Evaluation of shear strength parameters of granulated waste rubber using artificial neural networks and group method of data handling

Danial Rezazadeh Eidgahee[1], Abdolhosein Haddad[2*] and Hosein Naderpour[3]

1- Ph.D. Candidate, Geotechnical Engineering, Faculty of Civil Engineering, Semnan University, Iran
Email: d.rezazade@semnan.ac.ir

*2- Associate Professor, Geotechnical Engineering, Faculty of Civil Engineering, Semnan University, Iran (Corresponding Author)
Email: ahadad@semnan.ac.ir Phone No:

3- Associate Professor, Structural Engineering, Faculty of Civil Engineering, Semnan University, Iran
Email: Naderpour@semnan.ac.ir

Abstract

Utilizing rubber shreds in civil engineering industry such as geotechnical structures can accelerate generated waste tire recycling process in an economical and environmentally friendly manner. However, understanding the rubber grains strength parameters is required for engineering designs and can be acquired through experimental tests. In this study, small and large direct shear test was implemented to specify shear strength parameters of five rubber grains group which are different in gradation and size. Moreover, artificial neural networks (ANN) are developed based on the test results and optimized networks which best captured the shear stress (τ), and vertical strain (ε_v) behavior of rubbers, are introduced. Additionally, a prediction model using the combinatorial algorithm in group method of data handling (GMDH) is proposed for the shear strength and vertical strain in the arrangement of closed-form equations. The performance and accuracies of the proposed models were checked using correlation coefficient (R) between the experimental and predicted data and the existing mean square error (MSE) was evaluated. R-values of the modeled τ and ε_v are equal to 0.9977 and 0.9994 for ANN, and 0.9862 and 0.9942 for GMDH models, respectively. The GMDH proposed models are presented as comparatively simple explicit mathematical equations for further applications.

Keywords: Rubber Materials, Size Effect, Shear Strength, Vertical Strain, Direct Shear Test (DST), Artificial Neural Network (ANN), Group Method of Data Handling (GMDH), Combinatorial (COMBI)

1. Introduction

The increase of rubber wastes has become a thoughtful environmental problem particularly in the form of used tires due to the industrial life and population growth. Recycling process of the used tires and rubber made materials is the main problem which is associated with the complex structure and composition of rubber materials. Based on the available statistics, millions of tire wastes are being discarded every year all around the world [1–3]. Sustainable development might become possible through the management of used tires and rubber materials by grinding them and reuse of obtained materials in this process in the form of granulated rubbers as a component or filler. These materials can be considered environmentally friendly and economically efficient if they can be reused in industries such as civil engineering.

Furthermore, rubber materials must have some particular features in order to be suitably used in geotechnical applications. Different researchers have demonstrated the proficient use of rubber wastes in different purposes such as retaining wall backfills [4], road embankments [5], subsurface drainage systems and buried pipeline trenches [6, 7], and landfill leachates [8]. Additionally, shredded rubber masses in the form of mixed with sand or solely can be used as an aggregate replacement in highway construction particularly for flexible pavement structures are supposed to be designed [5, 9-10]. Structures that are utilizing shredded scrap tires should however be designed to minimize the potential for internal heating and combustion [11]. The guidelines presented in ASTM D6270 [12] for use of tire scraps in civil engineering applications should be followed to minimize that risk.

Using rubber materials in geotechnical structures require understanding the mechanical behavior and engineering properties of such materials, among which shear strength characteristics are the most important and common criteria. Properties of tire wastes such as durability, strength, resiliency, and high frictional resistance are the most significant parameters for consideration in the design of highway embankments [13]. Experimental

tests have been performed by many researchers on soil-rubber mixture to find out the most efficient fraction of the blend for which the shear strength parameters have maximum values and ameliorate geotechnical properties of the soil alone [14–26]. However, rubber shred masses can be used to act like sand and gravel grains in a lightweight and more compressible manner [27]. Conducted tests on rubber grains ranging in size from 10 to 1400 mm and reported friction angles varied from 19 to 38 degrees with the cohesion intercept of 0 to 11.5 kPa at normal stresses between 0 and 83 kPa [20, 28-29]. Moreover, large tire derived aggregates ranging in size between 30 and 300 mm were tested using a novel large scale direct shear device [30].
Implementing different grinding techniques, various rubber grain sizes and shapes can be obtained which have different mechanical properties and shear strengths [12]. Table summarizes previous studies on the shear strength parameters of rubber material grains which are resulted from the direct shear test (DST). However, the effect of gradation and factors involved in particle size distribution such as uniformity and curvature coefficients were not discussed.

Former researchers have shown evidence of the practical effect of gradation and grain size for design purposes [15, 21, 31]. The objective of this paper is to investigate the effect of particle size distribution of rubber grains on shear strength parameters through an experimental study on five different gradations. Furthermore, using direct shear tests (DST) results, artificial neural network (ANN) and group method of data handling (GMDH) are implemented for proving a general prediction model of rubber material shear stress-strain behavior further in this research.

2. Materials and Methods

2.1. Materials

Five different gradations according to particle size distribution of rubber materials used in this study, none of them contain steel wires, nylon or synthetic fibers. Grain sizes were varied in the range of 0.075 to 4.75 mm, and the specific gravity test resulted in an average value of 1.13 (between 1.10 and 1.16) which is consistent with those reported in ASTM D6270 for various tire shreds and tire chips (varies from 1.02 to 1.27 with an average value of 1.15). The recommendations of ASTM D6270 were generally followed in this study. Granulated rubber sets, GR1 and GR3, contains particles varying in diameter from 0.075 to 1.18 mm and 0.425 to 4.75 mm, respectively and GR2 which is widely distributed between the other two with grains diameters between 0.075 and 4.75 mm. Based on unified soil classification system (USCS) and according to ASTM D2487 [32], all the specimens were categorized as poorly graded sand (SP). Additionally, two other groups of rubber samples, RC1, and RC2 were classified as poorly graded gravels (GP) for which the rubber chips label is selected based on ASTM D6270 recommendations [12]. Particle size distributions of the samples are shown in Figure . It is obvious that GR1, GR3, and RC2 are uniformly distributed while GR2 and RC1 are extended between them to provide a wide distribution. In addition, uniformity coefficient (C_u), curvature coefficient (C_c) and mean size (D_{50}) are presented in Table for each specimen.

