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Proposing New Artificial Intelligence Models to Estimate Shear Wave Velocity of Fine-grained Soils: A Case Study

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A B S T R A C T

Dynamic parameters are the most important geotechnical data used to understand the behavior of soil media under dynamic loads and to recognize the seismic response of the soil. Several in-situ and laboratory geophysical tests, such as the down-hole test, are used to determine these parameters. Since this experiment is costly and time-consuming and the preparation of appropriate boreholes is not easy, it is preferable to estimate the results of this test with the help of empirical correlations or experimental models. The main output of the down-hole test is the shear wave velocity (V_S) of soils, which can be used to obtain the dynamic shear modulus (G_s) indirectly. The relationship between physical properties and mechanical specifications of soils is a well-known principle of geotechnical engineering. Utilizing the results of 19 down-hole experiments and available geotechnical data in the southern regions of Tehran, as well as the inputs of an adaptive neuro-fuzzy inference system (ANFIS). This study attempts to provide practical models to predict shear wave velocity of fine-grained soils in Tehran. Two new models have been proposed as a result of preprocessing and smart modeling. The independent variables of the first suggested model included the moisture content, plasticity index (PI), liquid limit (LL), depth of test, and grain size distribution of soils. In the second model, the number of standard penetration test (N_{SPT}) is also used in addition to the mentioned independent variables. The proposed models had coefficients of determination (R^2) of 0.74 and 0.8 for the total training and validation data, respectively.

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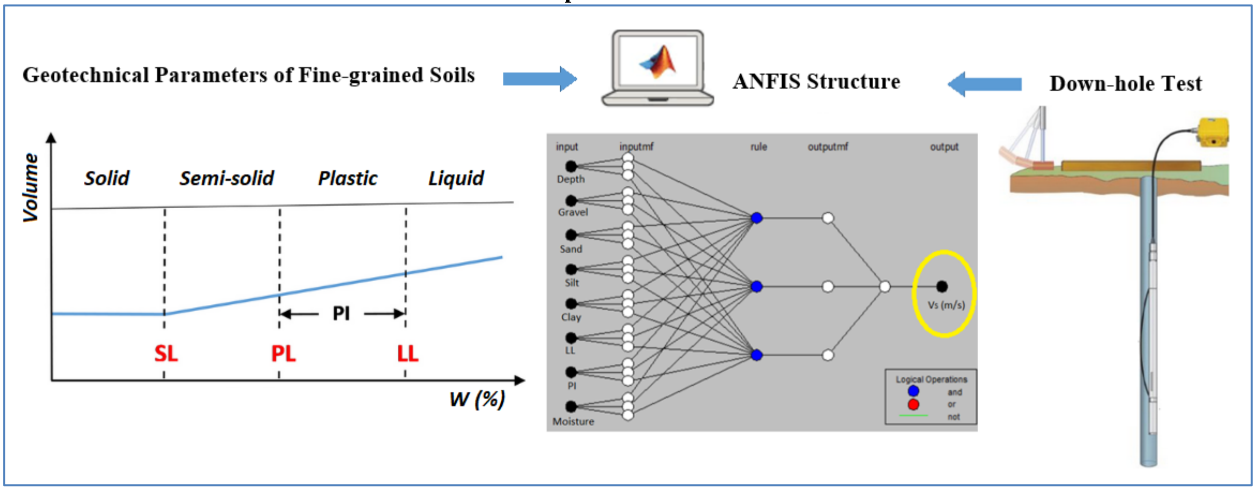
Graphical Abstract



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1. INTRODUCTION

Dynamic modulus (shear and Young's modulus) as a significant parameter in geotechnical analysis and especially seismic design of structures can be obtained by determining the shear wave velocity of soils. Down-hole test (1) is one of the most well-known geophysical tests used to determine the shear wave velocity of soils. This test is costly and time-consuming. Preparing appropriate boreholes is another challenge in performing this test. Also, some variables may influence the results. Due to the mentioned limitations, it is helpful to predict the results of this test by using empirical correlations or models.

Typically, using new artificial intelligence (AI) methods to solve complex multivariate problems leads to better outcomes compared to conventional regression methods. In recent years, researchers have utilized various AI methods to predict the results of geotechnical (2-9) and geophysical (10-12) tests.

In this regard, Table 1 summarizes the most important AI models available to predict the shear wave velocity obtained from in-situ tests. This table shows that despite numerous studies in this field, a comprehensive and acceptable model has not been yet proposed. Therefore, it seems that there is still a necessity for new models or relationships for different regions to predict the shear wave velocity of soils.

