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ORIGINAL ARTICLE

Assessment of shear stiffness ratio of cohesionless soils using neural modeling

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Abstract Properly estimating strain-dependent shear stiffness of soils is necessary for accurate analysis of soil-structure interaction and seismic ground response problems during earthquake motions. In this research, an artificial neural network (ANN) model was developed for shear stiffness ratio of cohesionless soils. The input variables in this model are shear strain amplitude (γ), effective confining pressure (σ'_0), mean grain size (D_{50}), and relative density (D_r) and output is shear stiffness ratio (G/G_{max}). A large experimental database was compiled from available published laboratory cyclic tests. Validation of model was carried out with using centrifuge tests results. Subsequently, sensitivity analysis and model accuracy was conducted. Finally, proposed model has been compared with other researcher's relationships. The results clearly demonstrate the good performance and capability of the proposed ANN-based model.

Keywords Experimental database · Shear stiffness · Cohesionless soils · Artificial neural network

Abbreviations

ANN	Artificial neural network
G	Shear stiffness
G_{max}	Shear stiffness at small strains
G/G_{max}	Shear stiffness ratio
D_{50}	Mean grain size
D_r	Relative density
σ'_0	Effective confining pressure
γ	Shear strain amplitude
e	Void ratio
R^2	Coefficient of determination
MAE	Mean absolute error
RMSE	Root mean squared error
Min.	Minimum
Max.	Maximum
S.D.	Standard deviation
N	Number of data
X_m	Measured value
X_p	Predicted value

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Introduction

Dynamic analysis to assess the reaction of the earth systems to stress applications, such as those created by wind loading, earthquakes or blasting are finding increased utilizations in practical projects in geotechnical engineering. Various analytical models and idealized procedures may be employed to display seismic response of a soil deposit (Nimtaj and Javdanian 2014). Regardless of kind of techniques, it is first essential to assess the precise dynamic properties of the soil deposits. Accurate evaluation of soil dynamic properties is partly a difficult issue in the solution of geotechnical earthquake problems.

One of the basic knowledge needed to evaluated the earthquake response and dynamic stability of ground is the dynamic properties of geomaterials. Several laboratory techniques are available to evaluate the dynamic soil properties at large strain and low strain amplitudes. To evaluate shear stiffness, *G*, of cohesionless soils, much laboratory research have been carried out using apparatuses such as cyclic simple shear, cyclic triaxial, cyclic torsional shear and resonant column (e.g., Kokusho 1980; Saxena and

Reddy 1989; Yasuda and Matsumoto 1993; Hardin and Kalinski 2005; Xenaki and Athanasopoulos 2008; Aghaei Araei et al. 2010; Jafarian et al. 2015, 2016a, b; Dammala et al. 2017).

Numerous studies have been performed to characterize the influential factors on the shear stiffness ratio of soils (e.g., Hardin and Drnevich 1972; Ishibashi and Zhang 1993; Stokoe et al. 1994; Darendeli 2001; Roblee and Chiou 2004). On the basis of these studies, the most significant parameters that affect G/G_{max} include effective confining pressure and shear strain amplitude.

Iwasaki and Tatsuoka (1977) and Tatsuoka et al. (1978) in their series of investigations relating to shear stiffness for different soils found that the grain size distribution affect the dynamic characteristics of sandy soils. Void ratio (e) or relative density (D_r) are as the parameters that control nonlinear soil behavior. These parameters can affect shear stiffness ratio of cohesive and cohesionless soils (Darendeli 2001).

The progress of computational methods for dynamic analysis has necessitated the precise specification and estimation of dynamic soil properties. In the past years, novel aspects of problem solving, modeling, and optimization have been evolved with respect to the universal development in computational software (Dehghani et al. 2017; Wagh et al. 2017). These aspects are referred to artificial intelligence such as artificial neural networks (ANNs). For intricate problems, experimentalists prefer these approaches in comparison to numerical and analytical methods. Many researchers utilized artificial intelligence approaches in different projects of geotechnical engineering such as behavior of shallow footings (Javdanian et al. 2012; Shahin et al. 2002), stress–strain modeling of soil (Ellis et al. 1995), soil slope stability (McCombie and Wilkinson 2002), soil liquefaction potential (Baziar and Jafarian 2007; Javdanian et al. 2017), dynamic properties of cohesive soils (Jafarian et al. 2014; Javdanian et al. 2015a, b), soil water content (Fashi 2016), ground lateral spreading (Javadi et al. 2006; Javdanian and Seidali 2016), strong ground motions (Jafarian et al. 2010), and deformation of rock masses (Gholami and Bodaghi 2017).

