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Research article

Predicting resilient modulus: A data driven approach integrating physical and numerical techniques

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ABSTRACT

Resilient modulus (M_R) is an important parameter in the design of pavement that helps to characterize the quality of sub-grade materials. Generally, it is not determined experimentally due to time consuming, uneconomical, laborious and lack of advanced equipment in many laboratories. The aim of this research is to determine M_R values using experimental (Ultrasonic pulse velocity (UPV) and Cyclic Triaxial) and Artificial neural network (ANN) techniques. For experimental study twenty-four soil samples comprising of coarse and fine-grained soils were collected from different locations. For ANN modelling, Input variables comprised of essential soil Atterberg limits (liquid limit, plastic limit, plasticity index) and compaction properties (maximum dry density, optimum moisture content). The validation of ANN model is done by comparing its results with the experimentally evaluated M_R from UPV and Cyclic Triaxial test. Experimental results showed that Cyclic Triaxial test yielded resilient modulus value that was 5 % more than obtained from the UPV test. Moreover, results showed that modulus of resilience (M_R) values determined by UPV, and artificial neural network (ANN) modelling have significant closeness with the cyclic triaxial results of resilient modulus; thus, making it a significant development in predicting resilient modulus efficiently.

1. Introduction

Pavement failure has emerged as a significant global concern over an extended period. The newly constructed or rehabilitated road infrastructure is experiencing rapid degradation [1,2]. Pakistan experiences a significant number of road-related issues annually subsequent to construction activities [3]. The most observed problems on road surfaces are rutting, cracks, potholes, sinking, corrugation, and shoving. In order to enhance the quality of pavement, it is important to use stronger materials and new construction techniques [4].

Subgrade Resilient modulus is a significant consideration in civil engineering, specifically in the design and assessment of pavement constructions. It shows the soil's stiffness and capacity for supporting loads underlying the pavement layers [5]. Engineers can evaluate a pavement's capacity to sustain traffic loads and environmental pressures by understanding the resilient modulus [6]. The resilient modulus is influenced by the subgrade's parameters, including the type of soil, water content, density, and additional mechanical traits [7].

The development of a modern road network is of the utmost importance for providing efficient, convenient, and environmentally sustainable transportation system [8]. The term "resilient modulus" which represents the ratio of cyclic axial deviator stress to

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recoverable axial strain, was initially introduced by Hveem [6]. However, reaction of different materials is influenced by test conditions. The resilient modulus of cohesive soil is not a constant measure of stiffness, but rather is significantly affected by factors such as stress conditions, soil structure, and water content [9].

The high rate of urbanisation in recent necessitates the development of innovative approaches for assessing the resilient modulus, with an emphasis on reducing time requirements and cost of construction [10]. Many attempts have been made to develop predictive equations that include state components such as confinement stress, bulk stress, deviator stress, and soil physical properties such as liquid limit(L.L), plastic limit (P.L), optimum moisture content (omc), maximum dry density (MDD), specific gravity and California bearing ratio (CBR) [11,12]. This is because of challenges associated with conducting resilient modulus testing.

The ultrasonic pulse velocity (UPV) test is an alternative solution to address these challenges, as it offers significant benefits in terms of mobility, durability, efficiency, and affordability. These advantages enhance the practicality and applicability of UPV, making it a valuable tool for both field and laboratory settings. Yesiller [13] investigated the application of ultrasonic technologies for the determination of compaction characteristics in clayey soils. The researchers observed a positive correlation between the compression velocity (V_p) and the compactive effort, indicating that an increase in compactive effort led to an increase in pulse. Additionally, they noted a similar positive relationship between pulse velocity and the drop in plasticity and clay content, suggesting that a decrease in plasticity and clay content resulted in an increase in pulse velocity. The researchers observed that the relationship between V_p and water content is like the relationship between dry density and water content. In a study conducted by Banerjee [14], it was shown that the values of γ_d and V_p exhibit an increasing trend until they approach the optimum moisture content. However, for moisture contents that surpass w_{opt}, γ_d and V_p display a decreasing trend. Although there are correlations available for compacted soils, there has been a lack of effort in determining the relationship between M_R and UPV.