Due to the access to geotechnical data of several projects in which both conventional geotechnical tests and down-hole tests were performed, it was possible to prepare a considerable amount of data that can be cited for this research. Then, it was attempted to apply the ANFIS method to introduce new practical models to predict the shear wave velocity of fine-grained soils in Tehran. It should be noted that the models developed in this research are different from the models of other researchers in terms of input variables, modeling method and applied data.

2. METHODOLOGY

In AI techniques for nonlinear multiple analysis, data sets are divided into two different sets of training and testing. The training data set is used to find the potential relationship between independent and dependent variables, and the reliability of this relationship is verified with the testing data set (13). Artificial Neural Network (ANN), Fuzzy, and Neuro-fuzzy are some examples of the widely used methods.

The ANN method can find the relationship between the input and output variables of a complicated problem with the help of self-learning ability. The performance of artificial neural networks is directly related to the given amount of training data (14). When the number of data is low, neural networks and fuzzy logic combinations (neuro-fuzzy) can improve the performance of the neural network system (15). A fuzzy system can simulate the qualitative aspects of human knowledge and reasoning processes, whereas it does not have any self-training abilities. Nevertheless, ANNs can do learning using data sets (16, 17). Then, ANFIS has the advantages of both neural networks and fuzzy systems (18). The main purpose of the ANFIS approach is to automate fuzzy modeling using real data. In the fuzzy Takagi-Sugeno method, the following If-Then rules apply:

$$\text{If } x=A_1 \text{ and } y=B_1 \text{ then } f_1(x,y)=p_1x+q_1y+k_1 \tag{1}$$

$$\text{If } x=A_2 \text{ and } y=B_2 \text{ then } f_2(x,y)=p_2x+q_2y+k_2 \tag{2}$$

where x and y are the inputs, A_i and B_i are labels of the fuzzy set (small, large, etc.) defined as suitable membership functions, and p_i, q_i, and k_i are output parameters resulting from the training. The process of ANFIS performance contains five steps (layers). The schematic structure of this method is displayed in Figure 1.

2. 1. ANFIS-FCM

The ANFIS model developed in the present study is based on the fuzzy clustering method (FCM). Fuzzy C-Means is an approach of data clustering in which a given dataset is grouped into some clusters according to the principles of the fuzzy C-partition. The introduction of this algorithm is generalized by Ming-Chuan and Don-Lin (19). In this algorithm, each data can belong to one or more clusters (groups) in soft fuzzy clustering, and the data closer to the center of a cluster has a higher degree of membership (20).

The coefficient of determination (R^2), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE), which are shown in Equations 3 to 5, are selected to assess the model.

TABLE 1. Summary of the some suggested AI models to predict V_S

Case study	Model	Ranges of V_S (m/s)	Method	Reference
A database from 10 different countries	$V_S = f(N_{60}, \sigma')$	66-169.66	PNN	(21)
Urmia City, Iran	$V_S = f(N_{60}, \sigma', FC, PI, d_{50})$	82-566	GRNN	(22)
Mashhad City, Iran	$V_S = f(D, N_{SPT}, FC)$	202-850	ANN-BP	(23)

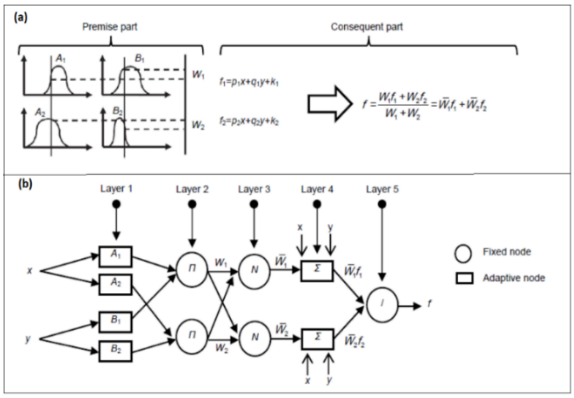

Figure 1. The process of ANFIS performance**;** (a) the first-order fuzzy model (b) schematic structure of ANFIS (16, 24, 25)

$$R^2 = \left(\frac{\sum_{i=1}^{n}(p_i-\bar{p})(a_i-\bar{a})}{\sqrt{\sum_{i=1}^{n}(p_i-\bar{p})^2\sum_{i=1}^{n}(a_i-\bar{a})^2}}\right)^2 \quad (3)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|a_i - p_i| \quad (4)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(a_i - p_i)^2} \quad (5)$$

In these equations, a_i is the real values (targets) of the V_S, p is the predicted V_S, $\bar{a}$ is the average of the actual V_S, $\bar{p}$ is the average of the predicted V_S, and n is the number of data sets.

