Estimating Dynamic Characteristics of Gravel-Tire Chips Mixtures Using Artificial Intelligence Techniques

by

Siavash MANAFI KHAJEH PASHA*, Hemanta HAZARIKA* and Norimasa YOSHIMOTO**

Scrap Tire Derived Geo-Materials (TDGM) mixed with soil are often being used as environmentally friendly granular materials in sustainable construction of civil engineering projects for reducing dynamic loads acting on geo-structures and soil liquefaction remediation purposes. Predicting dynamic properties of TDGM-soil mixture is a complicated task due to the numbers of factor involved in soil-TDGM mixture. This study presents application of artificial intelligence technique in estimating dynamic characteristics of granular mixture of Gravel and Tire chips (GTCM). Support Vector Regression (SVR) and Artificial Neural Networks (ANN) were used for predicting shear modulus and damping ratio of GTCM. Shear modulus and damping ratio models were developed using ANN and AVR techniques. The models were trained and tested using a database that included results from a set of laboratory tests on the GTCM. Stress controlled cyclic triaxial tests were conducted on specimens of gravel and tire chips with different volumetric portions of gravel in mixture (GF). The tests were performed on GTCM specimens at an initial relative density of 50% under different initial effective confining pressures. Test results have shown that shear modulus and damping ratio of the granular mixtures are remarkably influenced by volumetric fraction of gravel in GTCM. Furthermore, shear modulus was found to increase with the mean effective confining pressure and gravel fraction in the mixture. It was found that a feed-forward multilayer perceptron model with back-propagation training algorithm have better performance in predicting complex dynamic characteristics of granular mixture than SVR one.

Key words:
Shear modulus, Damping ratio, Gravel-tire chips mixture, Support vector machine, Artificial neural network.

1 Introduction
In each year, billions of the wastes are disposed due to either human or industrial activities. Cascade recycling of wastes into useful products is one of most effective approaches to deal with waste management crisis. In Japan the quantity of disposed scrap tires in the year of 2017 has been increased by 37 million tons from the previous year. Global statistics on the scrap tires production has shown a similar trend. About 1 billion of scrap tires are generated annually in the world. Large percentage of scrap tires end up in landfills or are illegally abandoned. In Japan, thermal recycling is the main recycling effort. This might increase emission of hazardous gases such as CO, CO2, and SO2 to the atmosphere.

Cascade recycling of scrap tires into Scrap Tire Derived Geomaterials (TDGM) such as tire chips, tire shreds leads to significant reduction of and consequently reduces the risk of global warming and natural geohazards1). TDGM have low carbon footprints and possess competitive advantages over conventional geosynthetics (such as geotextiles, geocomposites) and some of them are as follows: low unit weight, high hydraulic conductivity and high elastic deformability and vibration absorption capacity 2)-5). Recent studies have reported the successful implementation of TDGM as a new mitigation measure against geohazards such earthquake, liquefaction 6).

Sand tire chips mixture is a conventional granular mixture that has been thoroughly investigated in literature. Dynamic studies on sand tire chips as vibration absorption mixture revealed promising results in mitigating the earthquake induced loads on geo-structures 6). Soil dynamic analysis (such as ground response analysis) involving TDGM and soil mixture needs an assessment of dynamic behavior and estimation of dynamic properties of these materials.

Several studies have attempted to investigate the effect of waste rubber materials on small strain dynamic properties of granular mixtures7), 8), 9). Reported results show that rubber content has significant effect on the shear modulus and damping ratio of granular mixture with rubber. Furthermore, small strain shear modulus (G0) was found to significantly decreases with rubber content in mixture. Mean effective confining pressure was found to increase shear modulus of TDGM at low rubber content in mixture. Anastasiadis et al. (2011) introduced a modified hyperbolic model using equivalent void ratio taking into account important features of granular mixture such as rubber content ratio, effective confining pressure and particle size ratio. Their model has limitations such as large number of parameters that needs to be calibrated against the experimental data and is only valid for small range of shear strains 10).

On the other hand, few studies have taken look at the dynamic properties of sand-tire chips mixture in medium to large strains. Nakhahi et al. (2012) conducted a series of large-scale consolidated undrained cyclic triaxial tests to obtain...
shear modulus and damping ratio of gravelly sand mixed with different percentage (0, 8, 10 and 14% by weight) of granulated rubber at different effective confining pressures\(^1\). Results showed that regardless of level of the confining pressure, shear modulus steadily decreases as rubber content increases in mixture. They concluded that damping ratio decreases with an increase in rubber inclusion in the mixture for the confining pressures of 50 and 100 kN/m\(^2\). However, this trend was reversed for the confining pressures of 200 and 300 kN/m\(^2\).