2.2. Methods

2.2.1. Testing

For GR samples small direct shear test apparatus was performed which has a square specimen box (mold) with the side size of 100 mm. The initial thickness of all samples was 30 mm which were placed poured in the shear box by three 10 mm layers. However, for RC samples, the large direct shear test was used where side size of square sample box is 300 mm, and its depth is 150mm. RC samples were prepared in 5 layers of 30mm thickness. Horizontal displacement rate was set to be 0.5 mm per minute in order to perform shear tests on rubber samples. The mold was greased for reducing wall-particle friction effect and to ensure that it has no effect on the shearing plane. The tests were performed based on the procedure described in ASTM D3080 [33], and five different normal stresses (σ_n) of 5, 25, 50, 100 and 150 kPa were applied.
The results achieved from direct shear testing are shear stress (τ) and vertical strain (ε_v) responses which are changing with horizontal strain (ε_h) for the samples. Figure -Figure depict τ and ε_v changes versus ε_h. It should be noted that due to the fact that none of the shear stress curves have well-defined peaks, failure criterion is

chosen to be at 15 and 12 percent of horizontal strain for GR and RC samples, respectively which were performed using 10 and 30 cm shear boxes, respectively. The same procedure of rubber material testing was reported by other researchers [4, 6, 20, 28]. The shear strength parameters of samples were interpreted using Mohr-Coulomb failure criterion in form of cohesion intercept (c) and internal friction angle (φ). The summaries of shear parameters are briefly mentioned in Table in order to provide a comparison with other studies.

2.2.2. Data preprocessing

In order to offer appropriate information for soft computing based model development, DST test results on the rubber specimens were collected including 890 test result points. Five input parameters were selected based on their direct effect on the shear stress responses of the materials. Based on the acquired results, it can be concluded that the particle size distribution affected the shear stress and vertical strain responses. Moreover, the applied normal stress and the horizontal strain are two other variables in the direct shear test which directly effect on the results. Thus, input variables are normal stress (σ_n), horizontal strain (ε_h), uniformity coefficient (C_u) and curvature coefficient (C_c) and the dimension corresponding to 50 percent passing by weight (D_{50}). The target values that form the responses of DST are shear stress (τ) and vertical strain (ε_v) which can be presented versus horizontal strain (ε_h). Input and target data statistical summaries are presented in Table.

With the purpose of avoiding slow learning rate in soft computing model development, the standardization function and scaling technique was used, which converts values of each input parameter and experimentally measured value between 0.1 and 0.9 using the following equation:

$$Y_m^n = 0.8\left(\frac{X_m^n - X_{m,\min}}{X_{m,\max} - X_{m,\min}}\right) + 0.1 \quad \textbf{(1)}$$

In which, Y_m^n is the normalized and scaled value of X_m^n which is considered to be between 0.1 and 0.9, m is the mth parameters involved in the model and n indicates the nth experimental value of mth parameter. Used data were randomly shuffled before any model development to provide more authentic models. In addition, zero values involved in the calculations divided by zero while calculating relative values, especially in error estimation.

2.2.3. ANN model development

According to recent progressions in computational engineering and computer science, artificial neural networks (ANNs) have been widely adopted for modeling engineering problems. These methods demonstrated to be reliable to provide predictive models and due to their data-driven basis, there is no requirement to preceding knowledge of the associations of the variables [34]. Thus, ANNs do not include any pre-processed equations and the models are being trained in order to find the relationships associating a group of selected inputs to their target values [35, 36].

This computational tool has been adopted from a natural biological neuron in where dendrites in a neuron obtain information from preceding neurons and axons sending the processed information of one neuron to another. Signals through synapses are in charge of providing connections with other cells. An artificial neuron is alike biological neuron and has neuron cells, inputs, and targets [35, 37]. An artificial neural network comprises of two or more layers in where a set of neurons exists. Using weighted connections, each layer interrelates with others for creating a network. Input parameter data are then multiplied by the weight values and their sum with bias form the input to the net transfer function (f). In an artificial neuron, network inputs are y_j in which j is between 1 and m, and m is the mth input variable, correlate with each other using the net transfer function. A weighted linear combination can be described as below:

$$u = f\left(\sum_{j=1}^{n} w_j y_j + \theta\right) \quad \textbf{(2)}$$

u is the desired output and w_j are known as weights in which j varies between 1 and m, and θ value is called the bias which is used for model threshold [37]. Feedforward backpropagation network using the Levenberg – Marquardt algorithm was used in this study. These networks have been demonstrated to be capable of modeling complex engineering problems [35, 37–40]. Further details on this type of networks and their performance can be found in references [38] and are out of the scope of this paper.

In the direct shear tests (DST), acquired results were used to develop artificial neural networks (ANN) in which input variables are σ_n, ε_h, C_u, C_c, $D_{50,}$ and outputs are shear stress (τ) and vertical strain (ε_v). Thus, two sets of networks have been developed in order to provide a model of shear stress (τ) and vertical strain (ε_v) versus horizontal strain (ε_h). The architecture of networks in terms of input, hidden layer and the output layer is shown in Figure (a) and (b) for τ and ε_v, respectively. In this study, the presented artificial neural networks were called 5-n-1, where the first digit is the number of input nodes, n is the number of hidden nodes and third digit is the number of output nodes as shown in Figure (a) and (b). Training, testing and validation process of the network is performed using neural network toolbox in MATLAB 2014. Moreover, about 60 percent of whole data randomly was specified for training, 20 percent for validation and remaining 20 percent for testing.