2. 2. Sensitivity Analysis Method In the current study, a sensitivity analysis method of single variable training was used to identify the relative importance of inputs on the outputs of ANFIS-FCM models. The optimum ANFIS model is trained separately for each variable and then tested again in this technique. It should be noted that the optimal parameters obtained in the final model (including the type of membership function, the number of rules, the method of optimization, and the number of iterations) are also maintained in this step. Finally, any model which predicted outputs closer to the actual values (target) or, in other words, had the highest coefficient of determination, was introduced as the most effective variable [25, 26].

Figure 2 illustrates an overall strategy and main steps performed to achieve the purpose of the current study. It should be noted that in primary analyses of this study, ANFIS had a better performance in comparison with ANN method, therefore, only the results of ANFIS models are mentioned in the following.

3. DATA COLLECTION

In Tehran, geologically, from north to south of the city, the percentage of coarse aggregates is almost reduced, and the southern regions are mainly composed of fine-grained clayey soils. This study used the findings of 19 study projects in different regions of southern Tehran. The fine-grained soils include CL, ML, CH and CL-ML.

It should be noted that in all these projects, the same equipment and technicians were employed, as well as the method presented in ASTM-D7400 (1). As previously described, shear wave velocity is the most important direct output of down-hole test, which can determine the dynamic moduli of soils. In all boreholes in which down-hole test was performed, disturbed and undisturbed high-quality samples were taken and all conventional geotechnical laboratory tests were performed on the samples. Besides, the standard penetration test (SPT) was performed by ASTM-D1586 (26) in almost all depths where the shear wave was recorded.

3. 1. Effective Parameters on the Down-hole Test To accurately determine particle size, the percentage of different soils has been obtained through ASTM-D422 standard (27). By expressing the percentage of different soils, it is possible to make a good judgment of the type and initial characteristics of the materials. The desired properties of soils also included moisture content (w), liquid limit (LL), and plasticity index (PI) that have been determined through ASTM-D2216 (28) and ASTM-D4318 (29) standards, respectively.

Regarding the compaction condition of the tested soils, two indices of depth and number of standard penetration tests (N_{SPT}) were considered. In general, the density of soils increases with increasing depth. Standard Penetration Test (SPT) is one of the most common, inexpensive, and simplest geotechnical in situ experiments that can be utilized to determine soil compaction. In principle, this test is utilized to determine the relative compaction of soils. Therefore, considering that the depth of the test section and N_{SPT} can be easily determined, these two parameters were selected as the basic parameters to ascertain the compaction of soils.

3. 2. Preprocess of Independent and Dependent Variables Several different models were developed to investigate the relationships between independent variables and shear wave velocity in this section. To this end, several different data sets of fine-grained soils were evaluated. The two final models (relationships) were considered according to Table 2. It should be noted that these models are selected after several statistical analyses and data processing.

Independent variables related to the first data set (No. 1) included the percentage of soil particles (clay, silt, sand, and gravel), depth of test, liquid limit, plasticity index, and moisture content. The range of variation of these data were summarized in Table 3. The best simple regression between shear wave velocity and the independent variables is also displayed in Figure 3.