A group of machine learning models referred to as artificial neural networks (ANNS) are modelled after the neural network of the human brain. They are made up of layered networks of interconnected nodes, or neurons [15]. Each neuron takes in information, uses weighted connections to process it, and then generates an output. The neural network "learns" the relationships and patterns in the data by repeatedly changing the weights, which enables it to make predictions based on brand-new, unanticipated data [16]. Advanced machine learning algorithms called neural networks have the capability of deriving intricate patterns from incoming data [17]. The neural network is employed as a regression model for the purpose of estimating subgrade resilient modulus. It produces a predicted resilient modulus value after taking numerous subgrade-related input characteristics into account such as soil qualities, moisture content etc.

Historical data including input-output pairs is needed for training the neural network. This dataset contains different combinations of input factors and the associated recognised resilient modulus values that were discovered by in-situ measurements or laboratory tests [18]. To minimise the prediction uncertainty between its output as well as the actual robust modulus values within the dataset, the neural network modifies its internal parameters, referred to as weights, throughout training [17].

The ability of neural networks to capture intricate and nonlinear interactions among inputs and outputs is its main strength. Due to the variety and shifting conditions of the soil, it might be difficult to model the link between the input parameters (such as soil qualities) and the subgrade resilient modulus analytically [19]. For instance, depending on other circumstances, the effect of soil density upon resilient modulus may or may not be linear; it might have amplified or diminishing returns. Additionally, interactions between various input factors might result in emergent behaviours that are difficult to detect using conventional analytical techniques [19].

Since artificial neural networks (ANNs) are capable of dynamically learning and adapting to various data patterns throughout the training process, they are particularly good at approximate such complex relationships. The neural network improves its internal representation of the input as well as output connection by repeatedly modifying the weights based on prediction mistakes [20]. Through this process, the network is able to identify and generalise patterns seen in the data used for training, enabling it to predict new input combinations with a reasonable degree of accuracy [20].The resilient modulus, a fundamental characteristic of engineering materials, is utilized to explain the nonlinear stress-strain response of pavement materials subjected to cyclic loadings [21]. The recoverable strain under cyclic load can be defined as the elastic modulus.

Resilient modulus (M_R) is one of the most important parameters in pavement design which defines quality of sub-grade materials

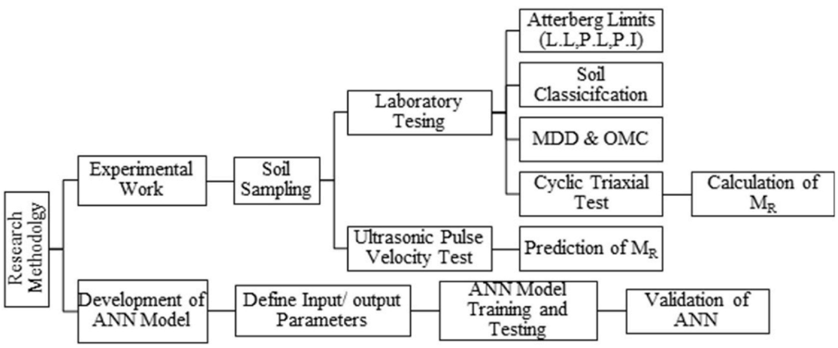

Fig. 1. Research methodology.

but being time consuming, uneconomical, laborious and lack of advanced equipment in many laboratories, generally it is not determined experimentally. This hinders the accurate and efficient evaluation of subgrade materials, which have an impact on the quality of road. The novelty of this research was to evaluate a more effective and efficient method for determining the M_R of the subgrade soils which will contribute to the development of high-quality infrastructure and reduce its maintenance cost. As dynamic triaxial equipment is uneconomical, an alternative, economical and less time-consuming method will be implemented. Past researcher relies only on physical testing or numerical techniques. Our research emphasizes on the strength of both by combing experimental data with advance numerical techniques to better understand the material behaviour.