2.2.4. Combinatorial GMDH model development

Group method of data handling (GMDH) model is an algorithm to find a complex polynomial function that is linear in the parameters. Combinatorial model is a subset of terms of a polynomial function generated from a given set of variables [41, 42]. For instance, if a data-set of two input variables x_1 and x_2 and an output (target) variable y is being modeled, the quadratic polynomial function for which the optimization of constants, a_p in where $p \geq 0$ must be performed is as follow:

$$y = a_0 + a_1 x_1 + a_2 x_2 + a_3 x_1 . x_2 + a_4 x_1^2 + a_5 x_2^2 \quad \textbf{(3)}$$

The maximum power of polynomial function is user-defined and the problem complexity would be increased in case higher orders are chosen. Combinatorial GMDH selects an optimally-complex model, for instance, $y= a_0 + a_3 x_1 x_2$ as a subset of terms of a complete polynomial with the smallest model at testing data. Data preprocessing stage allows applying different operators to variables x_1 and x_2, for example, exponent, a sigmoid function, time series lags, and so on. But the final model will be still linear in the parameters. A full combinatorial search of model components frequently takes too much time, so the search of models can be limited in a way that no more than n terms are included in the model. Models with only 2 terms, for example, allow search among thousands possible combination of variables and probably larger sets might be assembled. At the same time, the full search is not recommended for model spaces with more than 25 polynomial or linear terms. For a linear combination of three input variables, seven different possibilities exist (2^m-1 is the number of possibilities for linear combination, in which m is the number of input variables). Combinatorial GMDH, in general, is a time-consuming algorithm. However, it is capable to provide a closed form solution which can provide the target in a straightforward manner, if proper parameters, such as the appropriate fitness function, are chosen before running the algorithm. Further information about combinatorial GMDH approach can be found in the references [41, 43–45].

3. Results and discussion

3.1. Experimental and computational test results

Direct shear test (DST) results on GR1, GR2, GR3, RC1 and RC2 rubber samples are presented in Figure to Figure . Based on Figure (a) to Figure (a), it can be inferred that the maximum shear strength of GR2 and GR3 samples were 5.45 and 54.78 percent more than that of GR1, respectively in the case of applying 5 kPa normal stress. Moreover, there had been an increase of 16.14 and 30.21 percent when surcharge of 25 kPa was exerted. For higher normal stresses an average growth of approximately 9 and 12 percent was observed for GR2 and GR3 rubber samples, respectively. Thus, it can be concluded that the shear responses of GR samples is strongly dependent on the size of grains for which the larger D_{50} lead to higher maximum shear stress for entire exerted normal stresses. Additionally, for 5 and 25 kPa normal stresses, the maximum shear strength growth is considerably lager than higher normal stress levels. This behavior can also be correlated to the participation of larger particles in the shear plane when lower levels of normal stress were applied. While, in higher surcharges bigger grains were contracted and entire particles were responsible for shear stress bearing in the shear plane and forming the loading skeleton of rubber specimens. The trend is in agreement with what was reported by Kim and Santamarina [46] for large rubber particles. According to Figure (a) and Figure (a), maximum shear stresses of RC2 was 47.27 and 32.23 percent more than that of RC1 for 5 and 25 kPa normal stresses,

respectively. Moreover, the average growth of approximately 5 percent was occurred for 50, 100 and 150 kPa surcharges. The maximum shear strength of RC sets is less than that of GR group which can be related to the arrangement of the particles. In fact, the relative density of GR and RC samples was strained to be the same. Therefore, in RC samples, which were enclosed larger particles, the voids were not distributed all over the shear box and might lead to less shear strength particularly in large normal stresses.
Considering Figure (b) to Figure (b), it can be seen that samples are contracted firstly and then expansion behavior is observed for small normal stresses. For larger normal stresses (50, 100 and 150 kPa) GR specimens are steeply compressed up to 2.5 percent of horizontal strain and compression trend is smoothly continued. According to Figure (b) and Figure (b), dilation behavior is roughly witnessed in RC samples regardless of the normal applied stress. RC2 sample, which is the largest sample size, is less compressible than any other tested rubber sample. This can be related to the nature of rubber material particles which are comparatively large and less deformable.

Based on Mohr-Coulomb failure criterion, shear strength parameters including internal friction angle (φ) and apparent cohesion (c) of the tested samples were calculated which are presented in Table . As it can be seen, the values of φ and c for GR1 are 2.4^0 and 5.42 kPa, respectively greater than GR2 and 0.3^0 and 3.82 kPa, respectively greater than GR3 sample. The value of internal friction angle for RC1 sample is 0.8^0 less than that of RC2. However, cohesion intercept of RC2 sample is 3.53 kPa more than RC1.

3.2. Optimized network

The main concern in the artificial neural network is to find optimized network according to the numbers of neurons existing in the hidden layer for which the maximum regression value or correlation coefficient (R) and minimum mean square error (MSE) state occurs. Finding the optimized ANN in this research, networks containing 5 up to 25 neurons in the hidden layer were modeled for shear stress and vertical strain, separately.
Based on the results presented in Figure and Figure , it can be inferred that entire networks provide a good approximation, particularly with 13 and 24 neurons for shear stress and vertical strain, respectively. The selected combination as an optimized network is due to the very low value of MSE which are 0.000047965 and 0.00009467 for shear stress and vertical strain ANN models, respectively. Additionally, correlation coefficient (R) values for both of the selected networks are the maximum value between other networks. Figure depicts DST experimental shear stress and vertical strain values versus ANN predicted values. It can be seen that point distributions are close to the ideal fit line which shows maximum fitness and appropriateness of the ANN model. However, other criteria are available for model performance evaluation which is going to be discussed in the following sections.

