Analysis of Buried Plastic Pipes in Reinforced Sand under Repeated-Load Using Neural Network and Regression Model

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Abstract: *The safety of buried pipes under repeated load has been a challenging task in geotechnical engineering. In this paper artificial neural network and regression model for predicting the vertical deformation of high-density polyethylene (HDPE), small diameter flexible pipes buried in reinforced trenches, which were subjected to repeated loadings to simulate the heavy vehicle loads, are proposed.*

The experimental data from tests show that the vertical diametric strain (VDS) of pipe embedded in reinforced sand depends on relative density of sand, number of reinforced layers and height of embedment depth of pipe significantly. Therefore in this investigation, the value of VDS is related to above pointed parameters.

A database of 72 experiments from laboratory tests were utilized to train, validate and test the developed neural network and regression model. The results show that the predicted of the vertical diametric strain (VDS) using the trained neural network and regression model are in good agreement with the experimental results but the predictions obtained from the neural network are better than regression model as the maximum percentage of error for training data is less than 1.56% and 27.4%, for neural network and regression model, respectively. Also the additional set of 24 data was used for validation of the model as 90% of predicted results have less than 7% and 21.5% error for neural network and regression model, respectively. A parametric study has been conducted using the trained neural network to study the important parameters on the vertical diametric strain.

Keyword: *Neural network, Regression model, Soil reinforcement, Buried pipe, Vertical diametric Strain*

1. Introduction

The buried pipeline is decaying due to insufficient quality control, resulting in poor installation, little or no inspection and maintenance, and a general lack of uniformity and improvement in design, construction and operation practices. Many researchers have focused on this topic and developed the soil-pipe interaction experimentally, numerically or presented the mathematical relations or empirical equations. The original work was carried out by Marston and Anderson (1913) [1], and a theory for calculating diametric change under soil overburden, was used by Spangler (1941) [2] to obtain a formula for calculating the horizontal deflection of buried pipes under soil overburden. Masada (2000) was revisited the classical work of Spangler to derive a modified Iowa formula for estimating vertical deflection of flexible pipe under soil overburden [3].

These design methods, whether developed from empirical or theoretical bases, deal with predicted loading experienced by embedded flexible pipes as a result of static stress. Hence, study the pipe behavior under temporary or permanent repeated load similar to heavy vehicles is an important case. Many laboratory or field studies have been carried out by Rogers et al. (1995) [4], Faragher (1997) [5], Faragher et al. (2000) [6], Mir Mohammad Hosseini & Moghaddas Tafreshi (2002) [7], Arockiasamy et al. (2006) [8] performed field tests on polyethylene, PVC, and metal large diameter pipes subjected to highway design truck loading, then the numerical simulations using finite element method are performed to determine pipe-soil interaction under live load application. Bueno et al. (2006) were conducted an experimental testing program to evaluate the effect of geosynthetic reinforcements on vertical stresses acting on top of the pipe.

Above literature indicates that, in spite of extensive experimental or numerical studies which have been carried out to model the soil-pipe interaction on buried pipe embedded in unreinforced soil leading to many mathematical relations and empirical equations, no possibility was provided for studying of the pipe behavior under repeated loads conditions in reinforced sand.

In recent years, artificial neural networks (ANNs) and regression method have been successfully used for many civil engineering problems (Flood and Kartam, 1994 [10, 11]; Turkkan and Srivastava, 1995 [12]; Kartam et al., 1997 [13]; Lee, 2003 [14]; Ataeia et al., 2000 [15]; Bera et al.2005 [16]). The current paper investigates the feasibility of using artificial neural networks and regression model to evaluate the vertical diametric strain (VDS: Vertical Diametric Strain which defined as the reduction in vertical diameter divided by original vertical diameter) of buried plastic pipes in reinforced sand under repeated-loads such as heavy traffic at the end of the cyclic which the deformation of pipe is stabled. The effects of various vital parameters such as, relative density of sand (D_r), number of reinforced layers (N) and embedded depth of pipe (H/D) on VDS were studied by artificial neural networks and regression method. Finally, Comparison between predictions obtained from the trained neural network, regression model and those from experimental data are presented. The used experimental data for training and verification the neural network and regression model is obtained from the physical model which was developed in K.N. Toosi University of Technology by the first author.

2. Description of experimental model

The used data in the present study are obtained from experimental model test of 110 mm plastic pipe embedded in reinforced sand with geogrid layers. Fig.1 shows the schematic layout of the trench, which accommodates the soil, layers of reinforcement, pipe and steel plate (as loading surface). According to this figure the values of u/B= h/B and h/D are 0.35 and 4, respectively.

The properties of the materials used in the present research are given below:

Soils: Based on Fig. 1, two types of soil are prepared in the test tank as the surrounding materials.

Soil A: This soil which is used to simulate the natural ground (at bedding and two sides of the trench) was a granular soil of grains size between 0.08 and 20 mm, with D_{50}=3.7 mm, C_c=0.79 and C_u=13.75.