They proposed a modified version of Hardin Hyperbolic model\(^2\) to represent shear modulus reduction curves of reinforced soil. This model has introduced 5 new parameters that need to be calibrated against the experimental data. However, proposed model overestimates the values of shear modulus ratio (\(G/G_{max}\)) at very low confining pressures and underestimates it at high confining pressure, especially when higher percentage of rubber is used in mixture.

Gravel-tire chips mixture has recently been introduced as a new granular geo-material to overcome the limitation of sand-tire chips mixture such as low permeability and low liquefaction resistance\(^3,4\). However, to the best of authors knowledge, there is no study that can be found in literature to model dynamic properties of gravel-tire chips mixture in the range of confining pressures of 50 and 100 kN/m\(^2\). Mixtures of desired relative densities were obtained by mixing manually and carefully, placed into the mold and compacted in 10 layers. Samples were saturated by allowing de-aired water to flow through from bottom of the sample. The back-pressure technique was adopted to enhance the degree of saturation of samples. Full saturation was assumed to be achieved when Skempton’s B parameter (\(\Delta u/\Delta u_{sat}\)) was greater than 0.95.

An isotropic consolidation pressure was applied to samples, while maintaining constant initial backpressure (200 kN/m\(^2\)). Samples were consolidated to the effective confining pressure of 50 and 100 kN/m\(^2\). Stress-controlled undrained cyclic triaxial tests were conducted at a constant frequency of 0.1 Hz, relative density of 50% and different cyclic stress ratios (\(\sigma_d/2\sigma_3\)). Evaluation of shear modulus (\(G\)) and damping ratio (\(D\)) can be calculated from following expressions:

\[
G = \frac{\sigma_{max} - \sigma_{min}}{\sigma_{max} + \sigma_{min}} = \frac{1}{3} \left( \frac{4\sigma_{max} - 4\sigma_{min}}{\epsilon_{q,max} - \epsilon_{q,min}} \right) \tag{1}
\]

\[
D = \frac{\Delta u}{\Delta \sigma_d} = \frac{1}{4\pi W} = \frac{1}{4\pi \left( 0.125 \times 2\sigma_3 / \sigma \right)} \tag{2}
\]

Where \(\sigma_{max}\) and \(\sigma_{min}\) are maximum and minimum deviatoric stresses respectively, \(\epsilon_{q,max}\) and \(\epsilon_{q,min}\) are maximum and minimum deviatoric strains, respectively. \(\tau_{max}\) and \(\tau_{min}\) are the maximum and minimum shear stresses corresponding to the maximum \((\gamma_{max})\) and minimum shear strains \((\gamma_{min})\), respectively. Furthermore, \(\Delta W\) is the area of the hysteresis loop and \(W\) is the area of right triangle shown in Fig. 2a. Typical stress-strain hysteresis loop of GTCM is shown in Fig. 2b.

3 Shear Modulus and Damping Ratio

Evolution of shear modulus (\(G\)) versus the number of cycles for different fraction of gravel in mixture at cyclic stress ratio of CSR=0.3 is plotted in Fig. 3.

Fig.1 Particle size distribution and samples of gravel and tire chips.
4 Support Vector Machine

Support vector machines (SVMs) are one of the learning systems that employs learning techniques in the framework of structural risk minimization and theory of Vapnik-Chervonenkis (VC) bonds. This method has been introduced by Vapnik (1964) and utilizes a theorem space of linear equations in n-dimensional feature space, trained with learning algorithm according to optimization hypothesis that implements learning bias attains from statistical learning postulate. The support vector machine can be used for both data classification and regression problems. If the target variables involve categorical data, an SVM model need to be used, however when the target variables are continuous data support vector regression (SVR) model should be employed.