3.3. GMDH algorithm results

20 percent of entire data are randomly put aside for testing stage in the algorithm which provides more reliable predictions due to the fact that they are not being used in the model training and constant optimization. Eq. (4) and (5) are driven using combinatorial GMDH method for estimating shear stress (τ) and vertical strain (ε_v) after so many trials have occurred. It can be seen that the input parameters are formed the equations with different orders and combinations with constants.

$$\tau = 0.115 - \frac{0.022C_u}{C_c} + \frac{0.009\sigma_n}{C_u} + 0.425\sigma_n C_c + \frac{0.56\sigma_n}{D_{50}} - \frac{0.055\sigma_n}{\varepsilon_h} + 0.4\sigma_n\varepsilon_h \quad \textbf{(4)}$$

$$\varepsilon_v = 0.53 - \frac{0.0017\varepsilon_h + 0.00035\varepsilon_h^2 + 0.002\varepsilon_h\sigma_n + 0.0007\sigma_n^2}{C_u^2 D_{50}} + \frac{0.0002\varepsilon_h}{C_u^2 D_{50}\sigma_n} - \frac{0.099\sigma_n - 0.105C_u\sigma_n^3}{D_{50}} + \frac{0.0028\sigma_n C_u}{C_c^2\varepsilon_h} \quad \textbf{(5)}$$

It must be noted that these equations are developed based on the normalized and scaled input data which outcomes the normalized and scaled target values. Moreover, in order to show the suitability of the developed models, measures values versus GMDH predicted ones are depicted in Figure for both of the shear stress and vertical strain target parameters. It can be seen that the deviation of plotted points from the ideal fit line is not as well as ANN model. However, the closed form formulation is an advantage which overcomes the former model.

3.4. Evaluation of developed models performance

The performance of the developed models can be evaluated using some predefined expressions as yardsticks to show the models accuracy. Following criteria was suggested by Smith (1986) for assessing the fitness of a model [47]:

- A strong correlation exists between the predicted and target values when $|R| > 0.8$.
- A correlation exists between the predicted and target values when $0.2 < |R| < 0.8$.
- Existing correlation between the predicted and target values is weak when $|R| < 0.2$.

In any case, there should be only tolerable minimum error values and acceptable degree of accuracy can be achieved using the model with high R and low MSE values or other introduced criteria. The favorable performance of the model on both the training and testing data sets indicate that the model has achieved both accurate predictive capability and sufficient generalization. Previously, researchers suggested that the minimum value for one the slopes of the regression lines (k or k') through the origin should be close to unity, wherein k is the slope of the regression line in a plot of actual data (h_i) against predicted values (t_i), and k' is the slope of the regression line in a plot of predicted against actual values [48, 49]. Either the squared correlation coefficient (through the origin) between predicted and experimental values (ρ^2), or the coefficient between experimental and predicted values (ρ'^2) should be close to 1. The validation criteria and associated results obtained by the models are presented in Table which shows that the developed models satisfy the required criteria. Additionally, the achieved error benchmarks, mean absolute error (MAE), mean squared error (MSE) and root mean squared error (RMSE) are included in Table . It can be inferred that error value in ANN model is less than that of GMDH as well as regression values (R). However, there is a strong correlation between the predicted and measured values for both of the ANN and GMDH models.

Using the GMDH and ANN developed models, shear stress and vertical strain changes with horizontal strain are depicted in Figure to Figure as well as measured values. It can be seen that both methods are estimated shear stress changes for different applied normal stresses according to different sizes of the grains. However, ANN model for vertical strain provided more accurate values for entire samples rather than that of GMDH model.

4. Conclusion

Small and large direct shear tests were performed on five different sets of rubber wastes named granulated rubber (GR1, GR2 and GR3) and rubber chips (RC1 and RC2). Granulated rubber sets, GR1 and GR3, includes particles diameter ranging from 0.075 to 1.18 mm and 0.425 to 4.75 mm, respectively and GR2 which is widely distributed between the other two groups with grains diameters ranging between 0.075 and 4.75 mm. Rubber chips samples, RC1 and RC2 consist of particles with diameters varying from 0.425 to 25 mm and 4.69 to 50 mm. RC1 and GR2 are widely extended between other rubber samples. The results show that grain size can lead shear strength to undergo changes. Based on DST results, it can be stated that GR group tend to show larger shear strength due to its consistent and more uniform matrix which is resulted from grains arrangement in the shear box. Additionally, the load-bearing skeleton is formed in GR group which is not the same case in RC specimens.

Experimental data were used to introduce an artificial neural network (ANN) and combinatorial group method of data handling (GMDH) in order to simulate shear stress and vertical strain changes along with horizontal strain. Input variables for these models are σ_n, ε_h, C_u, C_c, and D_{50} which finally lead to achieving shear stress and vertical strain responses of the rubber materials. Optimized network architectures are 5-13-1 and 5-24-1 which can perfectly simulate the shear stress and vertical strain, respectively.

A GMDH approach using combinatorial algorithm was implemented for developing explicit equations which can capture shear stress and vertical strain responses. ANN and GMDH model performances have been checked using different criterions such as correlation coefficient (R) and the error values was relatively small for the introduced models. The offered closed form equation based on the GMDH gives reliable estimations for shear strength and vertical strain as it was checked with model verification benchmarks.

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Captions:

Table 1. Summary of some previous studies on rubber grains shear strength resulted from direct shear testing.
Table 2. Rubber samples particle distribution characteristics.
Table 3. Statistical characteristics of input and output data values.
Table 4. Summary of rubber grains shear strength parameters.
Table 5. Different regression values for model performance evaluation.