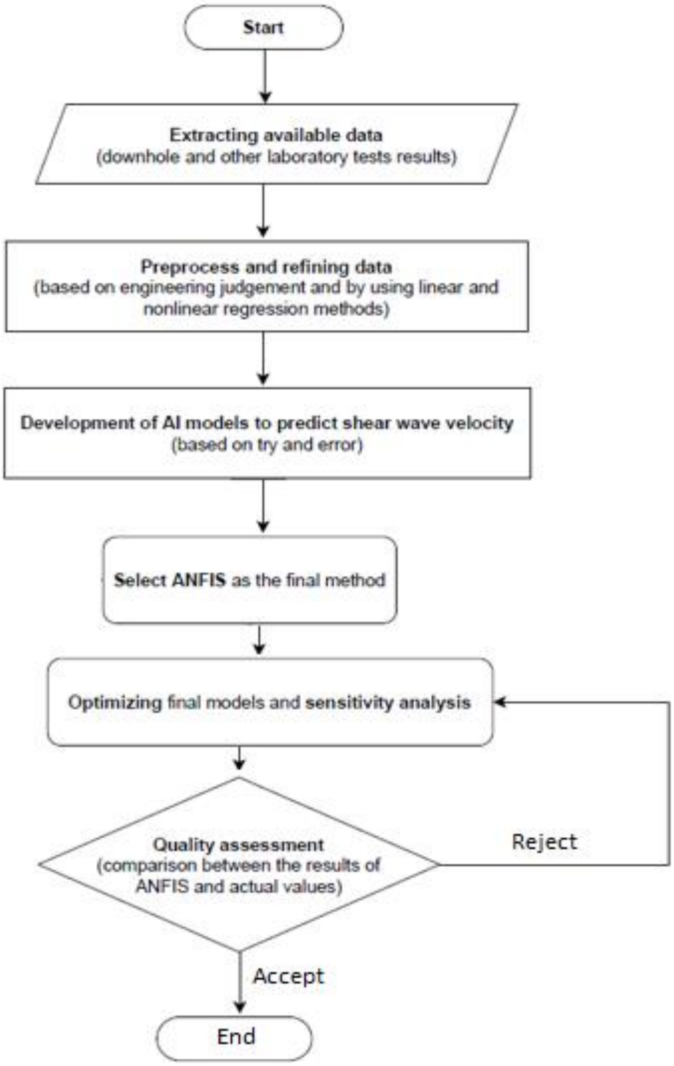

Figure 2. Overall strategy and main steps of the current study

TABLE 2. Proposed models obtained from preprocessing of data

No.	Equation/model	Number of data sets
1	$V_S = f(D, G, S, M, C, PI, LL, w)$	275
2	$V_S = f(D, G, S, M, C, PI, LL, w, N_{SPT})$	126

Parameters:
V_S (m/s): Shear wave velocity
D (m): Depth of test
G (%): Gravel-grained content
S (%): Sand-grained content
M (%): Silt-grained content
C (%): Clay-grained content
PI (%): Plastic Index
LL (%): Liquid limit
w (%): Moisture content
N_{SPT}: Uncorrected *SPT* blow counts

TABLE 3. Ranges of soil parameters for the first data set

Parameter	**Depth** (m)	**Gravel** (%)	**Sand** (%)	**Silt** (%)	**Clay** (%)	**Liquid limit** (%)	**Plastic index** (%)	**Moisture content** (%)	**Shear wave velocity** (m/s)
Min	2	0	0.10	18.40	16.90	21	2	5.40	130
Max	38	34.30	49.40	60.10	69.20	72	41	34.90	598
Mean	15.93	3.28	13.60	41.85	41.25	38.40	17.02	20.68	382.25
Standard deviation	8.43	4.97	11.43	8.02	10.56	9.84	7.08	5.19	104.78

