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Prediction of shear modulus and damping ratio of rubber-mixed sand by using Artificial Neural Networks

Boyina Manohar[1], Sanjit Biswas[2], G V Ramana[3], Kola Vikas[4]

1(Civil Engineering Department, National Institute of Technology Warangal, India)

2(Civil Engineering Department, National Institute of Technology Warangal, India)

3(Civil Engineering Department, National Institute of Technology Warangal, India)

4(Civil Engineering Department, National Institute of Technology Warangal, India)

ABSTRACT

Evaluating the dynamic properties of soil is an essential step for solving Geotechnical Engineering problems. Dynamic properties like shear modulus and damping ratio are required to estimate the response of soil and soil-structure systems when subjected to cyclic and dynamic loadings and machine vibration. In recent years, intelligent models for solving geotechnical problems have received considerable attention, and Intelligence systems have been used in many areas of Geotechnical Engineering applications. This study uses an Artificial Neural Network (ANN) to predict the dynamic properties like shear modulus and damping ratio of rubber-mixed sand. The inference system will be employed to predict the Dynamic properties of the soil samples as an alternative to lengthy laboratory testing. The database used for the model development is generated by collecting data from the published literature. The most important factors that affect dynamic properties are considered for the development of the model, and sensitivity analysis was performed using the connection weight approach to identify the critical influencing parameter.

Keywords- Artificial Neural Network (ANN), Damping ratio, Intelligence systems, Sensitivity analysis, Shear modulus.

1. Introduction

It is well known that Geotechnical engineers rely on evaluating dynamic soil properties to design structures, as they significantly impact the soil's response to dynamic loads like earthquakes and vibrations. Dynamic properties play a crucial role in soil-structure interaction analysis and in designing resilient and stable structures that can withstand dynamic loads. Dynamic soil properties like shear modulus and Damping ratio are used in geotechnical engineering for predictive modelling, enabling engineers to simulate soil behaviour under various loading conditions [1]. Numerous researchers have used various experimental methods to examine the dynamic behaviour of soils [2-11], while some researchers have undertaken experiments to determine the dynamic properties of rubber-mixed soils [12-16].

Advancements in artificial neural network (ANN) modelling have recently emerged as a promising method for predicting sand's shear modulus and damping ratio [17-20]. Artificial neural networks (ANNs) can capture intricate nonlinear connections and patterns within extensive datasets. This makes them very suitable for modelling the behaviour of granular materials such as sand [21]. While few investigations were conducted on strength-reinforced soils to predict their dynamic properties, numerous researchers developed equations for predicting these properties by employing intelligent models [18-20].

This work focuses on developing a model for rubber-mixed sand to accurately predict its dynamic properties, such as shear modulus and damping ratio. Accurately determining rubber-mixed sand's shear modulus and damping ratio is of utmost importance in geotechnical engineering. This has significant implications for various applications, including earthquake engineering, pavement design, and foundation building. Traditional methods for determining these parameters often involve extensive laboratory testing, which can be time-consuming and costly [21]. To overcome these limitations, researchers have turned to artificial neural networks (ANNs) as a promising tool for predictive modelling in geotechnical engineering [22-26].

This paper assesses the effectiveness of a neural network method employing Bayesian regularisation in determining dynamic parameters such as shear modulus and damping ratio. Multiple endeavours were undertaken to devise the most optimal neural network structure. The model was trained with the percentage of sand, rubber, and confining pressure along with the shear modulus and damping ratio. The developed ANN model can predict the shear modulus and damping ratio with fewer parameters than the conventional formula.

2. Artificial Neural Network

An artificial neural network (ANN) is a processing device, such as hardware or an algorithm, whose architecture is inspired by the structure and operations of human brains. Many artificial neurons, or basic processing units, comprise an ANN system. Artificial Neural Networks (ANNs) are numerical modelling, presenting, and processing frameworks that are especially helpful for information expectation and anticipation in complex settings [24].