Figure 1. Particle size distribution of rubber materials.
Figure 2. Developed network architecture (a) shear stress and (b) vertical strain versus horizontal strain.
Figure 3. Direct shear test, ANN and GMDH results for GR1 (a) shear stress and (b) vertical strain versus horizontal strain.
Figure 4. Direct shear test, ANN and GMDH results for GR2 (a) shear stress and (b) vertical strain versus horizontal strain.
Figure 5. Direct shear test, ANN and GMDH results for GR3 (a) shear stress and (b) vertical strain versus horizontal strain.
Figure 6. Direct shear test, ANN and GMDH results for RC1 (a) shear stress and (b) vertical strain versus horizontal strain.
Figure 7. Direct shear test, ANN and GMDH results for RC2 (a) shear stress and (b) vertical strain versus horizontal strain.
Figure 8. Shear stress (a) regression value (R) and (b) mean square error (MSE) for ANNs with different number of neurons in hidden layer.
Figure 9. Vertical strain (a) regression value (R) and (b) mean square error (MSE) for ANNs with different number of neurons in hidden layer.
Figure 10. (a) experimental shear stress and (b) experimental vertical strain versus ANN model predicted values.
Figure 11. (a) experimental shear stress and (b) experimental vertical strain versus GMDH model predicted values.

Table 1

Research	Direct Shear Test Type	Maximum Grain Size (mm)	σ_n (kPa)	*c* (kPa)	φ (Degree)	Failure Criterion Point
Humphery et al. (1993) [4]	Large scale	51	17-68	7.7	21	Peak or at 10% disp.*
		76	17-63	11.5	19	
		38	17-62	8.6	25	
Foose et al. (1996) [20]	Large scale	50,100,150	1-76	3	30	Peak or at 9% disp. *
Gebhardt (1997) [28]	Large scale	1400	5.5-28	0	38	10% disp.
Yang et al. (2002) [6]	Small scale	10	0-83	0	32	10% disp.
Fox et al. (2018) [30]	Large scale	320	76.7	NA	30.2	13% disp.

* The failure was considered to be the peak shear stress. If no peak was reached, the shear at a horizontal displacement equal to 10, 9 and 15% of the length of the shear box was taken. NA means that the data was not achievable through the corresponding reference.

Table 2

	Rubber Samples				
Parameter	GR1	GR2	GR3	RC1	RC2
D_{50}	0.28	0.97	1.71	7.50	19.10
C_u	2.20	5.00	1.61	3.22	2.03
C_c	0.89	1.08	0.99	1.15	1.23

Table 3

Statistical Value	C_u	C_c	D_{50} (mm)	ε_h (%)	σ_n (kPa)	ε_v (%)	τ (kPa)
Maximum	5.00	1.23	19.10	18.00	150.00	1.67	114.17
Minimum	1.61	0.89	0.28	0.00	5.00	-1.88	0.00
Average	2.80	1.07	5.94	5.45	66.32	-0.47	28.35
Standard Deviation	1.22	0.12	7.10	4.71	52.67	0.58	27.04
Coefficient of Variation	0.43	0.11	1.20	0.86	0.79	-1.24	0.95

Table 4

Material		Direct Shear Test Type	Maximum Grain Size (mm)	σ_n (kPa)	*c* (kPa)	φ (Degree)	Failure Criterion Point
Granulated Rubber (GR)	GR1	Small scale	1.18	5-150	11.02	34.6	15% of Horizontal Strain.
	GR2	Small scale	4.75		5.60	32.2	
	GR3	Small scale	4.75		7.20	34.3	
Rubber Chips (RC)	RC1	Large scale	15		8.69	31.3	12% of Horizontal Strain.
	RC2	Large scale	50		5.16	32.1	

Table 5

Method	Target	k	k'	ρ^2	ρ'^2	R= $\frac{\sum_{i=1}^{N}(X_i-\bar{X})(Y_i-\bar{Y})}{\sqrt{\sum_{i=1}^{N}(X_i-\bar{X})^2\sum_{i=1}^{N}(Y_i-\bar{Y})^2}}$	MAE= $\frac{1}{N}\sum_{i=1}^{N}\lvert X_i-Y_i\rvert$	MSE= $\frac{\sum_{i=1}^{N}(X_i-Y_i)^2}{N}$	RMSE= $\sqrt{\frac{\sum_{i=1}^{N}(X_i-Y_i)^2}{N}}$
ANN	ε_v	0.9944	1.0028	0.9888	1.0056	0.9977	0.0278	0.0016	0.0401
	τ	0.9979	1.0016	0.9958	1.0032	0.9994	0.6431	0.8452	0.9194
GMDH	ε_v	0.9743	1.0094	0.9493	1.0189	0.9867	0.0710	0.0095	0.0974
	τ	0.9953	0.9992	0.9906	0.9984	0.9942	2.0774	8.4918	2.9141

It should be noted that N is the number of data points which was presented to the model; X_i and Y_i are the measured and model predicted outputs, respectively. $\bar{X}$ and $\bar{Y}$ are the mean values of the experimentally measured and model predicted out puts, respectively.