2. Methods and experimental program

Fig. 1 illustrates the procedure in detail.

The soil samples were collected from different source as shown in Fig. 2 from the depth of 1.5–2m. The experimental program included determination of Atterberg limits i.e., sieve analysis according to ASTM D 422-6 [22], Atterberg limits according to ASTM D 4318-00 [23], proctor test according to ASTM 1557-02 [24] to calculate OMC and MDD. Dynamic Triaxial test sample were prepared and tested according to the ASTM D 4767 [25]. The Ultrasonic Pulse Velocity (UPV) test was conducted on moulded soil samples following the guidelines provided in ASTM-C597 [26].

The database of about twenty-four corresponding soil results has been developed for prediction of modulus of resilience (M_R) using artificial neural network (ANNs). Customized MATLAB code has been employed for the ANN analysis. The processing of the developed database includes sensitivity analysis and normalization of the input and target parameters for further utilization in ANN modelling. Ultimately validation of ANN predictions is done using experimentally measured modulus of resilience through UPV and cyclic triaxial test.

2.1. Development of ANN model

A computational model called an artificial neural network is motivated by the design and operation of biological neural networks seen in the human brain. ANNs are frequently employed in artificial intelligence and machine learning to resolve challenging issues involving recognition of patterns, regression, classification, and optimization. An artificial neural network is made up of inter-connected nodes, commonly referred to as artificial neurons or as "units." An input layer, one or more hidden layers, and an output layer are the layers that make up this network of neurons. Neuronal connections have corresponding weights that reflect the strength of the connections. A mechanism known as feed forward propagation with a learning process known as backpropagation are both essential to an ANN's basic operation as shown in Fig. 3.

2.2. Feed forward propagation

In the feed forward phase input data is introduced into the neural network's input layer. As the data flows through the neural network's input layer towards the corresponding number of hidden layers, neurons in these layers process the inputs based on their activation functions and corresponding weighted values to produce the output at the final output layer. The final output obtained is defined as the predicted output that is further compared with the target output and the resulting amount of error (E) is calculated which is nothing but the difference between the predicted and target results as given by equation (1). If the resulting errors are more than the acceptable range, then the back propagation phase started. It is important to note that the output of every neuron in the hidden levels serves as the input to neurons in the next layers.

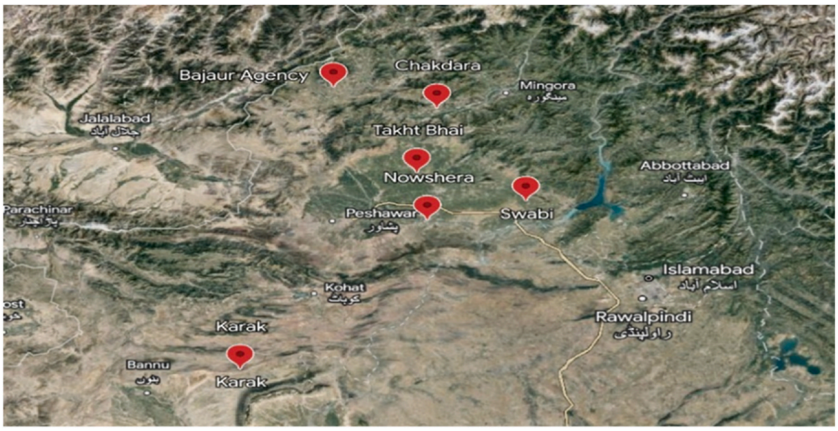

Fig. 2. Collection points of soil samples.