Numerous experimental data were recorded within the previous laboratory studies. These valuable data provide feasibility to develop a predictive model for the shear stiffness ratio (G/G_{max}) of soils. In spite of extensive practical applications of G/G_{max}, review of the available studies reveals lack of a precise model for this significant parameter. The current research aims to develop an ANN-based model for predicting the G/G_{max} of cohesionless soils in terms of confining pressure, σ'_0 (kPa), shear strain amplitude, γ (%), relative density, D_r (%), and mean grain size, D_{50} (mm) based on a comprehensive database of cyclic laboratory tests performed during the previous studies. It is clear that an accurate model is easier to be utilized in the usual geotechnical projects compared with the field-based assessment or laboratory techniques.

Description of ANN

During the past years, artificial neural network (ANN) based models have been utilized for estimation purposes in earth sciences extensively. Artificial neural networks (ANNs) are receiving increased consideration as a flexible, powerful, statistical modeling method for discovering patterns in various data (Javan et al. 2015; Parsaie et al. 2016; Keshavarzi et al. 2016).

Artificial Neural network is a mathematical form of the combinations of biological neural of the central nervous system (Wasserman 1989; Alexhander and Morton 1993; Arbib 1995; Anderson 1995). It can represent a significant number of characteristics of human brain e.g. learn from previous examples and experience to new problems. There are a lot of connections between inputs and outputs in ANNs. Using these connections between neurons receive a transmission value which is called as weight. For every new data the weights could be renewed. The ANNs are systems combined of many simple processing elements whose functions are specified on the basis of connection pattern primarily. These systems are capable of complex operations such as learning or adaptation, and simple operations such as pre-processing of data for various types of inputs. The main elements of process in the ANNs are neurons. A neuron includes three main parts namely activation function, bias and weights. The number of neurons in each layer of network may change in related to the problem. Details of the structure and operation of ANNs can be found in many publications (Smith 1993; Fausett 1994; Galushkin 2007).

Experimental database

A large experimental database was compiled from available published laboratory tests. The database consists resonant column (Iwasaki et al. 1978; Ribay et al. 2004; Senetakis et al. 2011, 2012), cyclic torsional shear (Iwasaki et al. 1978) and cyclic triaxial tests (Goto et al. 1992; Rollins et al. 1998) and. These studies conducted on sandy (e.g., Fontainebleau sand and Toyoura sand) and gravelly soils (e.g., riverbed of Tone river, north of Kumagaya-City, Saitama Prefecture) to determine the dynamic properties of cohesionless soils at large strain and low strain amplitudes. The G/G_{max} versus γ data gathered for cohesionless soils in this research shown in Fig. 1. Inputs and output variables employed in the development of ANN model introduced in Table 1.

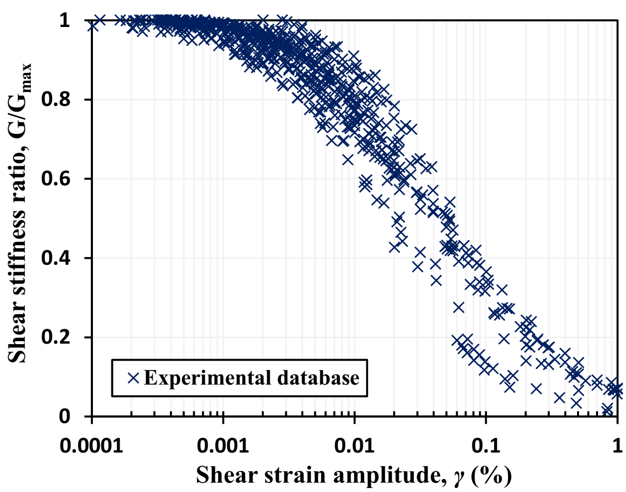

Fig. 1 Gathered experimental database for cohesionless soils based on laboratory cyclic tests

Table 1 Inputs and output variables

	Parameter
Inputs	
Effective confining pressure	σ'_0 (kPa)
Shear strain amplitude	γ(%)
Mean grain size	D_{50} (mm)
Relative density	D_r (%)
Output	
Shear stiffness ratio	G/G_{max}

The experimental database was separated into two groups denoted as training set and testing set including 80 and 20% of data, respectively. The testing data set was used to characterize when training stage must be stopped to avoid overfitting. The process of data division was conducted so that the main statistical index of the training data and testing data sets (i.e., minimum, maximum, standard deviation, and mean) become close to each other. Therefore, a trial selection method was performed and the most possible consistent division was specified (Masters 1993). Descriptive statistics of these two groups variables illustrated in Table 2.