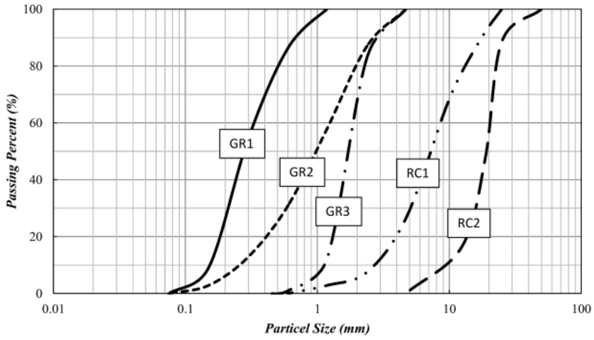
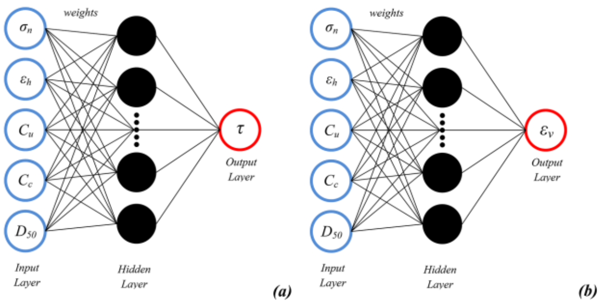


Figure 1



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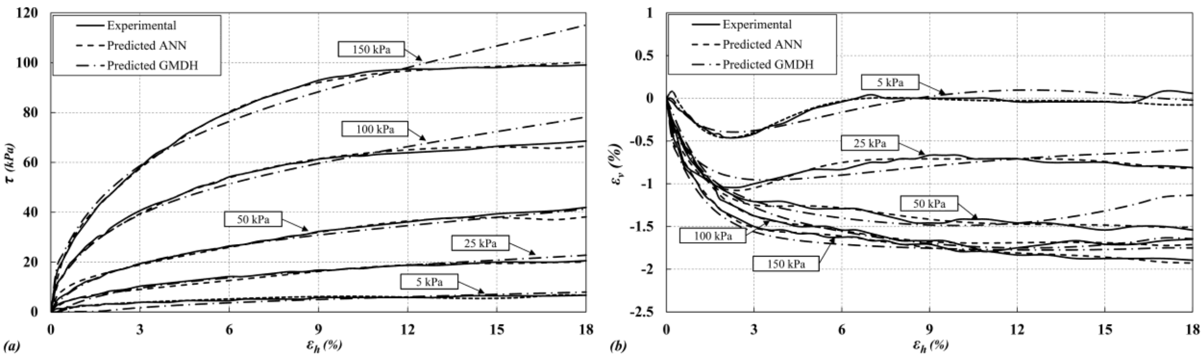

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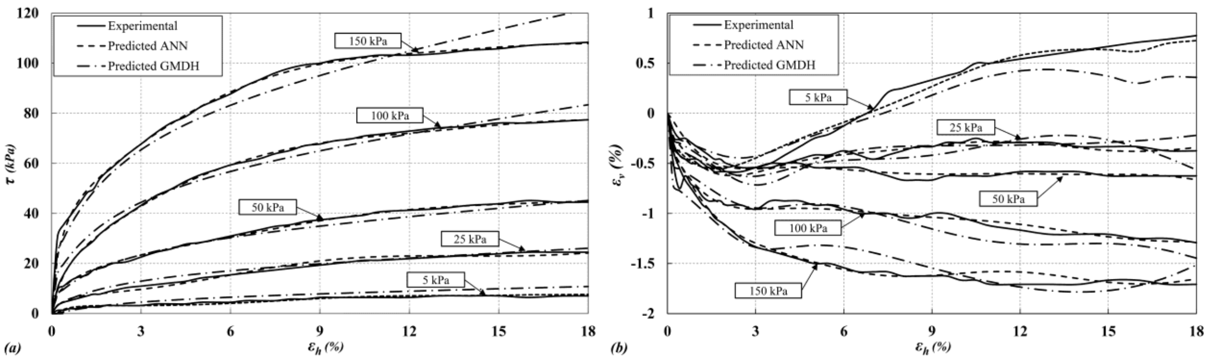

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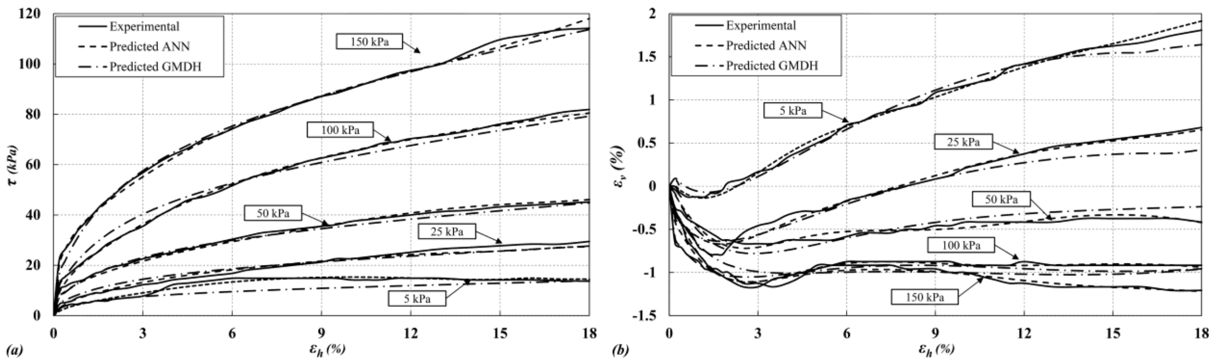

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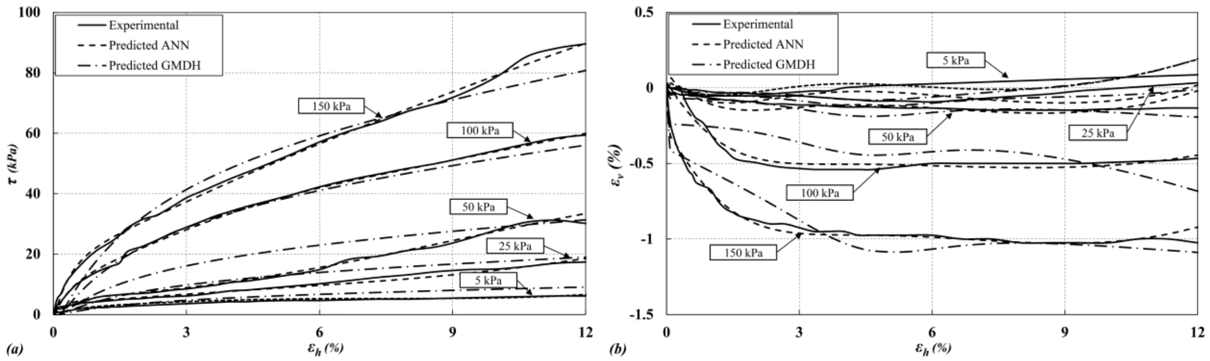