The fact that the artificial neural system may be thought of as a nonlinear discovery model is remarkable. Because Artificial Neural Networks (ANNs) only link inputs with output parameters, their popularity has skyrocketed in recent years.

Artificial Neural Networks are modelled after human brains. The human brain is made up of biological neurons shown in “Fig 1” that use axon terminals to interpret information supplied to them from various sources [21]. In the same way, artificial neurons replicate the key features of neural networks.

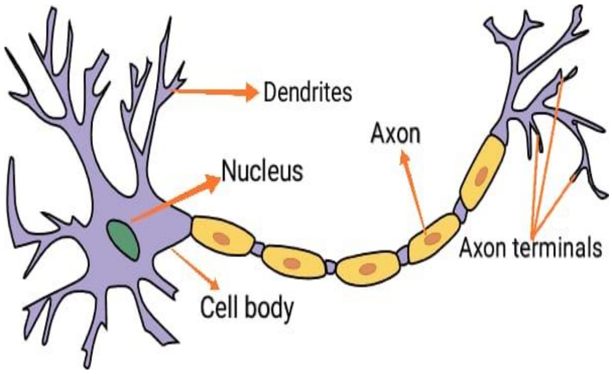

Figure 1: Biological Neuron

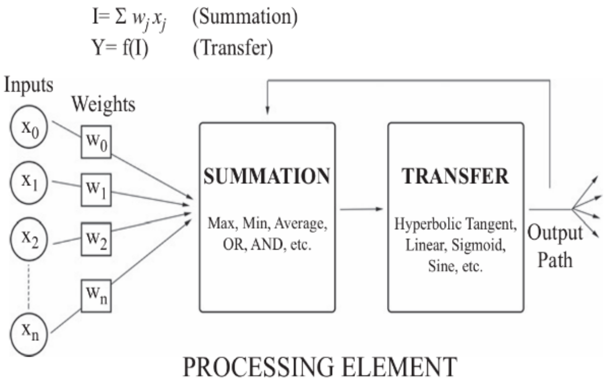

Figure 2: Artificial Neural Network

3. Model development in ANN for rubber-mixed sand

Model development includes several sections, each section will be explained in the following sections

3.1 Data Collection and Analysis

The published literature is the data source used in this study to build the model. Shear modulus, damping ratio, confining pressure, rubber percentage, and sand percentage are all included in the database. Sand percentage, rubber percentage, confining pressure, and shear modulus are input parameters, and damping ratio and shear modulus are regarded as output parameters based on the data collected. Of the 84 data points in this study, 25 were used for testing and validation, while 59 were used for training. Several techniques are employed to enhance the generalisation of the created ANN model, and several efforts are performed to obtain the intended result. Bayesian regularisation is one such algorithm. In the case of Bayesian regularisation, the weight values have been automatically regularised to minimise the combined error function [27]. NNTool Box in MATLAB has been utilised to implement the Bayesian regularisation approach.

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Table 1: Input and output parameters

Input parameters	Output parameters
Confining pressure (CP)	Shear modulus (G)
Sand% (s)	Damping ratio (D)
Rubber(R)	

3.2 Data Division

Data division in artificial neural networks (ANNs) involves splitting a dataset into subsets for training, validation, and testing. These subsets have distinct purposes in the ANN's training and evaluation. The following data division is considered for the model development.

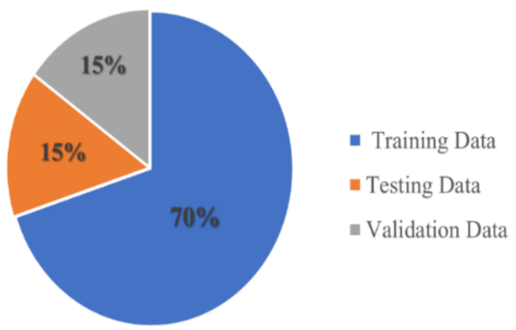

Figure 3: Data Division

3.3 ANN Architecture

The structure of the neural network for the model is obtained by representing the Input, hidden, and output layers. The selection of hidden layers should follow the equation below for the best model performance.