In addition to the training and testing subsets, the results of centrifuge modeling of Brennan et al. (2005) were also utilized as validation set for further generalization an examination of performance of the developed model. The number of data considered for training set, testing set and validation set illustrated in Table 3.

Another collection of experimental data employed to examine the generality of the developed ANN models for future predictions. In this research, 65 tests result of centrifuge physical modeling (Brennan et al. 2005) were utilized as validation set (Table 3).

Model development

Clearly, the importance of current subject is shown in extensive previous experimental studies and proposed. Hence, a powerful tool is needed to assess the shear stiffness ratio of cohesionless soils. A feed-forward with backpropagation algorithm was employed to develop the favorable ANN-based model. A network training rule that updates bias and weight values based on Levenberg–Marquardt algorithm (Levenberg 1944; Marquardt 1963) was utilized. This algorithm appears to be the fastest procedure for training process of moderate-sized feed-forward artificial neural networks. Also, this algorithm gives more accurate results in terms of convergence speed than various training algorithm (Zayani et al. 2008). Input parameters include: shear strain, confining pressure, mean grain size, and relative density of soil and output parameter is

Table 3 Number of data considered for various stages

Group	No.
All element tests data	635
Training set (80% of all element tests)	508
Testing set (20% of all element tests)	127
Validation set (Centrifuge data)	65

Table 2 Descriptive statistics of the variables used in the model development

Parameters	Training set				Testing set			
	Min	Max	S.D.	Mean	Min	Max	S.D.	Mean
D_{50} (mm)	0.162	10	3.09	2.51	0.162	10	3.04	2.56
D_r (%)	27	100	20.57	71.13	27	100	20.11	70.82
σ'_0 (kPa)	25	300	56.31	110.60	25	300	58.01	110.79
γ(%)	0.0001	1.267	0.1678	0.0521	0.0001	1.492	0.1994	0.0631
G/G_{max}	0.015	1.008	0.27	0.77	0.012	1.006	0.28	0.76

shear stiffness ratio. The correlation between the inputs (x_1, …, x_p) and the output (y_t) has the computational form as Eq. (1):

$$y_t = w_0 + \sum_{j=1}^{Q} w_j g\left(w_{0j} + \sum_{i=1}^{P} w_{i,j} x_i \right) + e_t \tag{1}$$

where, P is the number of input nodes; Q is the number of hidden nodes; $w_{i,j}$ and w_j are connection weights; e_t is the residual at time t; and g is the transfer function such as tan-sigmoid and log-sigmoid. Therefore, the feed-forward neural network model of Eq. (1) performs a nonlinear operational mapping from the past records to the future amount (y_t), as Eq. (2).

$$y_t = f\left(x_1, \ \ldots, \ x_p, \ W\right) + e_t \tag{2}$$

where f is a function defined by the structure of network and weights, and W is a vector of all parameters. Hence, above mentioned feed-forward based neural network is equivalent to a autoregressive nonlinear model.

The model architecture was constructed by one hidden layer. The input vector is fully connected to the hidden neurons with a transfer function of tan-sigmoid. Also, the neurons of hidden layer are fully connected to the output layer by a linear function. Statistical studies were begun with two hidden neurons to attain the desired number of hidden neurons and favorable precision (Haykin 1994).

In order to check the accuracy of the proposed models, the coefficient of determination (R^2), root mean squared error (RMSE), and mean absolute error (MAE) between the predicted and measured G/G_{max} ratios were calculated according to Eqs. (3–5):

$$R^2 = \frac{\sum_N (X_m)^2 - \sum_N (X_m - X_p)^2}{\sum_N (X_m)^2} \tag{3}$$

$$RMSE = \sqrt{\frac{\sum_N (X_m - X_p)^2}{N}} \tag{4}$$

$$MAE = \frac{\sum_N \left|(X_m - X_p)\right|}{N} \tag{5}$$

where X_m is measured values, X_p is predicted values, and N is the number of data.