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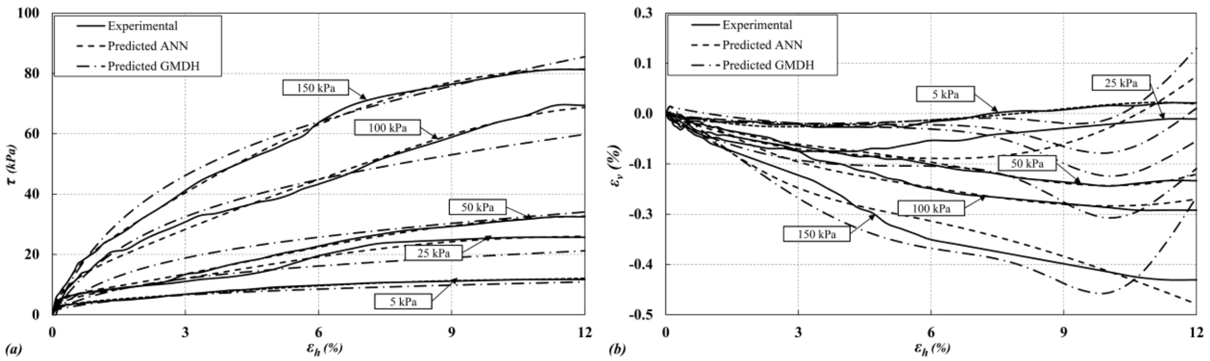

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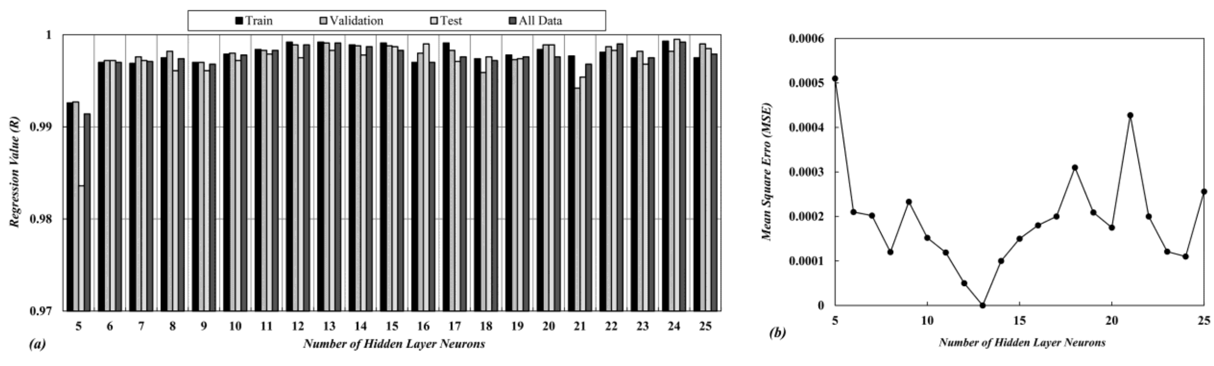