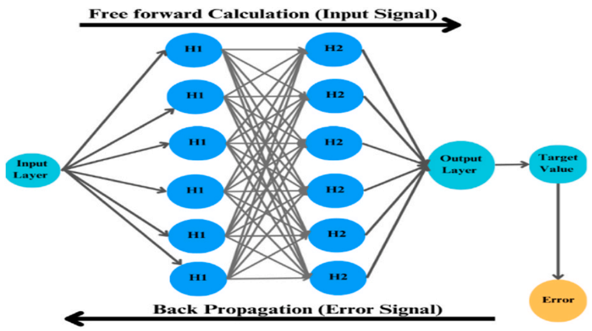

Fig. 3. Working mechanism of artificial neural networks.

$$E = \frac{1}{2}\sum i(\mathrm{T} - \mathrm{O}). \tag{1}$$

Where 'T' represents targeted values and 'O' represents the output predicted by artificial neural network model.

2.3. Backpropagation

Once the feed forward phase of the ANN model is reached, the neural network modifies its internal parameters such as weight and bias values throughout the learning process known as backpropagation based on the difference among its predictions and the actual target values. The weight and bias values are updated to reduce the errors and make the predicted output closer the target results. During this phase the artificial neural network propagates them backward through the network from output layers to input layers. The corresponding weights and bias values are updated at each neuron and the process are repeated until the final calculated error (E) reduced to an acceptable range. During the back propagation phase, optimization algorithms named gradient descent are used to evaluate the optimized values of weight (w) and bias (b).

Both feed forward and back propagation phases of ANNs are presented in Fig. 2. The weights and bias values are updated for each neuron until the computed error becomes close to the acceptable range i.e., predicted results of ANNs come closer to the target results.

2.4. Pre-processing of database

The database includes the experimental results of soil specimens with the targeted characteristics including Atterberg limits (L.L, P. L, and P. I), compaction properties (DD, mc, MDD and omc). Before importing these parameters in ANNs, a sensitivity analysis is performed on the complete included datasets to demonstrate the dependability of each soil parameter on the remaining parameters. The results of sensitivity analysis are given below in Table 1. The relationship between the various parameters is indicated by the correlation factor (R) value resulting from the sensitivity analysis. For any two or more parameters, the more the value of R close to 1, stronger is the correlation between the included parameters.

2.5. Development of architecture of ANNs

In the current study, seven input parameters including Atterberg's limits i.e., liquid limits (LL), Plastic Limit (PL), Plasticity Index (PI) and compaction parameters i.e., Sample dry density (SDD), Moisture content (M.C), Max. dry density (MDD) & optimum moisture content (OMC) are used to predict modulus of resilience (M_R). The architecture of the developed ANN model is presented in Table 2 given below.

The hidden layers allow the ANN to represent the relationship within the data. Each hidden layer thought different levels of abstraction. Two hidden layers provide better information about the levels of abstraction. The first hidden layer capture basic features and the second hidden layer capture more complex combinations of these parameters. The structure of the developed ANN model with

Table 1
Correlation (R) value indicating the relationship between different parameters.

	L.L	P.L	P.I	MDD	OMC	SDD	MC
L. L	1						
P. L	0.79724	1					
P.I	0.040189	0.247798	1				
MDD	0.81482	0.765563	0.320867	1			
OMC	0.329698	0.207683	0.112193	0.56973	1		
SDD	0.543242	0.34354	0.223164	0.734522	0.112324	1	
MC	−0.8297	−0.7076	−0.1121	−0.6697	−0.23641	−0.55212	1

Table 2
Architecture of the developed ANN model.

ANN model	Input parameters	ANN Structure
ANNM	LL, PL, PI, OMC, MMD, SDD, MC	*7-14-14-1: There are 7 neurons in the input layer corresponding to seven input parameters, 14 neurons in the first hidden layer (2 times of input layer neurons), 14 neurons in the second hidden layer (H2) and one (1) neuron in the output layer.

number of inputs, hidden and output layer including the number of neurons in each layer is given below in Fig. 4. The output layer contains one neuron with modulus of resilience (M_R) as single output.