Check For Hidden Neurons:

[(M*N) +(N*K)) +(N+K)] < No of Data samples

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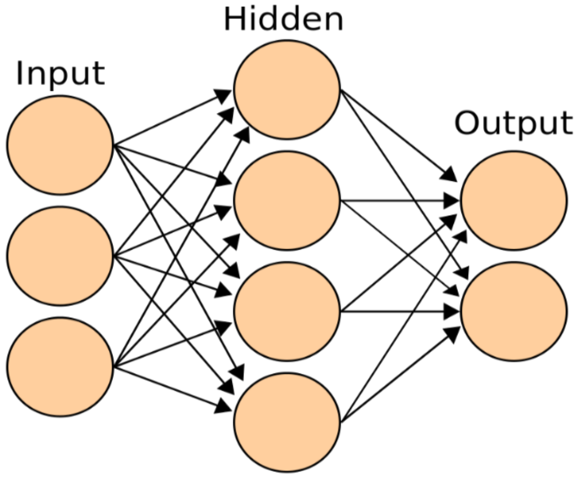

Figure 4: Structure of Neural Network

The data used for the model development, including the inputs, hidden layer, and output layer, are represented below.

No of Inputs=3 =M

No of Hidden Neurons = 4 = N

No of Outputs = 2 =K

No of Data samples = 84

[(M*N) +(N*K)) +(N+K)] < No of Data samples

[(3*N) +(N*2)) +(N+2)] < 84

In this case, four hidden neurons are considered (N = 4)

26 < 84

Therefore satisfied.

3.4 Network Analysis

Network Analysis of Neural Networks consists of information related to the Weights and Biases; in a neural network, biases and weights collectively define the network's parameters.

Network analysis is more important for performing sensitivity analysis and for better understanding the structure. Weights and biases are taken from the NNtool, and the values taken are tabulated in the following table.

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Table 2: Data for weights and biases

Neuron	Weights (W ik)					Biases	
	Input - 1	Input - 2	Input - 3	Output-1	Output-2	b_{hk}	b_0
Hidden neuron 1 (k=1)	0.39	-0.08	0.08	0.048	-0.41	0.14	-0.05
Hidden neuron 2 (k=2)	-0.11	0.01	-0.001	-0.01	0.11	-0.02	-0.20
Hidden neuron 3 (k=3)	0.21	-0.02	0.02	0.02	-0.21	0.05	_
Hidden neuron 4 (k=4)	0.18	0.5	0.54	-0.08	0.56	-0.01	_

3.5 Neural Network Interpretation Diagram

The present model consists of three input parameters, namely confining pressure(σ), sand%, and Rubber%, along with four hidden layers and two output parameters: shear modulus(G) and Damping ratio (**ζ).** Values between the input layer -hidden layer and hidden layer - output layer represent weights used to develop equations.