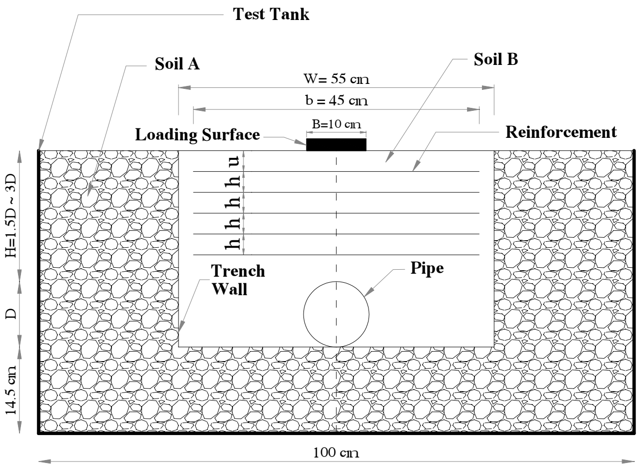


Fig. 1. The schematic layout of the trench.

Soil B: The main soil which is used in this study was a relatively uniform silica sand of grains size between 0.07 and 1.24 mm, with D_{50}=0.64 mm, C_c=1.29, C_u=1.51 and G_s=2.67. This sand is classified as SP in unified soil classification system. In order to study the effect of the soil density on the behavior of the buried pipe, three different relative densities: 42%, 57%, and 72% were selected as the relative loose, medium dense and dense states, respectively.

Pipe: The plastic pipes used in this research had 110 mm external diameter, 4.03 mm thickness and 210 mm length. The pipes were made of polyethylene (HDPE: High Density Polyethylene). The modulus of elasticity and the Poisson's ratio of pipe were 8160 Kg/cm^2, and 0.46 respectively.

Geogrid: The geogrid was used in this research made of HDPE (High Density Polyethylene). The engineering properties of this geogrid are: thickness 5.2 mm, mass per unit area 695 *gr/m^2*, ultimate tensile strength 5.8 kN/m, Poison ratio 0.4, modulus of elasticity 8000 kg/cm^2 and aperture size 27×27 mm.

The time history of repeated load which applied on the soil surface is shown in Fig. 2. It can be seen that the repeated load was returned to zero at the end of each cycle that is typical of a vehicle loading on a track or pavement support. The tests were carried out under repeated load with amplitude of 5.5 kg/cm^2 to simulate the heavy vehicle loading.

The typical trends of pipe deformation in term of change in VDS (Vertical Diametric Strain: defined as the reduction in vertical diameter divided by original vertical diameter) of pipe and with the time (or number of load cycles) under loading and unloading are shown in Fig. 3. This figure is shown that, the variation of VDS is stabled after short time (almost 400 sec) which is called maximum VDS. The influence of parameters such as number of reinforced layers (N); relative density of sand (D_r); and embedded depth of pipe (H/D) has investigated in the testing program.

3. Artificial Neural Networks (ANNs)

Recently, there has been a great resurgence of research in neural network classifiers. Artificial neural networks (ANNs) are introduced as computing systems made up of

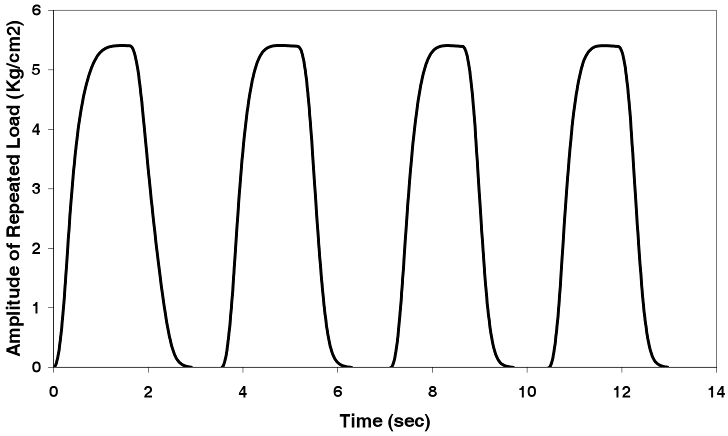


Fig. 2. Time history of repeated load on the soil surface.