3. Results and discussion

Table 3 shows the results of Atterberg limits, soil classification and proctor test. The compression and shear wave velocity using UPV is presented in Table 3. The determination of the resilient modulus of a sub-grade soil sample is significantly influenced by Atterberg limits, optimum moisture content, and maximum dry density [12]. According to Ref. [3], M_R is related to the mean particle size. The coarser the soil, higher is the resilient modulus [3]. Similarly, M_R is also effected by L.L and P.L. Soils having higher L.L and P.I tends to have low value of M_R. The results in Table 3 shows that fine grained soils tend to have high P.I and low compression velocity. The shear and compression wave velocity are entirely related on the soil structure. Wave velocity is higher in more dense soil. The granular soil exhibits favourable relative compaction and higher densities, resulting in increased in both the wave velocities.

3.1. *Resilient modulus from triaxial test*

M_R value calculated from cyclic triaxial test is represented in Fig. 5. The graph shows that A-2-4 has the highest resilient modulus because it is a silty or clayey gravel with sand. The average value of M_R for A-2-4, A-2-6, A-4 and A-6 is 120.7MPa, 97.3MPa, 81.9MPa, and 59.9MPa respectively. M_R is directly related to the soil density [27,28]. Higher the density, higher will be the M_R. It also depends on the particle size of soil [29]. A-2-4 soil is comparatively coarser than the other soils, resulted in higher M_R value. Each soil type is selected from six different locations at a depth of 1.5–2m and the difference in the resilient modulus of each soil is due to different soil matrix.

3.2. *Resilient modulus from UPV test*

The following equation is used to calculate the M_R as employed by Ref. [30].

$$M_R = \frac{[\rho V_c^2 (3V_c^2 - 4V_s^2]}{(V_c^2 - 2V_s^2)}. \quad (2)$$

V_c & V_s = velocity of compression and shear wave
ρ = mass density (kg/m^3)

Fig. 6 highlights the M_R calculated from UPV test based on shear and compression wave velocities. The M_R calculated from UPV test depends on compression and shear wave velocity, which depends on the density of soil. M_R values obtained from triaxial test are almost 5 % higher than the values obtained from UPV. Hence, a regression analysis is made to corelate M_R values from both the tests by finding a correlation factor.

Fig. 7 represents the linear correlation between UPV and cyclic triaxial test results. Equation 5 shows that the M_R calculated UPV is a linear function of M_R calculated from triaxial test involving some constant value. This equation can be use accurately measure the M_R from UPV test results.

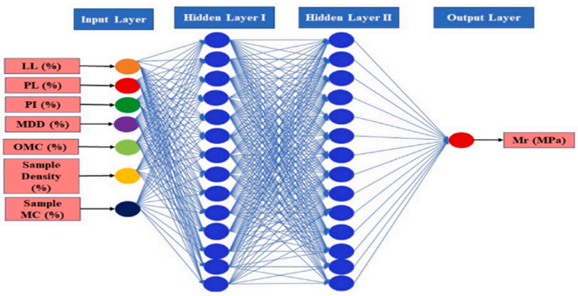

Fig. 4. Structure of the developed ANN model.

Table 3
Results of Atterberg limits, shear & compression wave velocities.