4.1 Support Vector Regression (SVR)

If a set of observation data are given as \{(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)\}, where \(x_i \in \mathbb{R}^n\) input values and \(y_i \in \mathbb{R}\) output values (actual values), where \(n=\)number of samples. The \(\epsilon\)-insensitive loss which is the magnitude of the difference between the predicted value and the radius \(\epsilon\) of the tube function can be expressed as follows:

\[
L_\epsilon(y) = \begin{cases} 0 & \text{if } |y - f(x)| \leq \epsilon \\ |y - f(x)| - \epsilon & \text{otherwise} \end{cases}
\]

The non-linear regression function can be presented as below:

\[
f(x) = \langle w, x \rangle + b = 0
\]

Where \(L_\epsilon(y)\) = loss function, \(b =\) bias and \(w =\) weight vector. The main objective in SVR is to look for a function, \(f(x)\) that approximately has a \(\epsilon\) deviation from the actual output \(y_i\) which is provided by training dataset. So, this goal can be achieved by minimizing the following expression:

\[
\psi(w) = \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{n} \xi_i
\]

considering the following constraints:

\[
\begin{align*}
+\gamma_i - \langle w, x_i \rangle & \leq \epsilon + \xi_i \\
-\gamma_i - \langle w, x_i \rangle & \leq \epsilon + \xi_i
\end{align*}
\]

By introducing slack variables \(\xi_i\), \(\xi_i^*\) (\(i = 1 \ldots n\)), optimization function now can be expressed (Fig. 5):

\[
\psi(w, b, \alpha) = \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{n} (\xi_i + \xi_i^*)
\]

Subject to the following constraints:

\[
\begin{align*}
\gamma_i - \langle w, x_i \rangle & \leq \epsilon + \xi_i \\
-\gamma_i - \langle w, x_i \rangle & \leq \epsilon + \xi_i^*
\end{align*}
\]

\(\|w\|\) = norm of \(w\) vector, Where \(\langle w, x \rangle\) = inner product of the two vectors, \(w\) and \(x\); \(C =\) constant known as the penalty parameter. By transforming the function in Eq. 8, the goal would be maximizing the following expression:

\[
W(\alpha, \alpha^*) = -\frac{1}{2} \sum_{i,j=1}^{n} \alpha_i \alpha_j^* \langle x_i, x_j \rangle - \sum_{i=1}^{n} \gamma_i \alpha_i^* - \sum_{i=1}^{n} \alpha_i \gamma_i - \frac{1}{2} \sum_{i,j=1}^{n} \alpha_i \alpha_j^* \langle x_i, x_j \rangle
\]
Where \( \alpha \) and \( \alpha^* \) = Lagrange multipliers; \( W(\alpha^*, \alpha) \) = the Lagrange function; \( K \) is the kernel function and defined as follows:

\[
K(x_i, x_j) = \Phi(x_i) \Phi(x_j)
\]

Kernel function is used to mapped from input-space to higher-dimensional space (feature-space) where the data is linearly separable by a mapping \( \Phi \). \( \alpha, \alpha^* \) and \( b \) are calculated by solving the above expressions considering following condition:

\[
\sum_{i=1}^{n}(\alpha_i - \alpha_i^*) = 0, \quad 0 \leq \alpha_i, \alpha_i^* \leq C, \quad i = 1, 2, 3, \ldots, n.
\]

The regression function can be rewritten as:

\[
f(x) = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*) K(x, x_i) + b
\]

in this among several popular kernel function used in nonlinear regression Gaussian kernel function as a popular radial basis function (RBF):

\[
K(x, x_i) = \exp(-\frac{(x - x_i)^2}{2\sigma^2})
\]

Where \( \sigma \) = kernel parameter. To obtain accurate prediction of dynamic properties of GTCM such as shear modulus and damping ratio, the important factors affecting shear modulus and damping ratio need to be determined and taken into account in developing of an efficient model. The results from a series of cyclic triaxial tests on GTCM with particle size ratio of \( d_{50,8}/d_{50,G}=1.2 \), are utilized in this section.

In this study, the SVR model has a gravel fraction (GF), effective confining pressure \( \delta_3 \), cyclic stress ratio (CSR=\( \sigma_d/2 \delta_3 \)), shear strain amplitude \( (\gamma) \) as input parameters and, shear modulus \( (G) \) and damping ratio \( (D) \) as output. A data set consisting of 3006 shear modulus and damping ratio measurements of GTCM were employed in our analysis. 2900 data sets out of 3006 were randomly chosen for training and validation of proposed model whereas the remaining 106 data sets were excluded from training data sets and used to test the constructed model.