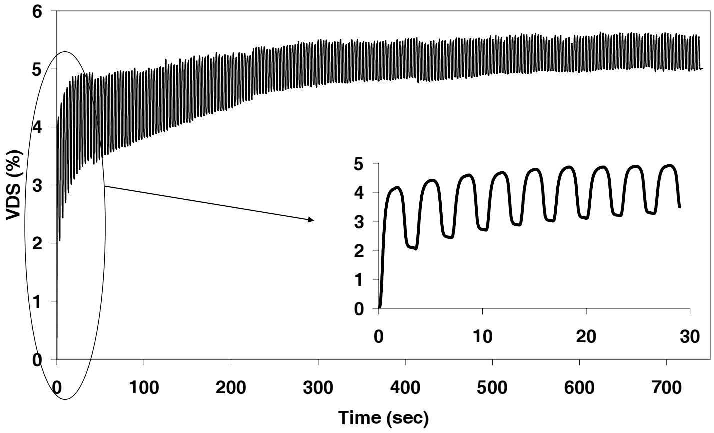


Fig. 3. Typical trend of VDS during repeated loads.

a number of simple, highly interconnected processing elements called neurons. The networks are represented by connective weights between the neurons. These weights are the parameters that define the non-linear function performed by the neural network. The process of determining these weights is called training or learning and depends on the presentation of as many reliable training patterns as possible. ANNs are capable of performing an amount of generalization from the data entries on which they are trained.

The most widely used connection pattern is the three layers back propagation neural network [17], which has proved to be useful when modeling input-output relations [18] and is also used in this study. The number of neurons of input and output layers coincide with the number of input and output variables in the data set whereas there is no specific rule to determine the number of hidden layers or the number of neurons in each hidden layer, hence the number of neurons in each hidden layer must be found experimentally. But usually, a network with two hidden layers (two sub-layers) is sufficient to handle most of complex problems in civil engineering applications.

By varying the weights, among neurons, a network may be trained to reproduce the desired input-output relationship. The nonlinear transformation between input and output is performed by neurons in hidden layer, which transforms the weighted inputs using a transfer function. The most commonly used transfer functions are the linear, sigmoid, log-sigmoid and the tan-sigmoid functions [17]. Training consists of (i) calculating outputs from input data, (ii) comparing the calculated outputs for each pattern with a target output for that pattern, and (iii) adjusting the weights for each neuron to decrease the difference between the measured and calculated values (calculating the error and propagating an error function backward through the neural network). This training procedure uses the back propagation algorithm [19].

4. Regression analysis

Regression analysis attempts to derive equations, which can be used to estimate the relationships between two or more variables. A general regression model is mathematical equation in the form of:

$$y = f(x_1, x_2, ..., x_p) \tag{1}$$

Where y is the dependent variable usually called response variable, and $(x_1, x_2, ..., x_p)$ are independent variables (the variables used to explain y).

A famous form of this model is linear function which has been assumed in the following form:

$$y = \sum_{i=1}^{p} \xi_i x_i \tag{2}$$

In this model ζ_i is the parameter related to ith independent variable and p is the number of independent variables and parameters.

In great of engineering problems a non-linear relationship between parameters established. Hence it is necessary which the non-linear models transform to linear models. For example; the non-linear model as below:

$$y = \zeta_0 \, x_1^{\zeta_1} x_2^{\zeta_2} ... x_p^{\zeta_p} \tag{3}$$

Can be linearized by using a logarithmic transformation, which is given as follows:

$$Log\, y = Log\, \zeta_0 + \zeta_1 \, Log\, x_1 + \zeta_2 \, Log\, x_2 + ... + \zeta_p \, Log\, x_p$$

Or

$$y_t = \zeta_{0t} + \zeta_1 x_{1t} + \zeta_2 x_{2t} + ... + \zeta_p x_{pt} \tag{4}$$

Where $y_t = Log\, y$, $\zeta_{0t} = Log\, \zeta$, $x_{1t} = Log\, x_1$, $x_{2t} = Log\, x_2$, $x_{pt} = Log\, x_p$

Standard regression techniques can now be used to estimate $\zeta_{0t}, \zeta_1, \zeta_2, ..., \zeta_p$ for Eq. (4). In practice, n observations would be available on y with the corresponding n observations on each of the p independent variables. Thus n numbers of equations, in the form of Eq. (4), can be written, one for each observation. Essentially, n equations will be solved for the p unknown parameters. Thus n must be equal to or greater than p ($p \geqq n$).

A simple method which solves this equation and estimates the unknown parameters ζ, is minimizing the sum of squares of the errors, $S = \Sigma\, e_i^2$; Where $e_i = (y_i - \hat{y}_i)$, and $\hat{y}_i$ is the predicted value of y_i .

Assessment of regression model can be done estimating of at least two indices: the multiple coefficient of determination (R^2)

Table 1 Range of input parameters of the experimental data used to train the ANNs and regression model.

Neural network input parameters	Range of parameter
number of reinforced layers, N	0 to 5
relative density of sand, D_r	42% to 72%
embedded depth of pipe, H/D	1.5 to 3

and standard error (E_s). The most powerful measure of quality of fit is R^2. The multiple coefficient of determination R^2 gives an indication of how good choice the independent variables $x_1, x_2, ..., x_p$ is in predicting, the dependent variable y. It describes the amount of variation in y values explained by the regression line. The range of R^2 is 0 through 1(or 0 through 100%); the larger value of R^2 and the smaller value of E_s, indicate the better regression model for the data.