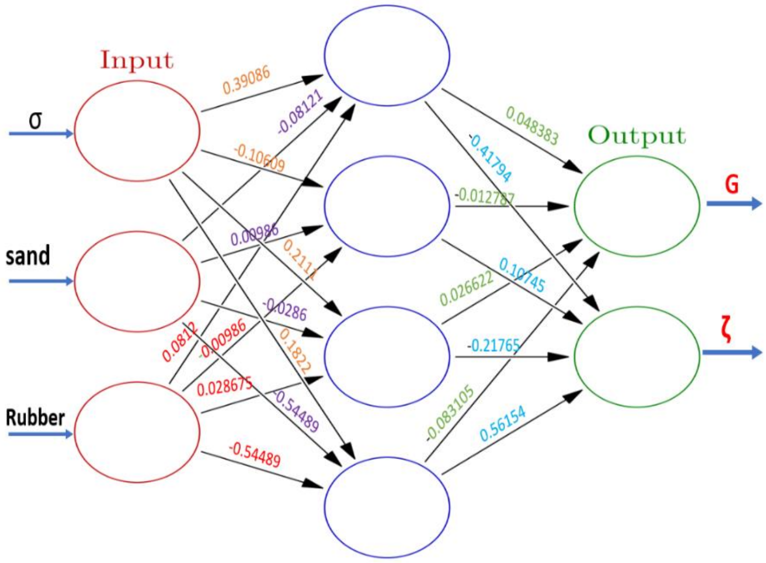

Figure 5: Neural Network Interpretation diagram for cohesionless soil

3.6 Development of ANN model equation

$\phi_{rn} = f_{sig}\{b_0 + \sum_{k=1}^{h} [w_k \times f_{sig}(b_{hk} + \sum_{i=1}^{m} w_{ik}X_i)]\}$ (1)[27].

$A_1 = 0.14 + 0.39\text{Cp} - 0.08\text{SA} + 0.\text{O8R}$

$A_2 = -0.02 - 0.11\text{CP} + 0.01\text{SA} - 0.01R$

$A_3 = 0.05 + 0.211\text{CP} - 0.02\text{SA} + 0.02R$

$A_4 = -0.01 + 0.18\mathrm{CP} + 0.54\mathrm{SA} - 0.54\mathrm{R}$

For output-1

$$B_1 = 0.04 \times \frac{e^{A_1} - e^{-A_1}}{e^{A_1} + e^{-A_1}}$$

$$B_2 = -0.01 \times \frac{e^{A_2} - e^{-A_2}}{e^{A_2} + e^{-A_2}}$$

$$B_3 = 0.02 \times \frac{e^{A_3} - e^{-A_3}}{e^{A_3} + e^{-A_3}}$$

$$B_4 = -0.08 \times \frac{e^{A_4} - e^{-A_4}}{e^{A_4} + e^{-A_4}}$$

$$C_1 = -0.05 + B_1 + B_2 + B_3 + B_4$$

For output-2

$$B_1 = -0.41 \times \frac{e^{A_1} - e^{-A_1}}{e^{A_1} + e^{-A_1}}$$

$$B_2 = 0.10 \times \frac{e^{A_2} - e^{-A_2}}{e^{A_2} + e^{-A_2}}$$

$$B_3 = -0.21 \times \frac{e^{A_3} - e^{-A_3}}{e^{A_3} + e^{-A_3}}$$

$$B_4 = 0.56 \times \frac{e^{A_4} - e^{-A_4}}{e^{A_4} + e^{-A_4}}$$

$$C_1 = -0.20 + B_1 + B_2 + B_3 + B_4$$

$$\phi_{rn} = \frac{e^{C_1} - e^{-C_1}}{e^{C_1} + e^{-C1}}$$

$$\phi_{\mathrm{r}} = 0.5(\phi_{\mathrm{rn}} + 1)(\phi_{\mathrm{r}max} - \phi_{\mathrm{r}min}) + \phi_{\mathrm{r}min} .$$

Where, $\phi_{\mathrm{r}max}$ and $\phi_{\mathrm{r}min}$ are the maximum and minimum values of ϕ_{r} respectively in the data set.

4. Results and Discussions

This section comprises results from the model development and sensitivity analysis section 4.1 deals with the results obtained from NNTool Box and section 4.2 deals with the results obtained from the sensitivity analysis

4.1 Model development in ANN for rubber-mixed sand

The result obtained from the development of the model is presented below

4.1.1 coefficient of correlation values of training and test data

The developed model provides results that consist of Training, and testing with a coefficient of correlation, and the following figure shows results obtained from the NNtool.