Before the training of SVM model data sets were randomly shuffled, in order to make sure that the model is not learning a specific order and faster convergence is observed. The algorithm utilized for data shuffling was simply relied on selecting two data rows (consisting of the input and outputs) randomly and swapping them together. In this study radial basis function was selected as optimal kernel function.

Support vector regression-based model for predicting shear modulus and damping ratio of GTCM can be expressed as follows:

\[
G = \text{SVR} (\text{GF}, \delta_3, \sigma_d/2\delta_3, \gamma)
\]

\[
D = \text{SVR} (\text{GF}, \delta_3, \sigma_d/2\delta_3, \gamma)
\]

Optimal values of \( C \), \( \varepsilon \) and kernel parameter \( \sigma \) are determined on a trial and error basis and performance of model is assessed using two statistical indices, namely coefficient of determination \( (R^2) \) and root mean squared error (RMSE).

\[
R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \bar{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y}^2)}
\]

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \bar{y})^2}{n}}
\]

Where \( y_i \) = observed value; \( \bar{y} \) = predicted value; \( n \) = number of data points; \( \bar{y} \) = mean of the observed value.

Optimal values of penalty parameter (C), loss function (\( \varepsilon \)) and kernel parameter (\( \sigma \)) for both shear modulus and damping ratio SVR models are given in Table 1.

Comparison between observed values of shear modulus and predicted values by SVR model for GTCM with different gravel fraction at effective confining pressure of 100 kN/m² is presented in Fig. 6. An SVR model with values of penalty parameter, loss function, and kernel parameter given in Table 1, provided \( R^2 \) and RMSE values of 0.95 and 1.19 for training data set. This means, as is shown in Fig. 6, observed values of shear modulus of GTCM are in good agreement with the predicted ones.

To evaluate the capability of proposed SVR model to generalize to new data, further analysis was performed on the independent testing data set which was excluded from main data set used for training the model. A comparison between predicted and observed values of shear modulus and damping ratio of GTCM with GF=87% at CSR=0.25 is displayed in Fig.7.

![Fig. 6 Comparison between observed and predicted values of shear modulus for training data sets using SVR at GF=87%.](image)

![Fig. 7 Comparison between observed and predicted values for new testing data sets using SVR at GF=87%.](image)

| Table 1 Optimal Values of Penalty Parameter, Loss Function, and Kernel Parameter for SVR Model Development |
|---|---|---|---|
| Radial basis kernel | Shear Modulus | Damping Ratio |
| RBF | (G) | (D) |
| **C** | 2.16 | 5.8 |
| **\( \varepsilon \)** | 0.02 | 0.05 |
| **\( \sigma \)** | 1 | 1 |
A series of cyclic triaxial tests on GTCM with particle size ratio are carried out to develop an efficient model. The results from shear modulus and damping ratio need to be determined and taken into account in the development of the model. The dynamic properties of GTCM such as shear modulus and damping ratio are important factors affecting the behavior of foundations.

In this section, a total number of 3006 shear modulus and damping ratio data sets were trained using SVM. 106 out of 3006 data sets were excluded from the main data set and used to test the constructed model. The regression function can be rewritten as:

\[ f(\mathbf{x}) = \sum_{i=1}^{n} \alpha_i y_i \prod_{j \neq i} \frac{1}{K(x_i, x_j)} \]

where the data are linearly separable by a mapping \( \phi \). \( \alpha \) and \( \alpha^* \) are Lagrange multipliers; \( W(\alpha^*) \) is the loss function. Among the activation functions, sigmoid and hyperbolic tangent are most popular functions for non-classification problems.

SVM technique has been implemented to estimate the soil characteristics such as soil compressibility, soil permeability, and shear strength parameters as well as predict the behavior of foundations. Selection of appropriate ANN architecture is one of the most essential and complicated tasks of building a model. In this study, the feed-forward MLPs in which information moves forward from the input layer directly towards output layer through any hidden layer was selected. Back propagation learning algorithm (BPP) which uses the gradient decent laws and is suitable for prediction problems, is implemented.

The computational procedure of a backpropagation can be summarized as: the feedforward computation of information and back propagation of errors by comparing target and neural network outputs. At the beginning of a neural network training process, the connection weights are assigned random values. The connection weights are adjusted during the training of the neural network in an iterative process. At the end of successful training process, the iterative process has converged, and the connection weights of whole neural network have been captured and stored.