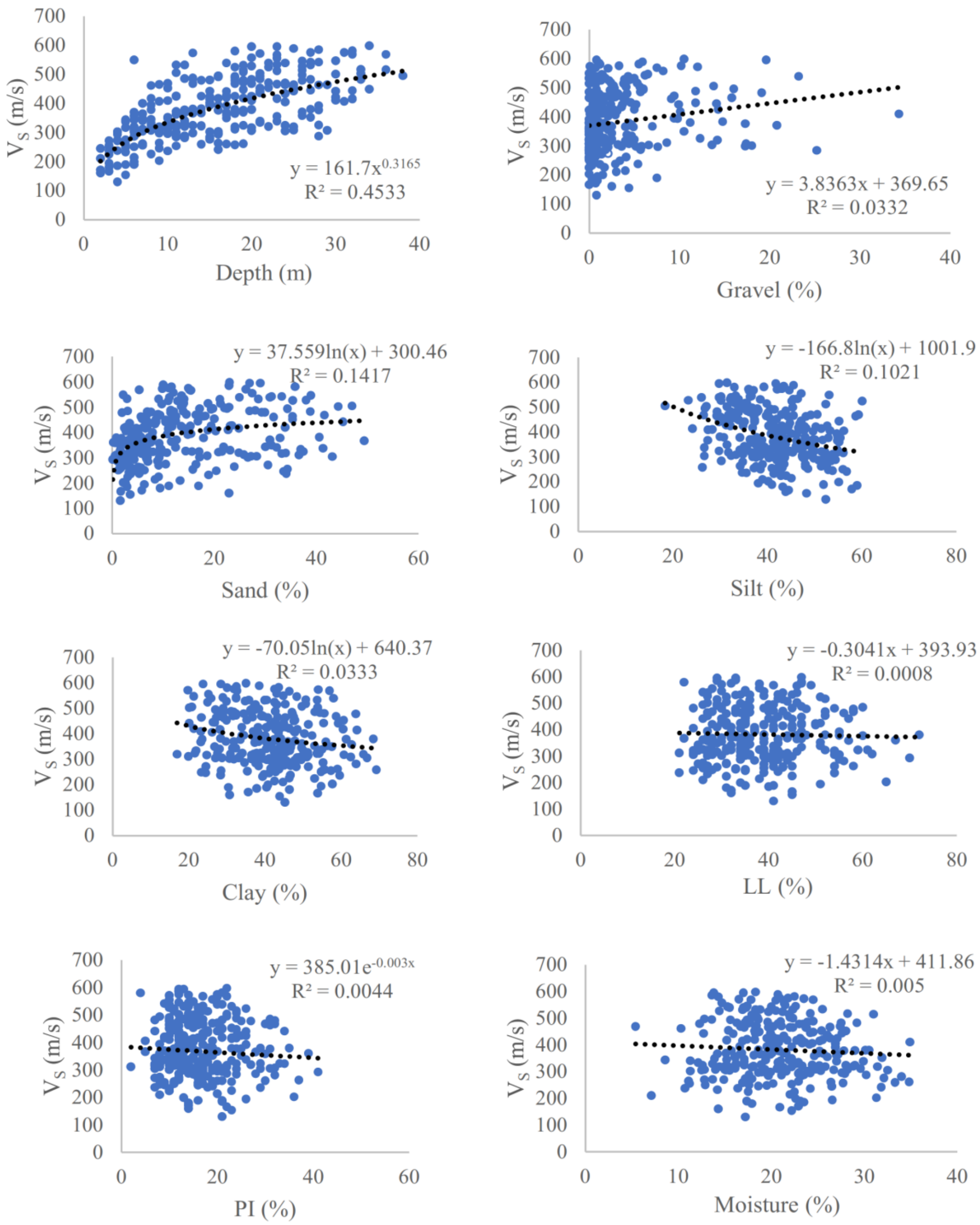

Figure 3. The best simple regression between dependent and the independent variables for the first data set

Independent variables related to the second data set (No. 2) includes the percentage of soil particles (clay, silt, sand, and gravel), depth of test, liquid limit, plasticity index, moisture content, and N_{SPT}. The range of variations of these data are presented in Table 4. Existing values of N_{SPT} indicate that the relative density of soils ranged from soft to hard. The optimum simple regression between V_S and the mentioned independent parameters is also illustrated in Figure 4.

TABLE 4. Ranges of soil parameters for the second data set

Parameter	Depth (m)	Gravel (%)	Sand (%)	Silt (%)	Clay (%)	Liquid limit (%)	Plastic index (%)	Moisture content (%)	N_{SPT}	Shear wave velocity (m/s)
Min	3	0	0.90	18.40	16.90	21	2	8.60	7	130
Max	36	20.80	47	58.70	65.80	65.80	36	3480	65	688
Mean	10	6.62	5.45	48.40	39.52	39.52	15.50	20.45	34.75	318.25
Standard deviation	3.05	5.14	3.01	3.34	3.97	3.97	4.04	1.58	5.51	27.42