5. Training of ANNs and Regression model for buried pipe in reinforced sand

The training of each model is carried out using the training data set. Out of the total 72 experimental data, 48 data are allocated (randomly chosen) for training the ANNs and regression model. The range of input parameters of the data used for training the ANNs and regression model according to experimental program is given in Table 1.

5.1. Training of ANNs

In this study, neural network is trained for maximum vertical deformation of embedded pipe in reinforced sand (VDS). The best neural network was identified after a number of trials. An input layer of three neurons (D_r, N, H/D), an output layer of one neuron VDS, and also two hidden layers are considered in the design of the ANNs for neural network which the number of optimum neurons in first and second hidden layer is obtained 6 and 28 neurons for predicting of VDS. It is noted that the number of neurons in each hidden layers is considered trained once the error of network reaches a minimum value [20]. The ANNs structure as schematically is shown in Fig. 4.

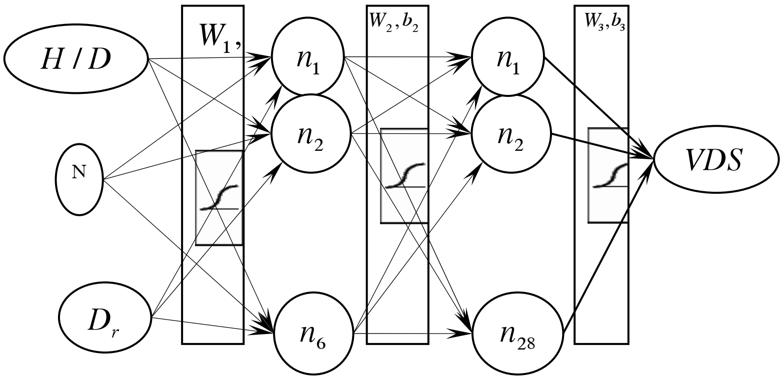
For a better network performance, the input and output data pairs are subjected to scaling process before being use in the network operation, because the compiled raw training data for different parameters can vary significantly in their actual values. When such non-scaled data are directly used in the training procedure, the network could exhibit ill-conditioning.

Also the selection of transfer functions plays an important role in ANNs problems. Hence, among the several different types of transfer functions, the log-sigmoid transfer function is used in this study.

In case of the log-sigmoid transfer function, the output is in the range (0, +1), and so the input is sensitive in a range not much larger than (0, +1). Scaling of data can be linear or non-linear, depending on the distribution of the data [21]. In this study, the scaling of the training data set, based on the positive range of input parameters in Table 1, was carried out a linear form using the following equation:

$$(x)_i^{scaled} = \frac{x_i}{\alpha} \tag{5}$$

Where $(x)_i^{scaled}$ and x_i are the scaled and



Input Layer 3 neurons	First Hidden Layer 6 neurons	Second Hidden Layer 28 neurons	Output Layer 1 neuron

Fig. 4. schematic of ANNs structure for training of VDS (for embedded pipe in reinforced sand).

un-scaled values of the training set, respectively and α is 5, 100 and 5 for scaling the N, D_r and H/D, respectively. The output of the network VDS is subjected to an inverse scaling to return the normal quantities of the output parameters. Also the neural network available in MATLAB version 7 [22] was utilized to construct the proposed neural network. A package of neural network comments has been used to model the problem using back propagation neural networks [23].

The training of the neural network is carried out using the training data set. Testing and monitoring of the developed neural network during the training stage is performed by computing the mean squared error overall training, validation and testing data sets. After each training iteration, the obtained weights are used to predict the corresponding VDS to the input parameters of the training, validation and testing data sets. The mean squared error was calculated for each pattern as the difference between the VDS obtained from the trained neural network and the corresponding experimental VDS.

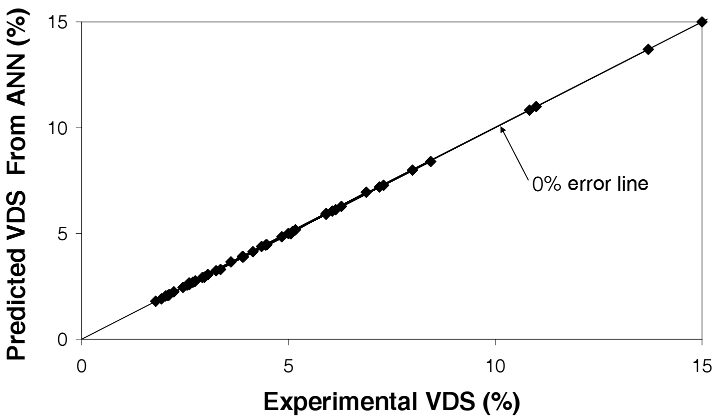
5.2. Training of Regression model

Based on existing experimental data, it's revealed that the relationship between dependent variable (VDS) and independent variable (N, D_r, and H/D) is nonlinear (see Figs 9-11). Therefore, in the present study a non-linear power model has been chosen for predicting VDS.