A total number of 3006 shear modulus and damping ratio values of GTCM are used as the database for building ANN model. 106 out of 3006 data sets were excluded from the main training database for verification purpose. The goal of the model is to predict shear modulus and damping ratio of GTCM for a given GF and confining pressure. The architecture of the network is determined as follows and is illustrated in Fig. 9.

### 5 Artificial Neural Network (ANN)

Artificial Neural Networks (ANN) are one of Artificial Intelligence (AI) techniques that inspired by function of human biological nervous system and mimics brain problem solving process. The first mathematical model of a neuron which is capable of logical operation, was proposed by McCulloch and Pitts. McCulloch and Pitts' ANN model is shown in Fig. 8. Fig. 9 shows a simple ANN model with single neuron which receives inputs \( x_1, x_2, \ldots, x_N \) and generates one output, \( y \). The inputs are processed in linear combination as follows:

\[
  u = b + \sum_{i=1}^{n} w_i x_i
\]

where \( w_1, w_2, \ldots, w_N \) are the strength of the synapses and \( b \) is the bias, which contributes to the output of neuron. For convenience the threshold, \( b \), is considered as another weight, \( w_0 \), transport an input \( x_0 = 1 \) into the neuron. Therefore, Eq. 20, can be rewritten as:

\[
  u = \sum_{i=0}^{n} w_i x_i
\]

In the next step, an activation function is employed to compute the output from combined inputs:

\[
  y = f(u)
\]
A MATLAB code is written to determine neurons (nodes) in the hidden layer by a trial and error method. In this method, training of networks starts with minimum number of nodes in the first hidden layer and sum squared error is calculated and compared with the allowable threshold error. If the error exceeds the threshold value, next neuron is added to the hidden layer. The above iterative process is repeated until the desired stopping criterion is met.

The Levenberg-Marquardt algorithm which has been shown to have better performance for training moderate size of a Multilayer Perceptron (MLP) was selected for training the ANN[26, 27].

The data is randomly divided into three subsets: training (60%), validation (20%), testing (20%). During the learning or training process, training data sets are used to obtain ANN parameters in each layer (Weights and biases) by minimizing the error function. The error on the validation data set is monitored during training process. The validation error normally decreases during the initial phase of training, as well as the error on training dataset. However, when the network starts to overfit the data, the error on the validation set begins to rise. The training will stop when the validation error keeps increasing for a certain number of iterations. The weights and biases of iteration with minimum validation error are recorded and returned. Further training of network will overfits data and prevent generalization. At the next stage, the testing data set is introduced to the ANN and its performance is evaluated.

The proposed neural network model has 4 nodes in the input layer, 6 nodes in the hidden layer, and 1 node (G or D) in the output layer (Fig. 9). Once the model structure is finalized, ANN is utilized to conduct a parametric study. Fig. 10 shows the evolution of mean squared error of finalized model during the training process for the training, validation and testing data sets. Training process terminated after 100 epochs and reaching to mean squared error of 0.422.

The performance of proposed model on predicting shear modulus of GTCM was assessed by plotting predicted values by model (output) against experimental values (target) for training, validation and testing data sets (Fig. 11).

![Fig. 10 Best validation performance of ANN model.](image)

Note that target is shear modulus values obtained from cyclic triaxial test on GTCM (as already presented section 3). R value (coefficient of correlation) > 99% and MSE=0.44 indicates a strong correlation between estimated and target values of shear modulus for all three datasets. To evaluate how well the proposed model approximates real dynamic behavior of GTCM system, the model is used to predict the behavior of GTCM under new condition. Therefore, an independent set of testing data (which was not included in training data set) is used to evaluate the performance of ANN model in predicting shear modulus of GTCM. Fig. 12a shows comparison between shear modulus predicted by ANN model simulation and experimental values for GTCM with GF=87% at the confining pressure of \( \sigma_3 = 100 \text{kN/m}^2 \) and stress ratio of \( \sigma_d/2\sigma_3 = 0.25 \).
training, validation and testing data sets (Fig. 11). The modulus of GTCM was assessed by plotting predicted values during the training process for the training, validation and testing data sets. The evolution of mean squared error of the finalized model during the output layer (Fig. 9) shows that once the model structure is finalized, the network starts to overfit the data, as the error on the validation set begins to rise. The training will stop when the validation error keeps exceeding the threshold value, next neuron is added to the hidden layer. The above iterative process is repeated until the desired stopping criterion is met.