In real, several ANN-based models with tests data were developed. Then, the more accurate model (i.e., higher coefficient of determination and smaller MAE and RMSE) for validation stage was chosen. In the other words, the ANN-based models were developed with the best performance for training, testing and validation stages concurrently.

The models are generated using the element tests data and then validated by the centrifuge tests results. Therefore, it is reasonable to expect that these models have enough generality for precise evaluation of shear stiffness ratio of cohesionless soils. Consequently, a model is proposed to be the best ANN-based model. The desired model has five hidden neurons and the number of epochs in which all stages (i.e., the training, testing and validation data sets) simultaneously result to best outputs is found to be 300.

Results and discussions

Numerous runs were conducted with different initial settings and the performance of developed ANN-based model was analyzed for each run. Thereupon, the best model was chosen on the basis of statistical criteria of R^2, MAE and RMSE. Moreover, a comprehensive sensitivity analysis was carried out to check the behavior of each ANN model against changes of input variables. The developed model that chosen as most suitable model was constituted by four input parameters (i.e., γ, σ'_0, D_{50} and D_r) and one output (i.e., G/G_{max}).

Accuracy of the developed model is examined by plotting the predicted versus measured values of the G/G_{max} for training set, testing set, and all element tests data as shown in Figs. 2, 3 and 4, respectively. The values of R^2, MAE, and RMSE are equal to 0.984, 0.026,