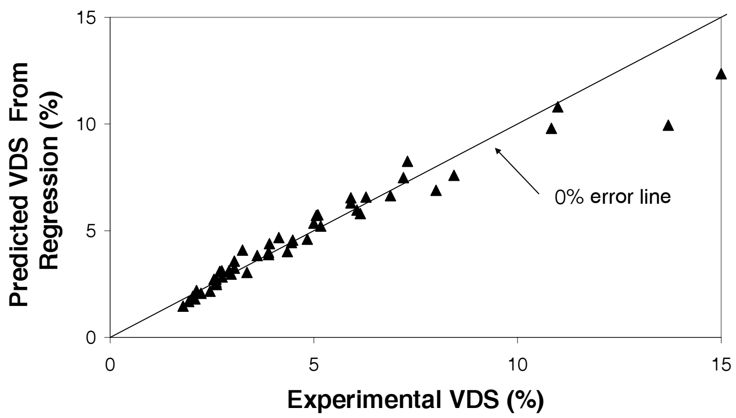
In order to determine the best fitted equation, a great number of non-linear power possible regressions model is used to select the best subset of predictors. Among the equations, by using least-squares technique, the final equation of the fitted model to estimate VDS is obtained as given below:

$$VDS = 17.4168 \times 0.8741^{\mathrm{N}} \times 0.8833^{(H/D)^2} \times 0.0073^{D_r^5} \tag{6}$$

Goodness of fit statistics, such as multiple coefficient of determination R^2(=0.9597) is the highest (near to 1) in case of the relevant parameters for model, and also the value of standard error, E_S (=0.048) for above model is the minimum considering the values of Es



(a)



(b)

Fig. 5. Comparison of trial ANNs and regression predicted values with experimental results, (a) ANNs, (b) Regression model.

for all of the models.

5.3. Result of training

A plot of experimental data and those obtained from the trained neural network and regression model for VDS are presented in Fig. 5(a) and (b), respectively. It is shown that, there is no serious out layer point around the 0% error line for ANNs in comparison regression model and it is in good agreement with experimental results. Hence, it is implied that the ANNs model can be used to predict the value of VDS.

Table 2 gives different statistical parameters estimated to measure the performance of the trained ANNs and regression method. The absolute average percentage of error (e_{ave}.) in estimating the value of VDS is less than 0.5% with ANNs and less than 8.33% with regression model, whereas the maximum percentage of error (e_{max}.) in estimating the value of VDS using the trained ANN and regression method are 1.56% and 27.4%,

Table 2 Statistical parameters for measuring the performance of the trained ANN and regression model.

Method	$e_{ave\,(\%)}$	$e_{max(\%)}$.	R^2	E_s
ANNs	0.5	1.56	0.9998	0.003
Regression	8.33	27.40	0.9597	0.048

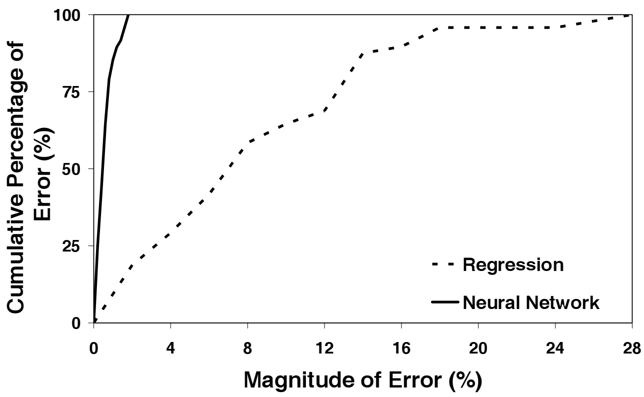


Fig.6. cumulative histogram percentage of errors for the prediction of VDS for ANNs and regression model.

respectively as given in Table 2.

The coefficients of determination of R^2 the ANN (=99.98%) is greater than regression method (=95.97%) as indicated in Table 2. The R^2 statistic indicates that the model as fitted explains 99.98% and 95.97% of the variability in VDS for ANN and regression method, respectively. Also the value of standard error E_s of the ANN (=0.003) is less than regression method (=0.048), the standard error of the estimation shows the value of standard deviation of the residuals. In addition, these statistical parameters show that the predicted VDS using the trained ANN and regression method are in good agreement with experimental results and the predictions obtained from the trained ANN are better than those obtained from regression method and it is identified that an ANNs can give satisfactory performance to apply in the final predicting.

Also, in order to clarify the magnitude of error, Fig. 6 shows cumulative histogram percentage of errors of ANNs and regression model for the prediction of VDS. For example it shows that 90% trained data have less than 1.2% and 16% error for ANNs and regression model, respectively.