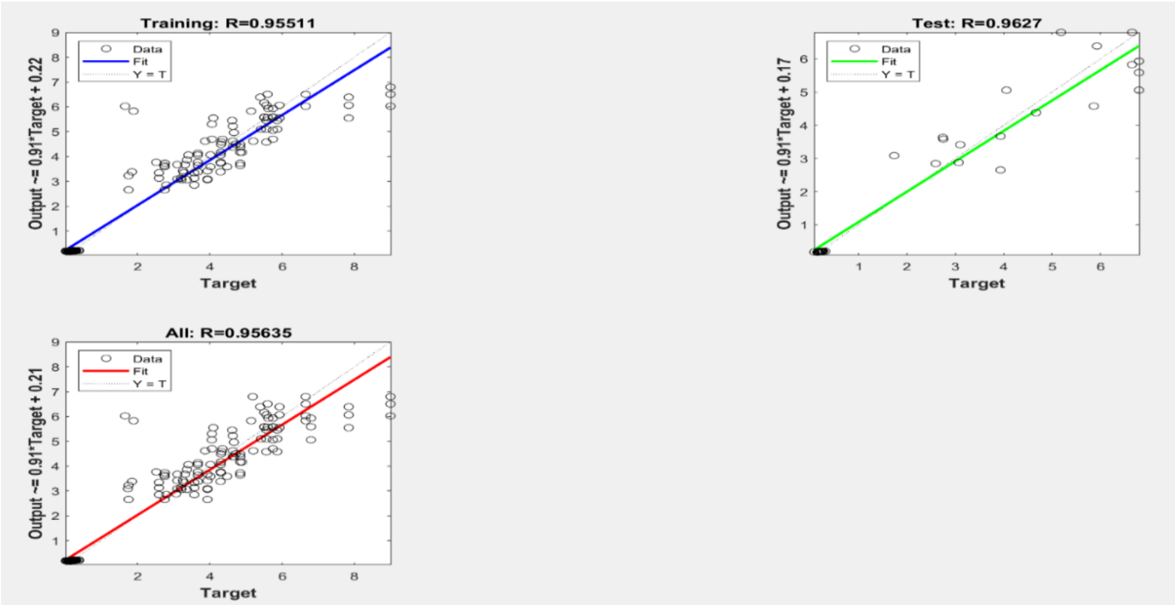

Figure 6: Results from NNtool

4.1.2 Best training performance is achieved with the minimum Mean Squared Error (mse):

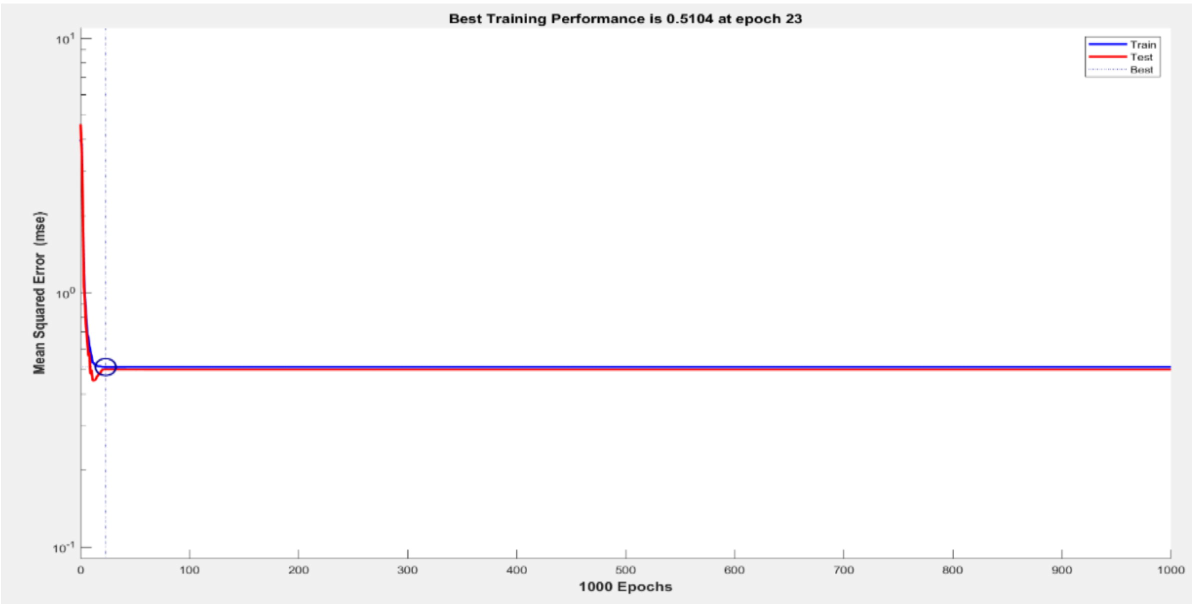

Figure 7: Mean Squared Error from NNtool

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4.1.3 overall coefficient of correlation and coefficient of determination for the predicted model

4.1.3.1 overall coefficient of correlation

The coefficient of correlation (R) value is obtained for the training, testing, and validation data sets along with all datasets which, are represented as All: R=0.956

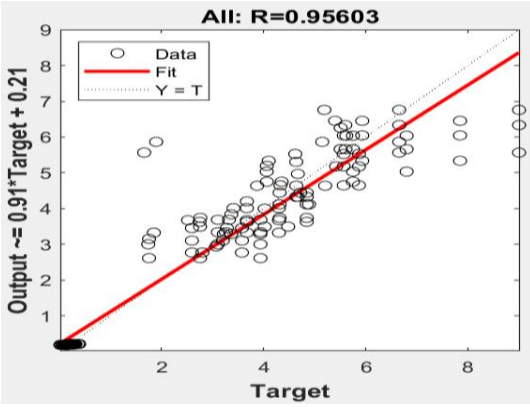

Figure 8: coefficient of correlation

4.1.3.2 Coefficent of determination

Data sets containing data of measured shear modulus and predicted shear modulus are taken from the NN-tool, and obtained data (predicted data) is used to find the coefficient of determination; similarly, prediction of damping ratio values is used for finding the coefficient of determination