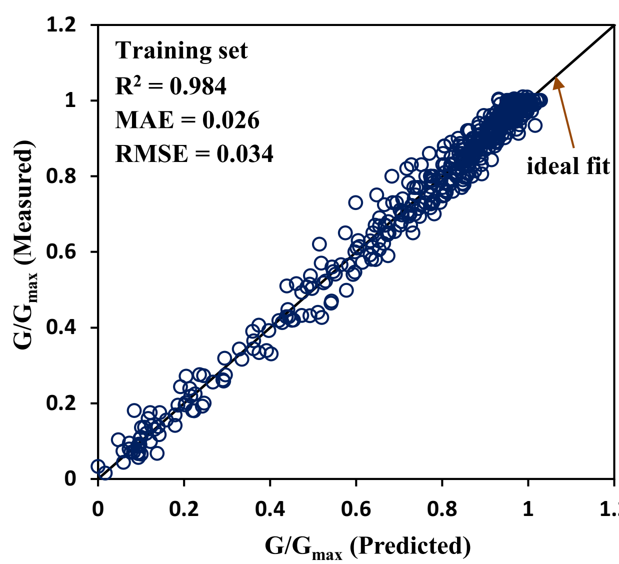

Fig. 2 Measured versus predicted values of G/G_{max} for training data set

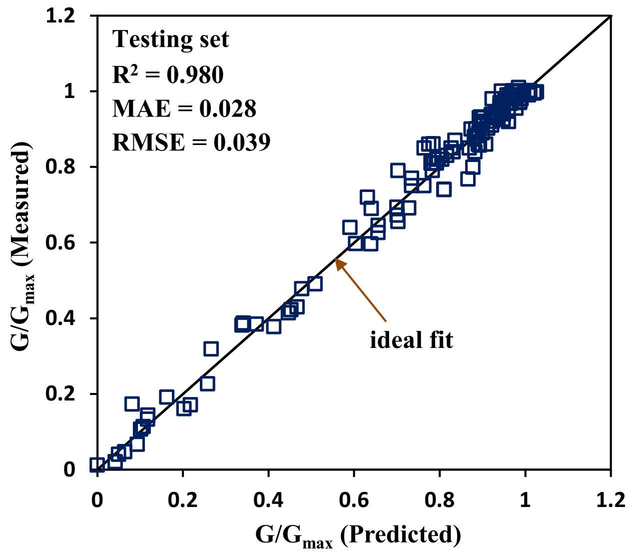

Fig. 3 Predicted versus measured values of G/G_{max} for testing data set

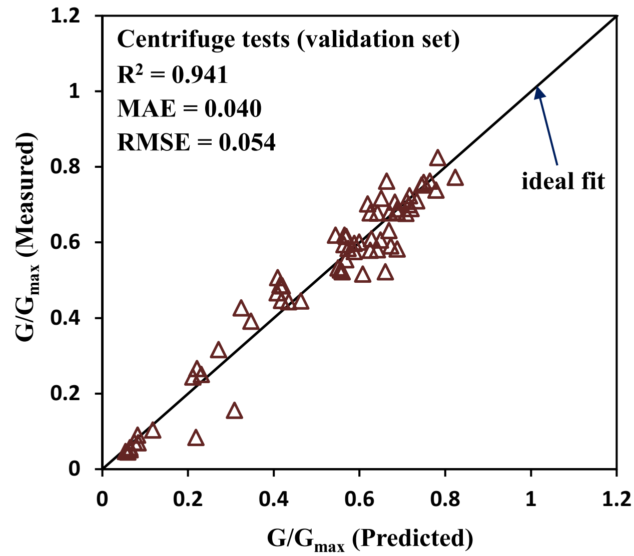

Fig. 5 Predicted versus measured values of G/G_{max} for centrifuge validation set

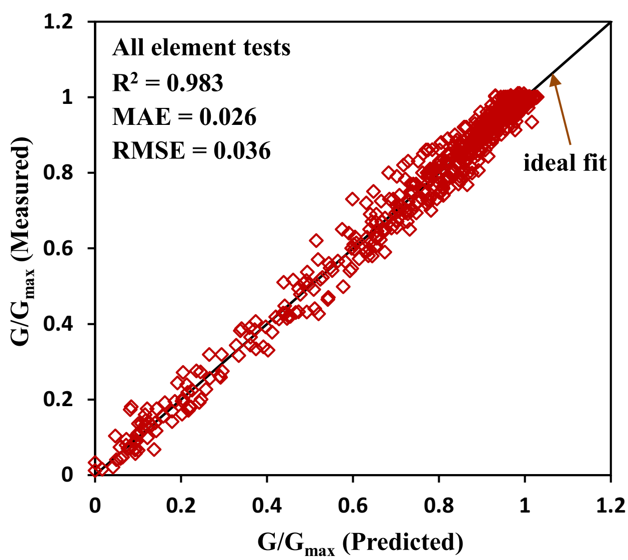

Fig. 4 Predicted versus measured values of G/G_{max} for all element tests data

Table 4 Statistical parameters for evaluation of ANN model performance

Group	Performance		
	R^2	MAE	RMSE
All element tests	0.983	0.026	0.036
Training	0.984	0.026	0.034
Testing	0.980	0.028	0.039
Validation (centrifuge)	0.941	0.040	0.054

and 0.034, respectively, for training data set (Fig. 2) and 0.980, 0.028, and 0.039, respectively, for testing data set (Fig. 3). Also, for all element data sets, the values of R^2, MAE, and RMSE are equal to 0.983, 0.026 and 0.036 respectively (Fig. 4).

To confirm the enough generality for field predictions, centrifuge validation result of Brennan et al. (2005) was employed as another testing set. They conducted these tests on dry and saturated sand. In their research, all physical modeling have been performed at 50 g on the 10 m diameter beam Cambridge centrifuge and earthquake lading is applied using the mechanical actuator. Figure 5 shows predicted versus measured G/G_{max} for the validation tests data. The values of R^2, MAE, and RMSE for this experimental data set were obtained equal to 0.941, 0.040, and 0.054, respectively. In fact, the evolved ANN-based model has obtained high precision for both testing and validation data sets.

Table 4 presents the amounts of R^2, MAE, and RMSE of the proposed ANN-based model for all test data and training stage, testing stage and also validation stage. From the plots presented in Figs. 2, 3, 4 and 5, it is concluded that the proposed model can predict the G/G_{max} of cohesionless soils with appropriate accuracy.

Sensitivity analysis and model accuracy

Further examination on the model performance under various conditions was carried out through a sensitivity analysis. This part of the research was conducted to evaluate whether the ANN model matches its prediction to those measured in experimental studies. For this purpose,

