the form of a function. They can also generalize the learning to provide predictions for new cases which not used in the construction of the model. The results obtained in this study indicate that the new NF-GMDH based model has ability to predict the lateral displacement with an acceptable degree of accuracy in both free face condition (R^2 = 0.911, MAE = 0.481, RMSE = 0.680) and slping ground condition (R^2 = 0.905, MAE = 0.256, RMSE = 0.315) for displacements ranging from 0.01 to 10.16*m*, and 0.01 to 3.36*m*, respectively. A comparison between the performance of the developed model and some previously published relations has been done. It is clearly observed that the NF-GMDH based model yields a much better performance than the previous relations. The results of comparison confirm higher precision of the proposed model. This accuracy shows the superiority of the proposed NF-GMDH model over relations and models, and suggests that the model can be applied in engineering practice.

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Assessment of Lateral Displacements using Neuro-Fuzzy Group Method of Data Handling Systems

M. Goharriz, S. M. Marandi

Department of Civil Engineering, Shahid Bahonar University of Kerman, Kerman, Iran

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چکيده

روانگرایی به عنوان یکی از علل عمده خسارتهای ناشی از زلزله شناخته شده است.گسترش جانبی نیز یکی از مخربترین آثار پدیدهی روانگرایی به شمار می آید. در مواقعی که میزان فشار آب حفرهای ایجاد شده در اثر بارگذاری زلزله فراتر از نرخ زهکشی باشد، احتمال بروز این پدیده بیشتر خواهد شد. برآورد میزان گسترش جانبی نیازمند شناسایی های زیرسطحی میباشد که خود یکی از پرهزینه ترین تحقیقات ژئوتکنیکی میباشد. از اینرو در این تحقیق، ترکیب فازی عصبی و الگوریتم دسته بندی گروهی داده ها (NF-GMDH) به منظور ارزیابی گسترش جانبی در شرایط زمین مسطح و وجه آزاد استفاده شد. ترکیب NF-GMDH با استفاده از الگوریتم ازدحام ذرات (PSO) توسعه داده شد. مجموعه وسیعی از نتایج زلزله های مختلف جهت ارائه ی مدلهای پیشنهادی بکار گرفته شد. انتخاب مهمترین پارامترهای مؤثر بر گسترش جانبی با استفاده از آنالیز حساسیت انتخاب گردید. عملکرد مدلهای مبتنی بر NF-GMDH-PSO با روابط و مدلهای موجود مقایسه گردید. نتایج بیانگر دقت بالای مدلهای پیشنهادی در ارزیابی گسترش جانبی ناشی از روانگرایی میباشد.

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