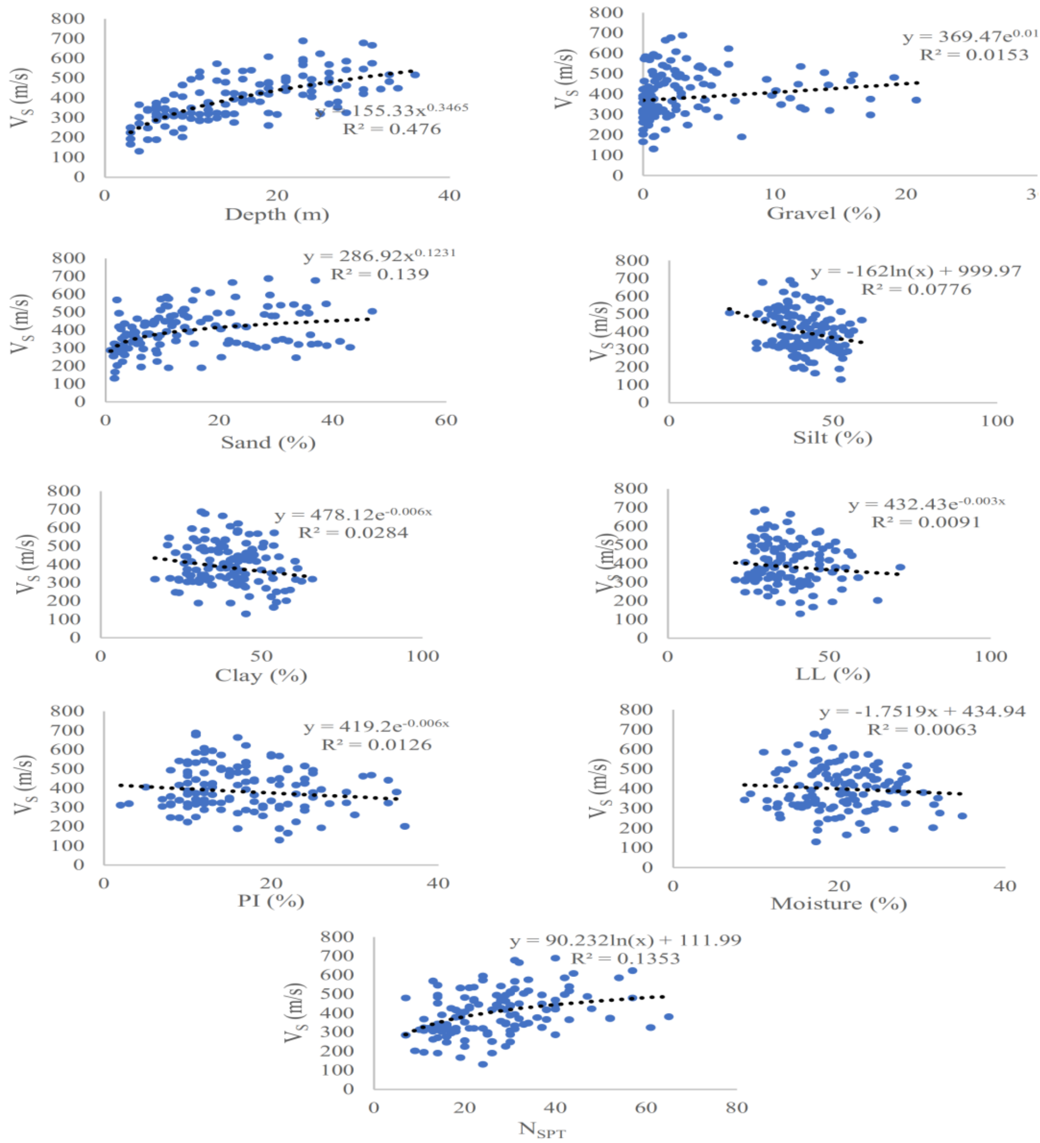

Figure 4. The best simple regression between dependent and the independent variables for the second data set

4. MODEL DEVELOPMENT TO PREDICT SHEAR WAVE VELOCITY

4. 1. The Optimum Model for the First Data Series

The settings relevant to the best structure of the ANFIS-FCM model, which includes the number and type of membership functions (MF_S), the training algorithm, and the number of iterations, are obtained based on the trial and error approach. The available data sets were randomly divided into training data (220 data sets) and test data (55 data sets). After completing the learning phase, the final model was validated. The specifications of the most appropriately designed ANFIS model are given in Table 5. The constructed structure consists of five layers and three if-then rules that are connected by the "and" operator (Figure 5). The results and the suggested model determination coefficient graph for the two training and testing stages are indicated in Table 6 and Figure 6, respectively.

Then, with the mentioned sensitivity analysis method, the effect of each independent variable was investigated separately for the performance of the designed ANFIS model. As shown in Figure 7, the depth of test and the percent of sand-grained content were the most effective, and the variables of liquid limit and plasticity index had the least impact on the performance of the optimum model.

TABLE 5. Main parameters for the optimal ANFIS-FCM model

Parameter	Type/value
Number of MF_S	3
Input MF	Gaussian
Output MF	Linear
Optimization method	Hybrid
Number of rules	3
Epoch	100

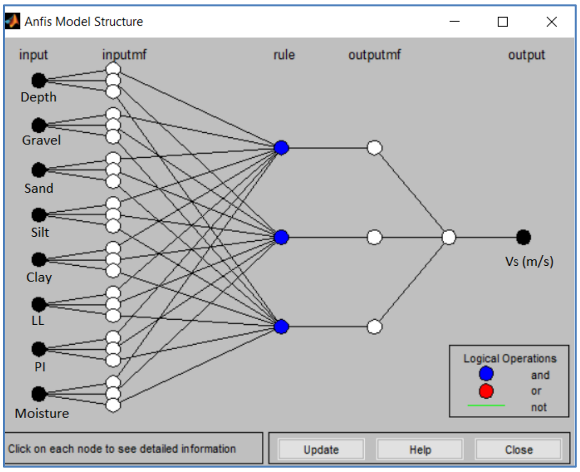

Figure 5. Optimal ANFIS-FCM structure for the first model

TABLE 6. Results and error values of ANFIS-FCM model for training, testing, and all data sets

Data	R^2	MAE	RMSE
Train	0.75	40.09	52.69
Test	0.73	48.04	59.61
All	0.74	42.34	54.19