Further training of network will overfit the data and return. Biases of iteration with minimum validation error are recorded to prevent generalization. At the next stage, the testing data set is introduced to the ANN and its performance is evaluated. The performance on generalization and prediction of dynamic characteristics of granular mixture in terms of performance parameters i.e. R-value, RMSE, but ANN based model yields better performance on generalization of training data sets in comparison to that of SVM.

In contrast to classical statistical techniques, artificial neural network models offer several advantages. For instance, they can implicitly detect the non-linear relationships between input and output variables (dependent or independent) within a complex system. They need less formal statistical training to develop. However, they are known to be a Blackbox and limited in explicitly (in form of mathematical model) capturing the relationship between variables in system (SVR models also suffer from same drawback). They are also in risk of overturning.

Finally, ANN and SVR models, like all other machine learning methods, perform best in interpolation rather than extrapolation. Consequently, the developed ANN and SVR models performs best when it is used for the ranges of input variables.

The authors would like to express their sincere gratitude to Progress 100 for their partial financial support.

5 Conclusion

Estimating the dynamic behavior of TDGM geomatials has been a topic of increasing interest in recent years. Complex relationship between different factors affecting the dynamic properties of these materials together with dispersed behavior of some of dynamic characteristics of these materials such as damping ratio opened new research area in geotechnical engineering.

Two different AI techniques, ANN and SVM were used to model the dynamic characteristics of GTCM. Four input parameters, confining pressure, gravel fraction, cyclic stress ratio and shear strain; also shear modulus and damping ratio was considered as outputs. The results from the cyclic triaxial tests on the specimens of GTCM were used to develop the models. Based on the findings of this study following conclusion are drawn:

- Based on the findings of this study, a feed-forward artificial neural network model with back-propagation training algorithm can be employed to model sophisticated dynamic characteristics of granular mixtures with relatively high resolution.
- Outcome of this study show that the Support Vector Machine with the RBF kernel function shows satisfactory performance on generalization and prediction of dynamic properties of GTCM yields relatively low statistical error.
- Although result of ANN and SVR model showed that both the models are suitable tools for estimation dynamic characteristics of granular mixture in terms of performance parameters i.e. R-value, RMSE, but ANN based model yields better performance on generalization of training data sets in comparison to that of SVM.

References

1) H. Hazarika, H. Yokota, S. Endo and T. Kinoshita, “Cascaded recycle of waste tires—some novel approaches toward sustainable geo-construction and climate change adaptation”. In Geotechnics for Natural and Engineered Sustainable Technologies- GeoNEst, Krishna, A. M., Dey, A. & Sreedeeep, S., Editors, Springer Singapore, Singapore, pp. 63–81. (2018).
2) T. Edil and P. Bosscher, “Engineering properties of tire chips and soil mixtures”, Geotechnical Testing Journal, Vol. 17, No.4, pp. 453-464 (1994).
3) G. J. Foose, C. H. Benson and P. J. Bosscher, “Sand reinforced with shredded waste tires”, Journal of Geotechnical Engineering, Vol. 122, No.9, pp. 760-767 (1996).
4) H. Hazarika, K. Yasuhara, Y. Kikuchi, A. K. Karmokar and Y. Mitarai, “Multifacetted potentials of tire-derived three dimensional geosynthetics in geotechnical applications and their evaluation”, Geotextiles and Geomembranes, Vol. 28, No.3, pp. 303-315 (2010).
5) S. M. K. Pasha, H. Hazarika and N. Yoshimoto, “Physical
and mechanical properties of Gravel-Tire Chips Mixture (GTCM)*, Geosynthetics International, Vol. 26, No.1, pp. 92-110 (2019).

6) H. Hazarika, K. Yasuhara, A. K. Karmokar and Y. Mitarai, “Shaking table test on liquefaction prevention using tire chips and sand mixture”, Scrap Tire Derived Geomaterials—Opportunities and Challenges (Hazarika and Yasuhara Eds.), Taylor and Francis, London, UK, pp. 215-222. (2008).

7) H. H. Tsang, “Seismic isolation by rubber–soil mixtures for developing countries”, Earthquake Engineering & Structural Dynamics, Vol. 37, No.2, pp. 283-303 (2008).