6. Verification of the trained ANNs and regression model

For verification of the proposed models, to predict the value of VDS; the models have been tested with 24 additional experimental data that were not used in training stage. A comparison of VDS from experimental data and those obtained from the ANNs and regression model predicted results are given in Fig. 7. It can be clearly observed that the values of VDS are predicted by the neural network better than regression model

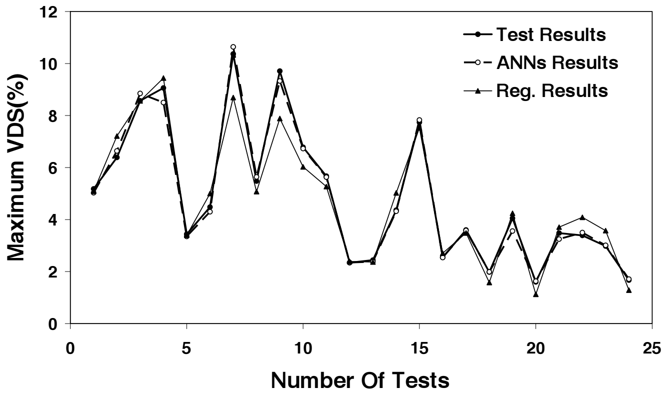


Fig. 7. Comparison of ANNs and regression predicted values with experimental results for data not used in training stage.

Table 3 Comparison of the statistical parameters of the ANN and regression for data not used in training stage.

Method	e_{ave} (%)	e_{max}(%).	R^2	E_s
ANNs	2.81	13	0.9950	0.0183
Regression	10.83	29.8	0.9445	0.0653

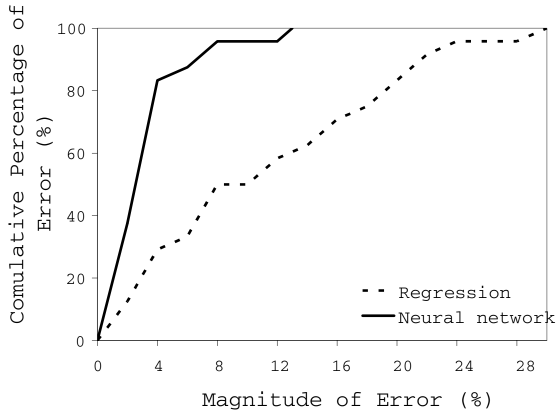


Fig. 8. cumulative histogram percentage of errors for the prediction of VDS for ANNs and regression model for data not used in training stage.

significantly, as the average percentage of error is less than 2.81% and 10.83% for ANNs and regression model, respectively.

Table 3 compares the different statistical parameters to measure the performance of the trained ANN and regression method. In general, it is identified that the neural network approaches performed better and produced more consistent results than the regression model.

The cumulative histogram percentage of errors of the final models for the prediction of VDS for data not used in training the models is shown in Fig. 8. It shows that the maximum percentage of error is less than 13% for ANNs and less than 29.8% for regression model. Also 90% predicted data have less than 7% and 21.5% error for ANNs and regression model, respectively. It is obvious that the ANNs and regression model for estimating the value of VDS have a good

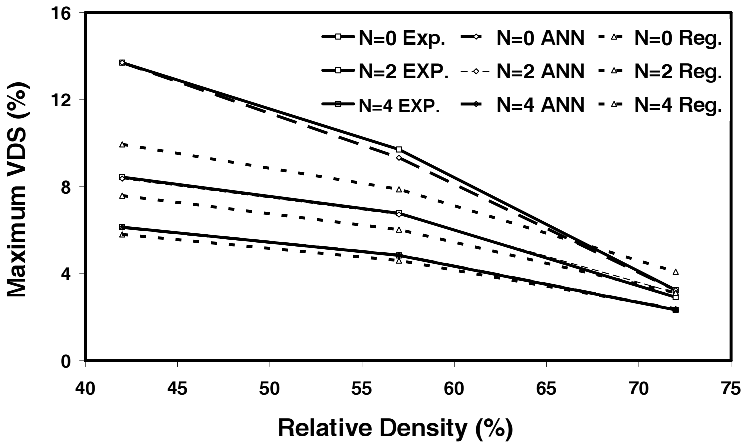


Fig. 9. comparison of ANNs and regression model predicted with experimental data of VDS versus soil relative density.

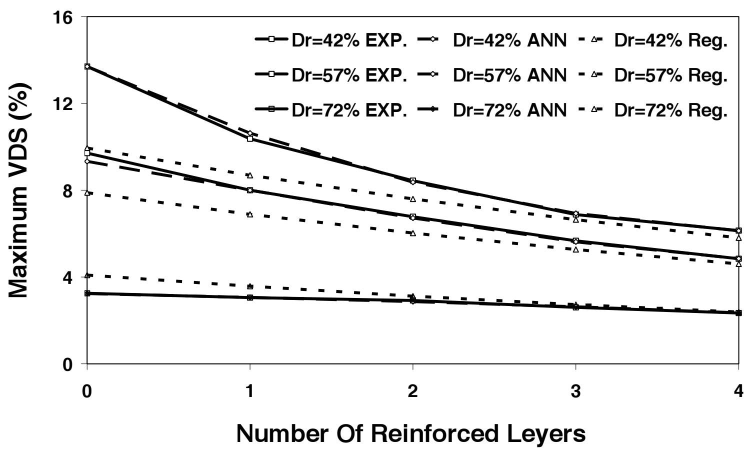


Fig.10. comparison of ANNs and regression model predicted with experimental data of VDS versus soil reinforcement.