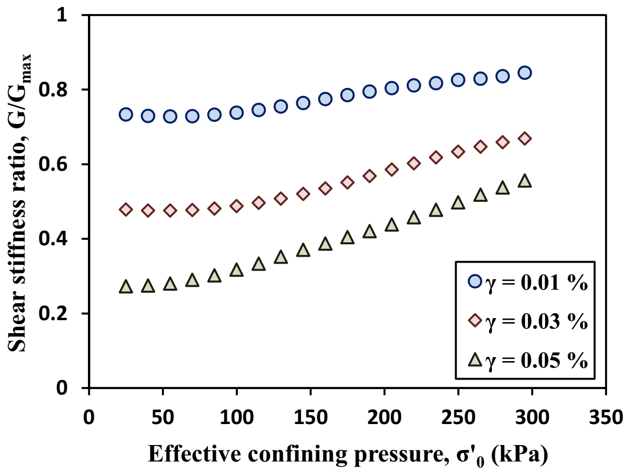

Fig. 6 Variation of ANN-based predicted values of G/G_{max} against σ'_0 at different levels of γ

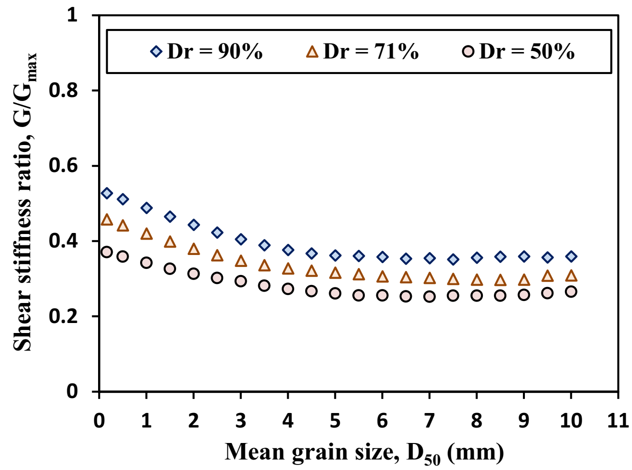

Fig. 8 Variation of G/G_{max} predicted by ANN model against D_{50} at different relative densities

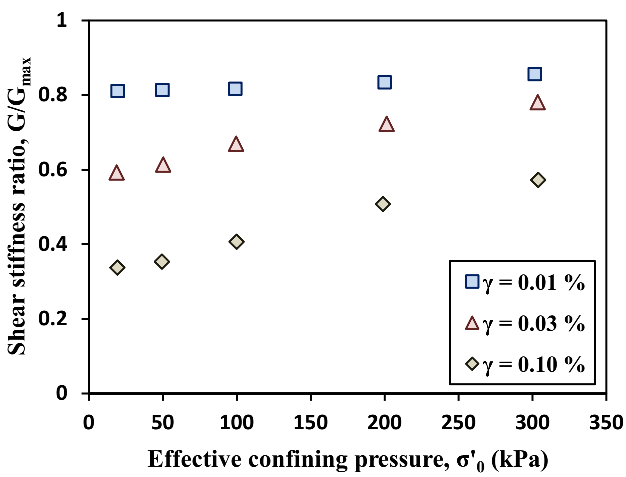

Fig. 7 Variation of G/G_{max} measured in cyclic triaxial tests on Toyoura sand with D_{50} = 0.19 mm (Kokusho 1980)

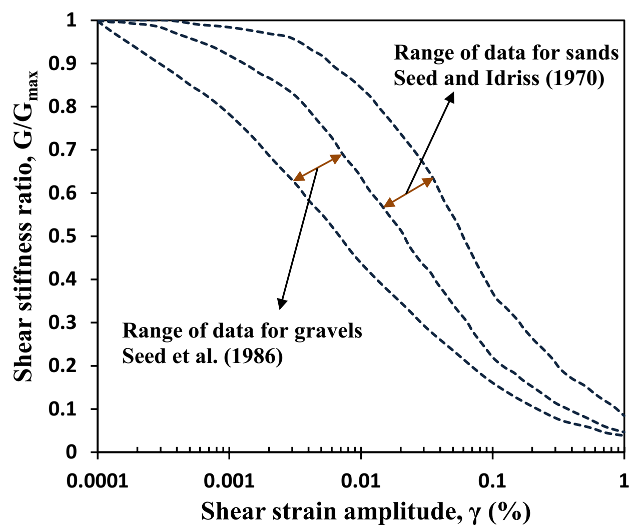

Fig. 9 Curves defining range of G/G_{max} data for sands (Seed and Idriss 1970) and gravels (Seed et al. 1986)

changes of each input parameters on the amounts of G/G_{max} were investigated while the other parameters were kept fix at their mean values in data set (Table 2).