8) A. Edinçliler, G. Baykal and K. Dengili, “Determination of static and dynamic behavior of recycled materials for highways”, Resources, conservation and Recycling, Vol. 42, No.3, pp. 223-237 (2004).

9) Z.-Y. Feng and K. G. Sutter, “Dynamic properties of granulated rubber-sand mixtures”, Geotechnical Testing Journal, Vol. 23, No.3, pp. 338-344 (2000).

10) A. Anastasiadis, K. Senetakis, K. Pitilakis, C. Gargala and I. Karakasi, “Dynamic behavior of sand/rubber mixtures. Part I: effect of rubber content and duration of confinement on small-strain shear modulus and damping ratio”, Journal of ASTM International, Vol. 9, No.2, pp. 1-19 (2011).

11) A. Nakhaei, S. M. Marandi, S. Sani Kermani and M. H. Bagheripour, “Dynamic properties of granular soils mixed with granulated rubber”, Soil Dyn Earthq Eng, Vol. 43, No., pp. 124-132 (2012).

12) B. O. Hardin and V. P. Drnevich, “Shear modulus and damping in soils”, Journal of the Soil Mechanics and Foundations Division, Vol. 98, No.7, pp. 667-692 (1972).

13) H. Hazarika and A. Abdullah, “Improvement effects of two and three dimensional geosynthetics used in liquefaction countermeasures”, Japanese Geotechnical Society Special Publication, Vol. 2, No.68, pp. 2336-2541 (2010).

14) B. O. Hardin, “The nature of stress-strain behavior for soils”, In Proceedings of the ASCE geotechnical, Vol. 1. Engineering Division Specialty Conference on Earthquake Engineering and Soil Dynamics, pp. 3-90, Pasadena, California. (1978).

15) H. I. Park, “Development of neural network model to estimate the permeability coefficient of soils”, Marine Georesources & Geotechnology, Vol. 29, No.4, pp. 267-278 (2011).

16) A. Besalatpour, M. A. Hajjabasi, S. Ayoubi, M. Afyuni, A. Jalalian and R. Schulin, “Soil shear strength prediction using intelligent systems: artificial neural networks and an adaptive neuro-fuzzy inference system”, Soil Science and Plant Nutrition, Vol. 58, No.2, pp. 149-160 (2012).

17) J. K. Park, D. H. Cho, S. Hossain and J. Oh, “Assessment of settlement profile caused by underground box structure installation with an artificial neural network model”, Transportation Research Record, Vol. 2672, No.52, pp. 258-267 (2018).

18) M. A. Shahin, “Load–settlement modeling of axially loaded steel driven piles using CPT-based recurrent neural networks”, Soils and Foundations, Vol. 54, No.3, pp. 515-522 (2014).

19) ASTM D3999/D3999M-11, “Standard test methods for the determination of the modulus and damping properties of soils using the cyclic triaxial apparatus”. In Annual Book of ASTM Standards. West Conshohocken, PA: ASTM International (2011).

20) R. Ladd, “Preparing test specimens using undercompaction”, Geotechnical Testing Journal, Vol. 1, No.1, pp. 16-23 (1978).

21) V. Vapnik, “A note one class of perceptrons”, Automation and remote control, Vol., No., (1964).

22) W. S. McCulloch and W. Pitts, “A logical calculus of the ideas immanent in nervous activity”, The bulletin of mathematical biophysics, Vol. 5, No.4, pp. 115-133 (1943).

23) T. F. Kurnaz, U. Dagdeviren, M. Yildiz and O. Ozkan, “Prediction of compressibility parameters of the soils using artificial neural network”, SpringerPlus, Vol. 5, No.1, pp. 1801 (2016).

24) F. Pooya Nejad and M. B. Jaka, “Load-settlement behavior modeling of single piles using artificial neural networks and CPT data”, Computers and Geotechnics, Vol. 89, No., pp. 9-21 (2017).

25) D. E. Rumelhart, G. E. Hinton and R. J. Williams, “Learning representations by back-propagating errors”, Nature, Vol. 323, No.6088, pp. 533-536 (1986).

26) K. Levenberg, “A method for the solution of certain nonlinear problems in least squares”, Quarterly of Applied Mathematics, Vol. 2, No.2, pp. 164-168 (1944).

27) D. W. Marquardt, “An Algorithm for least-squares estimation of nonlinear parameters”, Journal of the Society for Industrial and Applied Mathematics, Vol. 11, No.2, pp. 431-441 (1963).