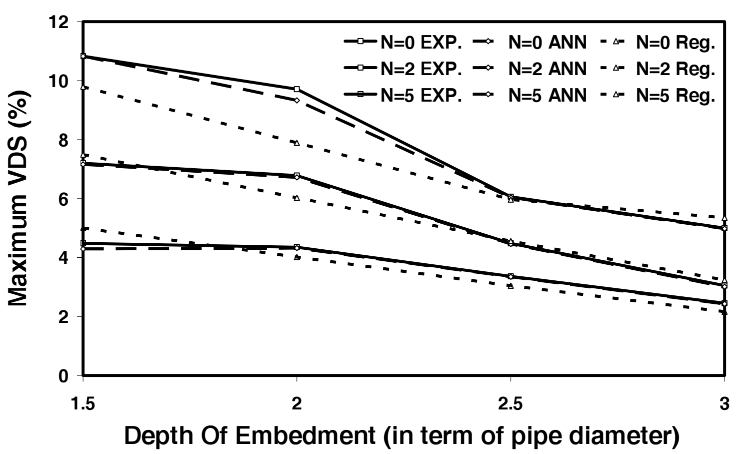


Fig. 11. comparison of ANNs and regression model predicted with experimental data of VDS versus embedment depth of pipe.

fitting to data but the accuracy of ANN model is better than regression model and it can be used to predict the value of VDS.

In order to show more clearly the accuracy of predicted results using ANNs against the regression model, a comparison of VDS from experimental data and those obtained from ANNs and regression model predicted results by considering the effect of soil relative density (D_r), soil reinforcement (N) and embedment depth of pipe (H/D) are presented in Fig. 9-11. As it can be seen, the ANNs predicted results are almost identical to the experimental results, and it is in good agreement with observed data. On the other hand, these predictions agree significantly (favorably) with the general experimental observations for ANNs better than those obtained from the regression model.

Some points are necessary to discuss as below:

1. As it can be shown, the accuracy of predictions from ANNs are better than regression model, but the presentation a simple equation by regression method comparing to ANNs can be accounted an important advantage for regression model as it can be obtained the value of VDS, easily, quickly and inexpensive, as 90% predicted data have less than 21.5% error.

2. The regression model can be applied for extrapolation as the predictions from this model, provide reliable results, whereas the prediction from the trained neural network should be reliable provide that the input data within the range used in the training set as given in Table 1, and out of the pointed range should be used carefully. On the other hand, beyond these ranges of the parameters and for other field conditions, the model should be checked through for at least one set of laboratory model test results.

3. It can be expected that, with the increase of the size and diversity of the database for the training of the ANNs and regression model, it will be possible to obtain more robust models for the prediction of VDS studying the effects of input variables in a wider variation range.

7. Parametric study

After training and verification, the trained ANNs and regression model can be used to simulate the effect of the input parameters on the value of VDS. As it has observed, the neural networks can be predicted the values of VDS better than regression model. Hence the trained neural networks are used to predict the values of VDS for any combination of the input variables so long as their values are within the coverage range of the training database as given in Figs. 12-14. Fig. 12 shows the variation of VDS versus soil relative density for different values of reinforced layers and 2D of embedment depth. From these figures, the key role of the soil density on the deformational behavior of the pipe (VDS) is quite evident. It is clear that, VDS decreases due to increase in the relative density, irrespective of the number of the reinforced layers.

The influence of the soil reinforcement on the maximum VDS at 57% of relative density and various embedment depths is given in Fig. 13. As expected, the value of VDS decreases due to addition of reinforced layers, irrespective of embedment depth of pipe. It can be observed that the decrease in VDS due to additional layers of reinforcement begin to converge at around the fourth layer and almost constant at the fifth layer of reinforcement.

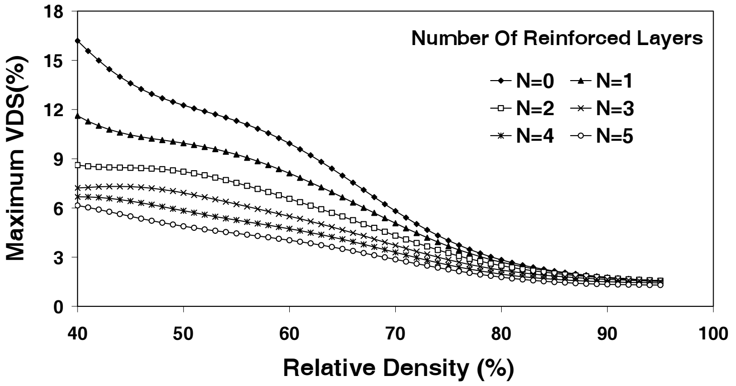


Fig. 12. Effect of soil relative density for H/D= 2 on the maximum VDS.