Soil Sample	L.L (%)	P. L (%)	P. I	AASHTO Classification	MDD (lb/cft)	OMC (%)	V_c (m/s)	V_s (m/s)
1	23.8	20.8	3.0	A-2-4	142.0	6.5	483.27	192.37
2	28.5	22.5	6.0		133.0	8.5	469.44	188.26
3	18.8	15.5	3.3		138.0	5.5	424.56	169.69
4	30.9	21.1	9.8		120.0	11	434.72	153.27
5	25.9	19.3	6.6		135.4	5.5	469.14	188.26
6	27.6	20.7	6.9		128.9	8.5	455.56	172.69
7	33.6	21.7	11.9	A-2-6	114.5	10	373.27	152.37
8	32.0	18.8	13.2		113.5	10.9	349.44	148.26
9	29.5	18.5	11.0		112.0	12	354.56	149.69
10	35.4	22.1	13.3		112.5	11.5	374.72	153.27
11	34.8	23.7	11.1		116.0	9.0	359.14	151.26
12	35.4	23.1	12.3		114.5	9.5	365.56	152.69
13	25.6	20.3	5.3	A-4	119.8	12.5	180.24	82.96
14	23.7	20.1	3.6		120.8	12.5	197.41	88.23
15	26.3	18.2	8.1		120.1	10.0	205.43	91.32
16	27.9	20.4	7.5		121.7	13.0	208.54	92.62
17	28.6	19.7	8.9		120.3	12.5	237.15	98.25
18	31.7	24.9	6.8		116.3	13.0	205.54	91.30
19	29.2	18.1	11.1	A-6	126.0	11.0	130.64	42.69
20	38.4	24.2	14.2		116.0	12.0	127.45	48.43
21	33.7	21.7	12.0		116.4	12.5	140.74	61.35
22	35.7	20.4	15.3		120.0	12.0	138.54	52.69
23	36.1	23.0	13.1		112.0	13.0	137.35	58.23
24	32.0	18.6	13.4		115.9	11.5	140.74	61.35

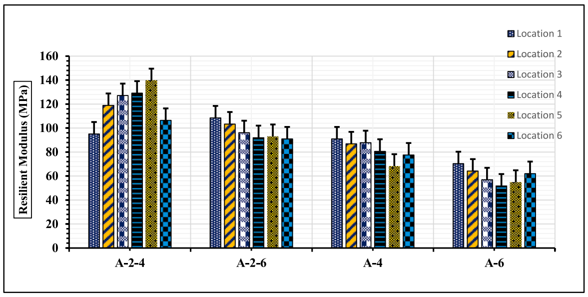

Fig. 5. Resilient modulus from cyclic Triaxial test.

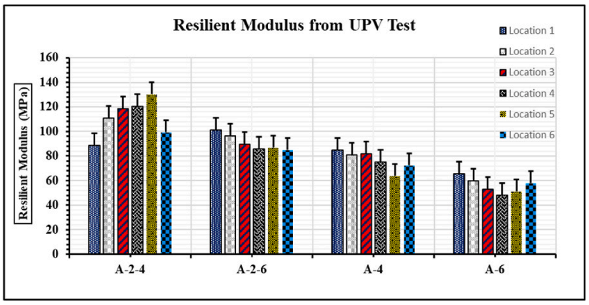

Fig. 6. Resilient modulus from UPV.

$$M_{R\ (Triaxial)} = 1.0714 * M_{R\ (UPV)}. \tag{3}$$

3.3. *Resilient modulus from artificial neural network (ANN)*

The modulus of resilience (M_R) predicted by artificial neural networks (ANNs) by utilizing seven input parameters (LL, PL, PI, SDD, MC, MDD and OMC) and one output parameter (M_R). The developed ANN model contains one input layer, two hidden layers and one output layer. The neurons in each hidden layer are double the neurons of the input layer. Resilient modulus predicted by ANN model is

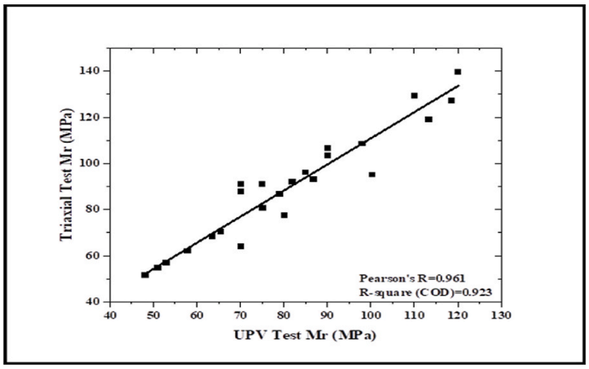

Fig. 7. Correlation between MR Values from triaxial and UPV.

compared with the targeted resilient modulus (M_R) measured using triaxial compression test. The backpropagation phases of the developed ANN model are run based on the difference between the predicted and targeted modulus of resilience (M_R) till the error as per equation (1) becomes too short in an acceptable value. Fig. 8 given below represent the modulus of resilient values for all four types of selected soil A-2-4, A-4, A-2-6 and A-6 respectively.