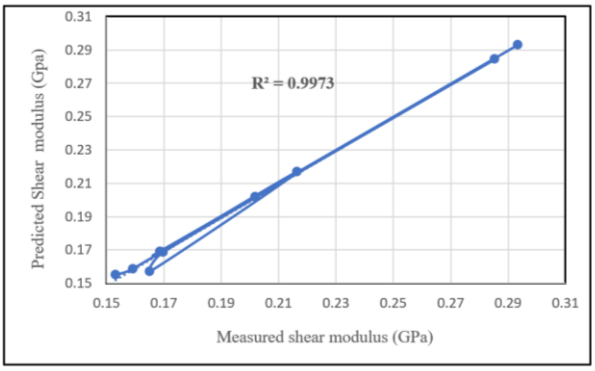

Figure 9: Predicted vs measured shear modulus

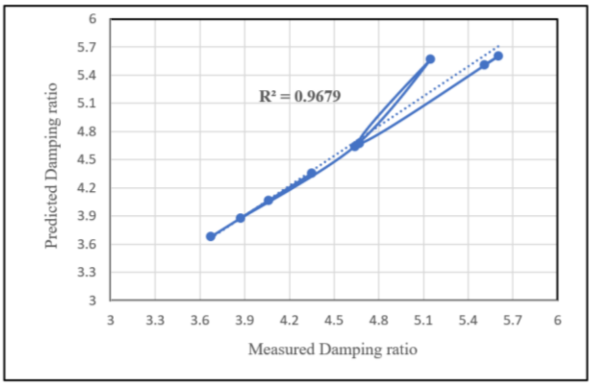

Figure 10: Predicted vs measured damping ratio

4.2 sensitivity Analysis

Sensitivity analysis is a valuable technique employed in Artificial Neural Networks (ANNs) to assess how variations in input variables affect the network's predictions or output. Sensitivity analysis aims to identify the specific variables that exert the most significant influence on the model's performance and gain insights into their relative importance.

4.2.1 Importance factor for shear modulus

Network Analysis plays a crucial role in developing an equation; similarly, it also plays a major role in sensitivity analysis. Values between the connections are treated as weights and biases, and these connections are used to find the importance factor.