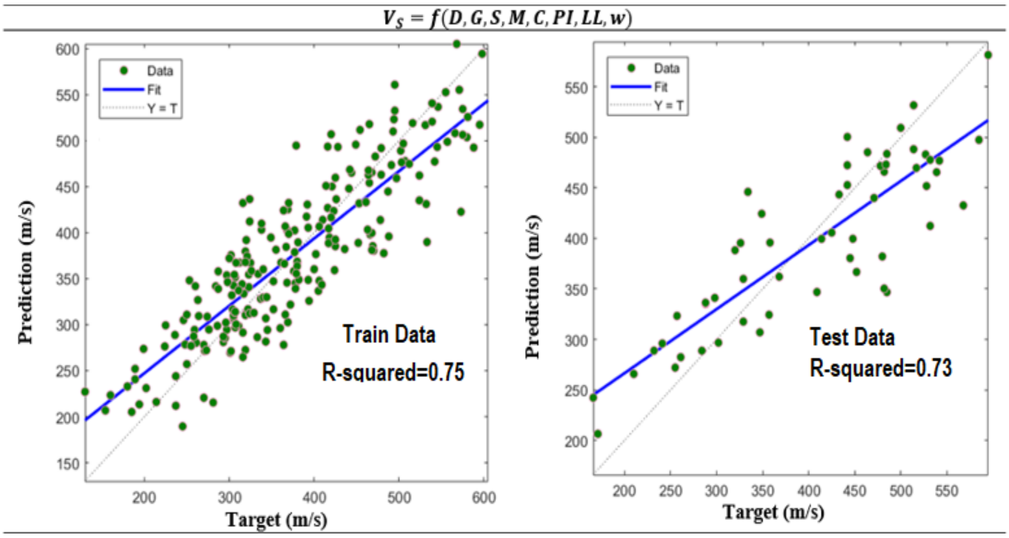

Figure 6. The obtained determination coefficients from the first model

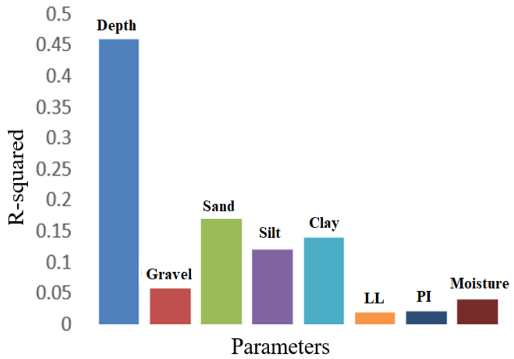

Figure 7. The results of sensitivity analysis on independent variables

4. 2. The Optimum Model for the Second Data Series

The same as previous step, the settings relevant to the optimum structure of the ANFIS-FCM model, which contains the number and type of membership functions (MF_S), the training algorithm, and the number of iterations, are determined. The available data sets were randomly divided into training data (101 data sets) and test data (25 data sets). The specifications of the developed model are given in Table 7. The structure of the optimum model is illustrated in Figure 8. The results and the proposed model determination coefficient graph for all stages are indicated in Table 8 and Figure 9, respectively.

Using the mentioned sensitivity analysis method, the effect of each independent variable was investigated separately to evaluate the performance of the designed ANFIS model. As shown in Figure 10, the depth of test and the percentage of sand-grained content have the most effect, and the variables of liquid limit and moisture content have the least impact on the performance of the optimum model.

TABLE 7. Main parameters for the optimal ANFIS-FCM model

Parameter	Type/value
Number of MF_S	2
Input MF	Gaussian
Output MF	Linear
Optimization method	Hybrid
Number of rules	2
Epoch	100

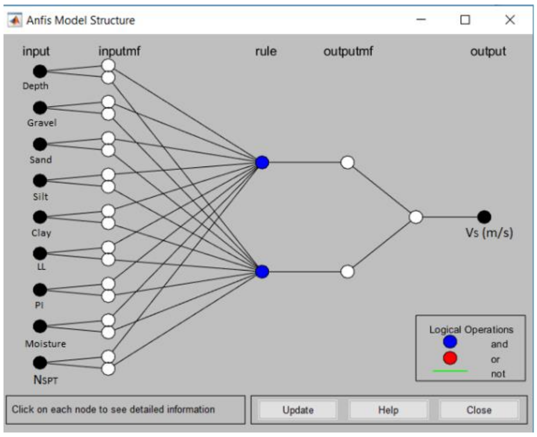

Figure 8. Optimal ANFIS-FCM structure for the second model

TABLE 8. Results and error values of ANFIS-FCM model for training, testing, and all data sets