3.4. Regression results of ANN model

The four regression plots explaining the training, validation, and testing (TVT) performance of the developed ANN model based on the processed database are presented in Fig. 9. The quality of the regression plots is indicated by Pearson's correlation factor (R) values. According to smith, the value of Pearson's correlation factor (R) greater than 0.8 indicates satisfactory prediction performance of artificial neural networks (ANNs) [31]. The overall R value obtained during the regression analysis in ANN including training, validation and testing phases is above 0.8. An Artificial Neural Network (ANN) adjusts its weights and biases throughout the training phase by using forward propagation, computation of errors, backpropagation, including gradient-based optimization to identify patterns in the data. In the validation phase, hyperparameters are adjusted while the model's performance on hypothetical data is evaluated. The evaluation of the model's final performance on newly collected data during the testing phase ensures that the ANN can generate accurate predictions outside of the training set of data.

The result of the whole procedure is to produce an ANN model that generalizes well to new data and makes precise predictions on instances from the actual world. To provide unbiased assessment and prevent overfitting, it's crucial to keep the validation as well as testing datasets apart from the training data. The comparison between the modulus of resilience values measured experimentally in the laboratory from triaxial compression test and that predicted by artificial neural network (ANN) model is presented in Fig. 10 below. The goodness of the linear fitting is indicating that ANN predictions are quite close to the experimental results with higher values of Pearson's correlation factor ($R = 0.953$) and coefficient of determination ($R^2 = 0.908$). The closeness between the experimental and ANN predictions describes that ANNs are reliable tools in predicting the strength properties of soil based on developed database. Moreover, higher the data points in database, more could be the size of database and more accurate predictions are quite possible using artificial neural networks (ANNs).

3.5. Comparison of resilient modulus results

The modulus of resilience values obtained for all four categories of soils from the experimental testing (triaxial tests and UPV) and artificial neural networks (ANNs) are compared and presented in Fig. 11. Statistical *t*-test analysis is used to find the significancy of the data. The two-tail probability values of 0.2 and 0.4 are greater than 0.05 which shows that there is no significant difference between the mean of the two data sets. It can be seen from the figure that modulus of resilience (M_R) values determined by UPV, and artificial neural network (ANN) modelling have significant closeness with the cyclic triaxial results of resilient modulus. The real-life applications highlight the versatility of the UPV in many industries. These techniques can be used researcher where cyclic triaxial equipment in not available because it is very costly and time consuming. Hence, ultrasonic pulse velocity techniques can be used to calculate the resilient modulus of the subgrade due to its low cost and easily availability.

4. Conclusions

- The resilient modulus of subgrade soil can be predicted using the Atterberg limits of soil such as L.L, P.I, OMC and MDD by artificial neural networks techniques.
- Coarse-grained soils tend to have higher M_R value compared to fine-grained soils having same density and moisture content. Similarly, soils with higher plasticity characteristics such as L.L and P.I tend to have lower resilient modulus and vice versa. Similar trend was observed for calculation of M_R values based on UPV and triaxial compression tests data.

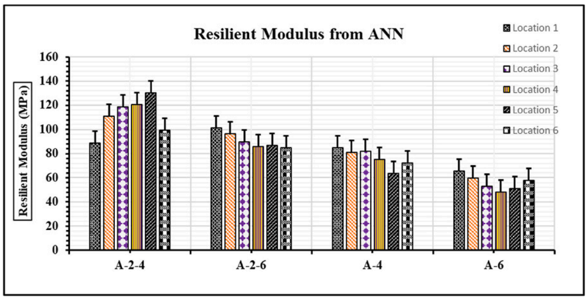

Fig. 8. Resilient modulus from ANN.