Figure 6 shows variation of shear stiffness ratio, G/G_{max}, versus confining pressure, σ'_0, at different levels of shear strain, γ. G/G_{max} increases with increase and decrease of σ'_0 and γ, respectively. This trend of variations is similar to the results of laboratory cyclic triaxial experiments carried out by Kokusho (1980) on Toyoura sand with mean grain size of 0.19 mm (Fig. 7). The tendency of G/G_{max} versus effective confining pressure, σ'_0, at different levels of shear strain amplitude, is in qualitatively well agreement with the experimental results of Kokusho (1980). Comparison between Figs. 6 and 7 confirms the results of the sensitivity analysis for σ'_0 and γ, and reasonable performance of the ANN-based model.

Variation of shear stiffness ratio, G/G_{max}, versus mean grain size, D_{50}, at different relative densities are depicted in Fig. 8. G/G_{max} increases with increase of D_r (decrease of void ratio, e), and decreases with increase of D_{50}. In the range of G/G_{max} data proposed by Seed and Idriss (1970) for sands and Seed et al. (1986) for gravels (Fig. 9) the main value of curve defining G/G_{max} versus γ for gravels is typically 10–30% less than those for sands. Of course, there is a slight overlapping in the range for sand and gravels. However, variation trend of G/G_{max} with respect to D_{50} is consistent with their results.

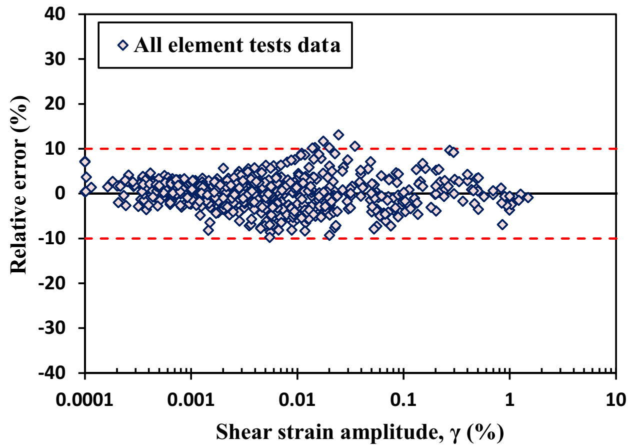

Fig. 10 Difference between the ANN-based predicted and experimental values of G/G_{max} with respect to γ

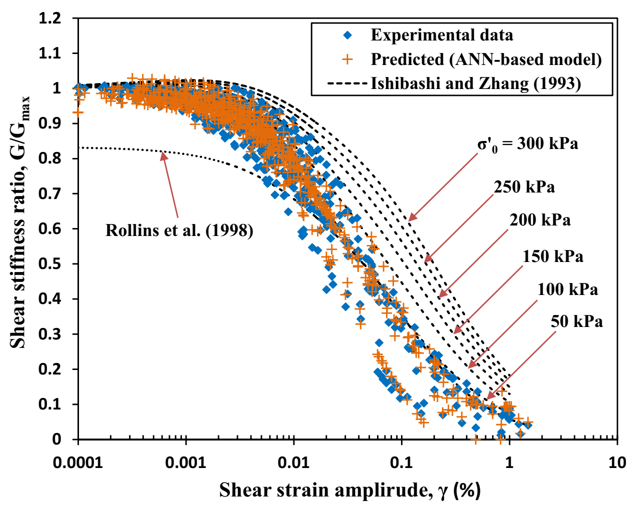

Fig. 11 Comparison of proposed ANN model with the previous studies

The results of sensitivity analysis show that D_r and D_{50} have a less important effect on shear stiffness ratio than σ'_0 and γ. However, the results show good performance of ANN model.

Besides, difference between the measured G/G_{max} to the amounts predicted by the ANN-based model as relative error, with respect to the shear strain amplitude, γ, for all element tests data is illustrated in Fig. 10. In this figure, as the scattering increases, the precision of the model consequently decreases. It is observed that the developed ANN model can predict the G/G_{max} of cohesionless soils with satisfactory accuracy because the relative error is reasonably distributed between two lines illustrating ±10% relative error.