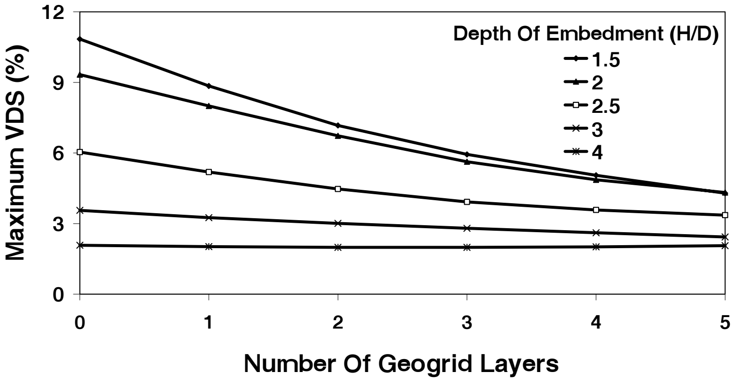


Fig. 13. Effect of number of reinforced layers for D_r= 57% on the maximum VDS.

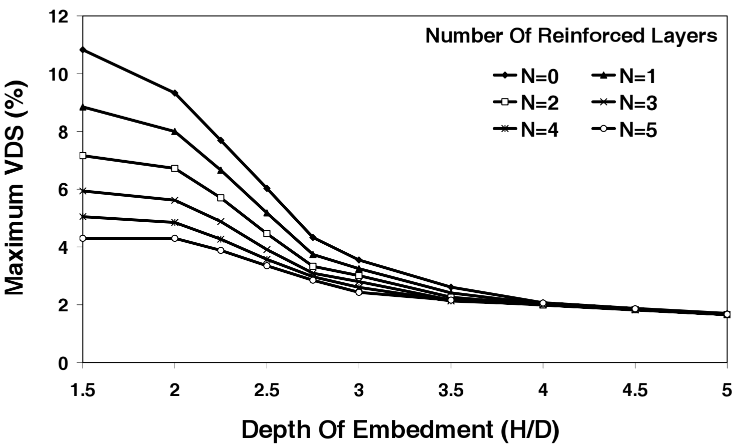


Fig. 14. Effect of embedment depth for D_r= 57% on the maximum VDS.

Fig. 14 presents the effect of embedment depth on the maximum VDS in reinforced sand for different values of reinforced layers and for 57% of relative density of soil. It can be seen that, an increase in the embedment depth of the pipe in the ranges of 1.5D to 2.5D results in a sharp decrease in the maximum VDS of the pipe, while increasing the depth more than 2.5D, the rate of reduction decreases considerably. It shows that, the efficiency decreases with the increase of the embedment depth of pipe.

Finally, from Fig. 12-14 can be observed that, the variation of VDS out of the coverage range of training database is feasible, as the results is similar to experimental data, and with increasing the relative density or embedment depth, the value of VDS converge to a constant value.

8. Conclusions

This paper demonstrated the possibility of adopting neural networks and regression model to predict the vertical deformation (VDS) of high-density polyethylene (HDPE) pipes buried in reinforced (or unreinforced) trenches. The training and verification of the ANNs and regression model was achieved using experimental data prepared by the first author. The prediction from the trained neural network and regression model should be reliable provide that the input data within the range used in the training set as given in Table 1.

On the basis of analysis of the results obtained from the present investigation, the following conclusions can be extracted:

1. The variation of VDS is nonlinearly affected by the soil relative density (D_r), soil reinforcement (N) and embedment depth of pipe (H/D).

2. All of the three parameters (D_r, N, H/D), have the influential effect on the VDS, significantly. An increase of each can be decreased the value of VDS.

3. The comparison of VDS from the experimental data and those obtained from the ANNs and regression model show a good consistency and satisfactory accuracy, as 90% predicted data have less than 7% and 21.5% error with ANNs and regression model, respectively. It is obvious that the ANNs and regression model have a good fitting to experimental data but the predictions obtained from ANNs are better than those obtained from regression approach and it can be used to predict the value of VDS.

4. The reinforcement of soil for the high value of embedment depth of pipe (H/D>3.5) and high degree of compaction (D_r>75%) on reduction of VDS is not effective, thus it is not recommended using reinforced sand for high value of H/D and D_r.

5. The value of soil relative density (D_r), soil reinforcement (N) and embedment depth of pipe (H/D) have a large influence on the value of VDS and increasing of each parameters (H/D, D_r and N) can be decreased the value of VDS. It states that the cost optimization is necessary to determine the economic value of each parameter.

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