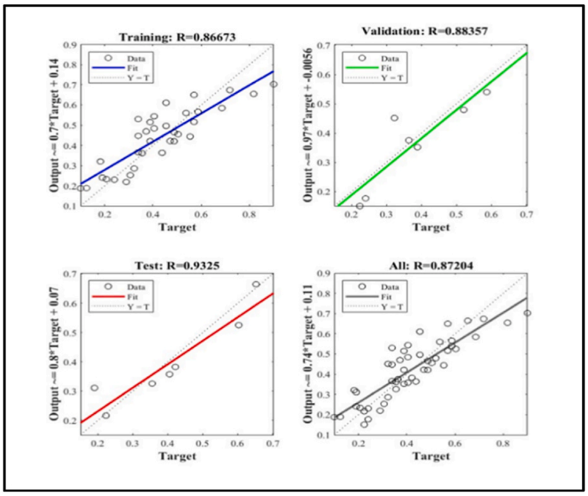

Fig. 9. Regression results of TVT datasets.

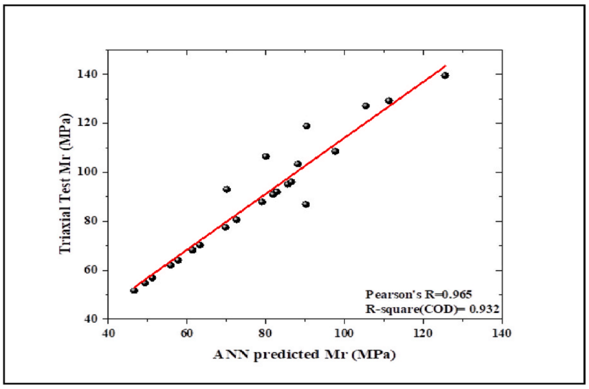

Fig. 10. Comparison between experimental M_R and ANN predicted M_R.

- Soil density plays an important role in controlling resilient modulus values for both fine and coarse-grained soils and it increases linearly with density.
- Resilient modulus from UPV depends on soil density, shear and compression wave velocities and a linear correlation exists between resilient modulus values obtained from UPV and dynamic triaxial tests. The ANN model predicts closely the experimental results, demonstrating its reliability in predicting soil strength properties. The Pearson's correlation coefficient (R) values obtained for training, validation and testing during regression analysis using ANN are 0.86, 0.88 and 0.93, respectively indicating high degree of accuracy in predicting modulus of resilience (M_R). The developed ANN models based on the degree of accuracy in predicting the

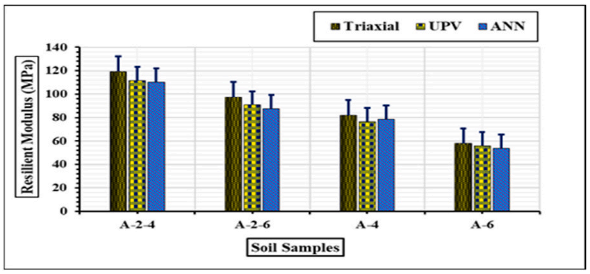

Fig. 11. Comparison of M_R results from Triaxila, UPV and ANNs.

strength properties of soil can be utilized as a reliable tool for wide range of geotechnical engineering problems with proper training and validation of the ANNs on corresponding database.

Recommendation

Further research can be carried out with additional data to enhance the reliability of model by taking into consideration the dynamic nature of the pavement conditions and incorporation of experimental data with advance numerical approaches.

Data availability

No, the data has not been deposited into a publicly available repository.
Data will be made available on request.

CRediT authorship contribution statement

Kashif Riaz: Writing – original draft. **Naveed Ahmad:** Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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