Comparison with the previous studies

For comparison purposes, predictions of some previously published relationships which are only in terms of γ (Rollins et al. 1998), or γ and σ'_0 (Ishibashi and Zhang 1993) are also presented in the Fig. 11. Ishibashi and Zhang (1993) collected an experimental database on dynamic shear stiffness of soils. Their study is one of the most comprehensive studies on the dynamic properties of soils. They presented a unified formula for shear stiffness ratio of cohesionless soils in terms of cyclic shear strain amplitude and effective confining pressure (Ishibashi and Zhang 1993) as Eq. (6–8):

$$\frac{G}{G_{max}} = K(\gamma)\, \sigma'^{\,m(\gamma)-m_0}_0 \tag{6}$$

$$K(\gamma) = 0.5\left[1 + tanh\left\{ln\left(\frac{0.000102}{\gamma}\right)^{0.492}\right\}\right] \tag{7}$$

$$m(\gamma) - m_0 = 0.272\left[1 - tanh\left\{\left(\frac{0.000556}{\gamma}\right)^{0.4}\right\}\right] \tag{8}$$

In order to define the shear stiffness ratio (G/G_{max}) against shear strain amplitude (γ) Rollins et al. (1998) employed a hyperbolic model for cohesionless soils based on a large database (Eq. 9).

$$\frac{G}{G_{max}} = \frac{1}{[1.2 + 16\gamma(1 + 10^{-20\gamma})]} \tag{9}$$

The comparison (Fig. 11) shows that the values predicted by ANN model can reasonably predict the G/G_{max},

Table 5 Comparison between statistical index for ANN model and the previous studies

Model	Performance		
	R^2	MAE	RMSE
Rollins et al. (1998), Eq. (9)	0.750	0.121	0.136
Ishibashi and Zhang (1993), Eqs. (6–8)	0.882	0.071	0.095
ANN-based model (present study) all element tests data	0.983	0.026	0.036
ANN-based model (present study) centrifuge data	0.941	0.040	0.054

while the available relationships generally under-predicted or over-predicted the measured these amounts.

The values of R^2, RMSE, and MAE for the proposed ANN model and the values of G/G_{max} estimated by Ishibashi and Zhang (1993), and Rollins et al. (1998)'s equations for cohesionless soils are presented in Table 5. The statistical results presented in Table 5 confirm higher accuracy of the proposed ANN model in comparison to the other researcher's relationships.

In order to conduct the seismic site response analysis, the dynamic curves must be predicted. The ranges of shear stiffness reduction for cohesionless and cohesive soils are quite wide. Overall, selections of dynamic curves have an important effect on the dynamic analysis such as site-response analysis. However, the range of variation in the select of curves shows the uncertainties associated with the dynamic, nonlinear behavior of soils. Therefore, in these analysis uncertainties must be reduced by more detailed shear stiffness ratio curve. These curves must be calculated based on accurate computational method such as ANN.

Summary and conclusions

The accurate prediction of shear stiffness ratio parameter is a significant issue in earthquake and geotechnical engineering. In the present research, relatively large experimental database consisting laboratory cyclic experiments include cyclic torsional shear, resonant column, and cyclic triaxial tests on cohesionless soils were utilized. Artificial neural network (as a powerful intelligent tool) was used to develop a shear stiffness ratio model. On the basis of the observations in the previous experimental studies on cyclic and dynamic behavior of cohesionless soils, four parameters; effective confining pressure, shear strain amplitude, mean grain size, and relative density were employed as input parameters to develop the ANN-based model. Moreover, results of several centrifuge modeling tests results, which were not employed during model development, were utilized for further examination of the G/G_{max} model as validation set. The proposed model demonstrated a good performance for all tests data ($R^2=0.983$) and centrifuge data set ($R^2=0.941$).

A sensitivity analysis was conducted to check the behavior of the ANN-based model under various conditions and to verify model behavior with those recorded in experimental studies. The results demonstrate that G/G_{max} increases with increasing σ'_0 and D_r, while other influential factors were kept constant. Also, G/G_{max} decreases due to increasing γ and D_{50}. Based on sensitivity analysis results, D_r and D_{50} have a less important effect on shear stiffness ratio than γ and σ'_0. These variation trends in sensitivity analysis of the developed G/G_{max} model are in good agreement with the previous experimental results.

Finally, the performance of the developed G/G_{max} model has been compared with some of the previously empirical relationships. It is clearly shown that the ANN-based model have a much good performance than the previous famous relationships. Target statistical criteria such as R^2, RMSE, and MAE for the proposed ANN model and previous studies presented in Table 5. The results illustrated in this Table confirm higher accuracy of the proposed G/G_{max} model.

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