Figure 8

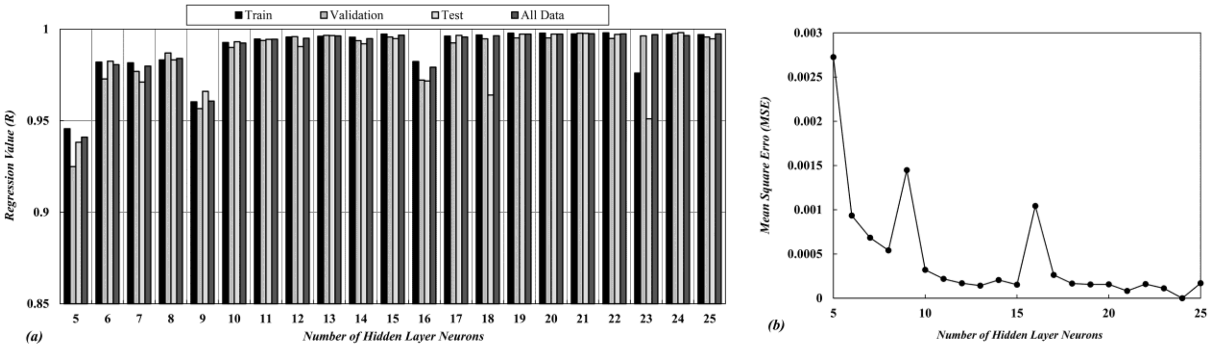

Figure 9

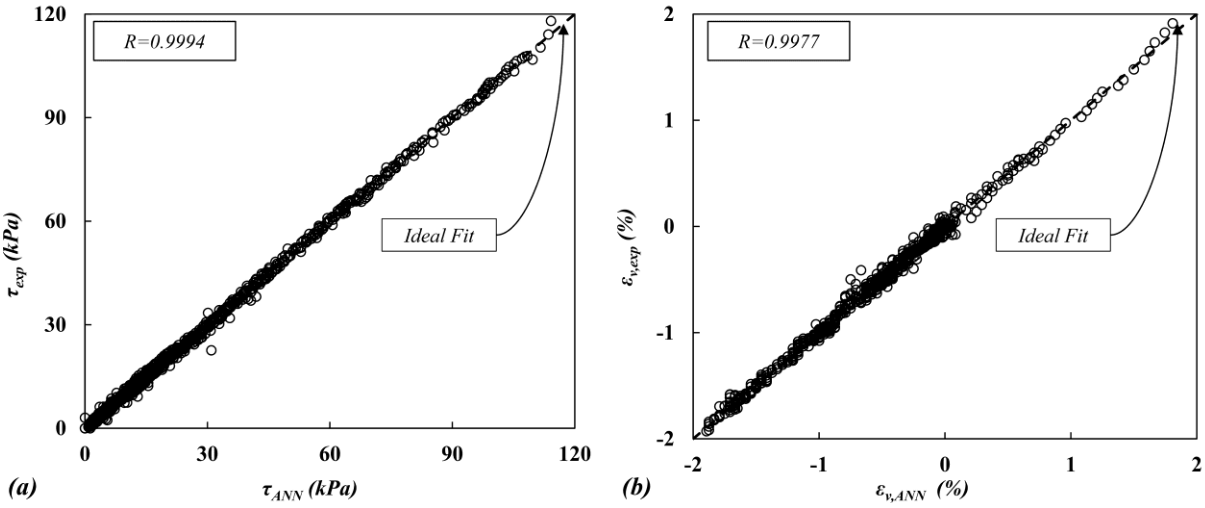

Figure 10

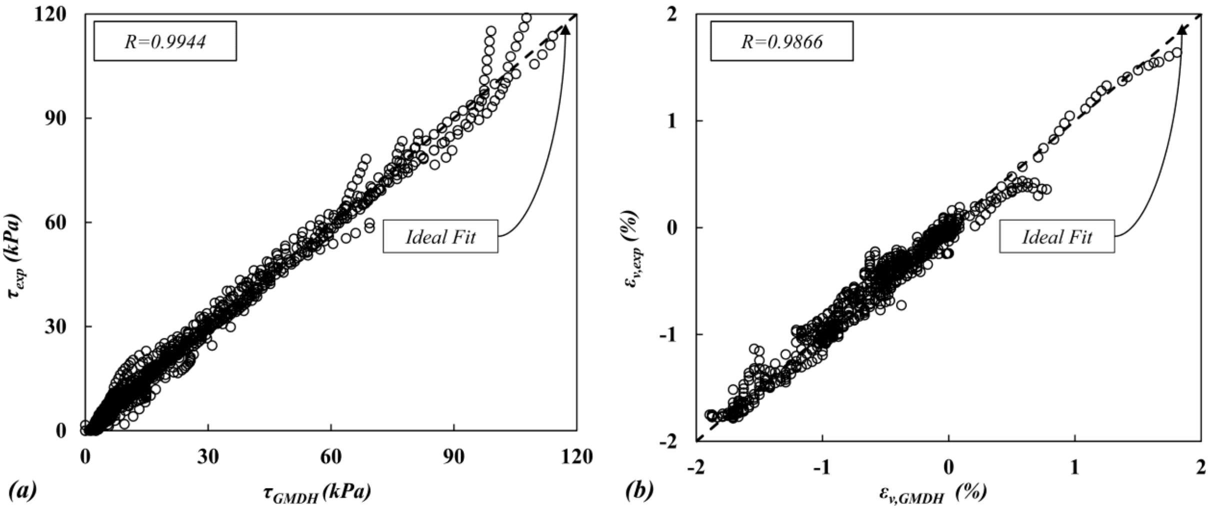

Figure 11

Danial Rezazadeh Eidgahee's Bio:

Danial Rezazadeh Eidgahee is currently a Ph.D. candidate in Geotechnical Engineering, Semnan University, Semnan, Iran. He obtained his M.Sc. degree in 2013 from the Ferdowsi University of Mashhad in the area of discrete element modeling (DEM) of granular materials. His Ph.D. researches include experimental and numerical investigations on the geomaterials mechanical behavior. He is interested in applications of soft computing approaches and probabilistic studies in the field of geotechnical and foundation engineering.

Dr. Abdolhosein Haddad's Bio:

Abdolhosein Haddad obtained a M.Sc. degree from Iran University of Science & Technology, Tehran and a Ph.D. from engineering school of Shiraz University, Shiraz, Iran. He is associate professor of geotechnical engineering and head of the geotechnical Eng. department at the Semnan University. He has been involved in geotechnical research, consulting and education for more than 17 years. He has authored or co-authored 3 books in geotechnical engineering and more than 50 scientific papers. Also, he is a member of the editorial board of the journal of rehabilitation in civil engineering (JRCE), published by Semnan university press.

Dr. Hosein Naderpour's Bio:

Hosein Naderpour received his Ph.D. degree with high honors in Structural Engineering. He then joined Semnan University where he is presently Associate Professor of Structural Engineering. Since joining the faculty of Civil Engineering at Semnan University, Dr. Naderpour has taught a variety of undergraduate and graduate courses in the areas of structural engineering, numerical methods, mechanics of materials, structural stability, concrete structures, structural reliability, as well as soft computing. Dr. Naderpour is author of 70 papers published in journals and about 150 papers presented at national and international conferences. He has given several speeches in Switzerland, China, Australia, South Korea, Romania, Turkey, Canada, Hong Kong, Belgium, Portugal, Spain, Japan, Germany, Italy, Czech Republic and France. He is currently a chief member of Iranian Earthquake Engineering Association, Iran Concrete Institute (ICI), Iranian Society for Light Steel Framing (LSF), Iran's National Elites Foundation, Safe School Committee, Organization for Development, Renovation and Equipping Schools of Iran (DRES). His major research interests include: application of soft computing in structural engineering, seismic resilience, structural reliability, structural optimization and damage detection of structures.