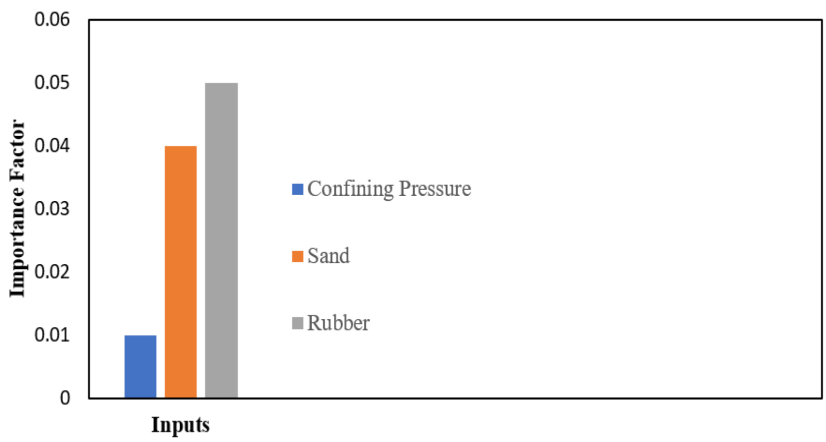

Figure 11: Importance factors for shear modulus

The importance factor is obtained from the connection weights. Using the Input, hidden layer, and output layer connection, the product of connection weights will be taken there using the connection weight approach. The sensitivity of input parameters is decided. The following table shows the importance of input parameters in predicting output

Table 3: Sensitivity analysis for shear modulus

Parameters	Connection weight Approach	
	Importance factor	Ranking of input as per relative importance
Confining Pressure	0.01	3
Sand	0.04	2
Rubber	0.05	1

4.2.2 Importance factor for Damping ratio

Similar to the importance factors considered for shear modulus, same for the damping ratio is also considered here. The product of connection weight is done using damping ratio outputs. Therefore, important factors are considered when predicting the damping ratio.

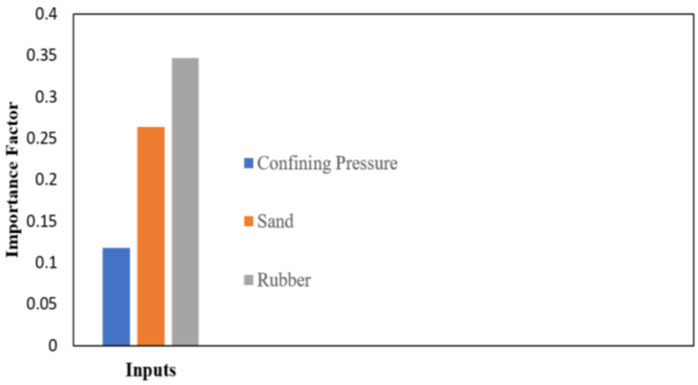

Figure 12: Importance factors for input parameters

Table 4: Sensitivity Analysis for Damping Ratio

Parameters	Connection weight Approach	
	Importance factor	Importance factor
Confining pressure	0.118	3
Sand	0.264	2
Rubber	0.347	1

5. Conclusions

Based on statistical parameters and correlation coefficients for training and testing data sets, the optimal model is the ANN model equation developed with confining pressure and percentages of sand and rubber as input parameters. Based on the ANN's training weights, a model equation is generated. The connection weight method sensitivity study revealed that the percentage of rubber is critical in achieving the intended results.

The current study's results demonstrate the effectiveness of the ANN approach as a powerful tool with enormous potential for predicting soil's dynamic properties. Additionally, this study discovered that a Bayesian regularization artificial neural network may successfully generate a data-driven prediction of the dynamic properties of rubber-mixed sand with a nonlinear reliance on its governing parameters. An ANN-based method like this will offer a dependable and affordable tool for predicting the dynamic properties of rubber-mixed sand.

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