Data	R^2	MAE	RMSE
Train	0.79	41.95	55.94
Test	0.82	37.91	51.57
All	0.8	40.91	54.95

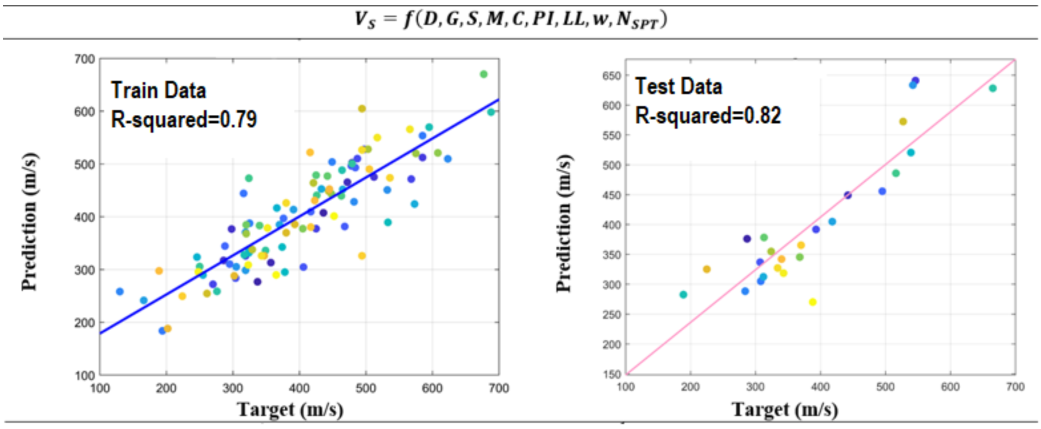

Figure 9. The obtained determination coefficients from the second model

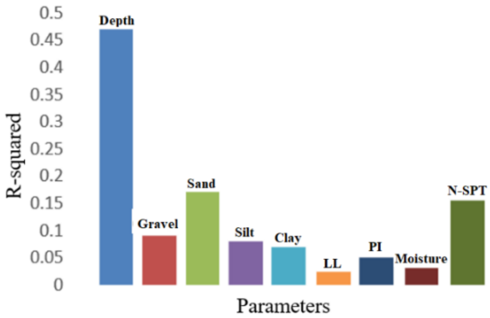

Figure 10. The results of sensitivity analysis on independent variables

5. RESULTS AND DISCUSSIONS

The obtained results from the two final ANFIS models are presented in Table 9. In general, both models can be roughly similar in terms of correlation and error values. For the whole first data series, the coefficients of determination and the mean absolute error are 0.74 and 42.34, respectively. Also, For the whole second data series, they are 0.8 and 40.91, respectively. It is worth mentioning that this study is the first attempt to use neuro-fuzzy to predict V_s; therefore, there are some limitations to compare the results of the current study and other studies using the same database. Moreover, the proposed models have two advantages compared to previous studies. The first one is that more independent variables in this research make the final performance of the models less affected by one or more data. In other words, the possible error in the values of one of the data will not affect the output of the model. Typically, smart models that have this feature are also called robust models. Another advantage of this research (related to the first data) is that SPT results are not required to estimate the shear wave velocity of soils. It should be noted that according to the obtained results, the model presented for the second series data was superior model of this study.

TABLE 9. Comparison between the results of the first and second proposed models

Model	**No. 1**			**No. 2**		
Data	Train	Test	All	Train	Test	All
R^2	0.75	0.73	0.74	0.79	0.82	0.8
MAE	40.09	48.04	42.34	41.95	37.91	40.91

6. CONCLUSIONS

In this study, two series of data, with different numbers and variables were employed to develop new smart models to predict the shear wave velocity of the fine-grained soils. The most important results of this study are as follows:

- Considering the diversity of the studied soils, the results and suggested models can be evaluated as acceptable for most fine-grained soils in Tehran while considering the range of data changes. It is evident that the scope of application of the smart models proposed in current research is only relevant to the data used; therefore, these models need to be evaluated and validated again for new data.
- The performance of the proposed model for the second data (No. 2) has been slightly superior to the data model in terms of the coefficient of determination and error values. Determination coefficients obtained from ANFIS-FCM models for the whole data set numbers 1 and 2 were 0.74 and 0.8, respectively. Also, the choice of the FCM clustering method for making ANFIS models has simplified fuzzy rules and model structure.
- According to the preprocessing and sensitivity analysis performed on the optimal ANFIS models, the depth at which the test has been implemented, the percentage of sand-grained content, and N_{SPT} had the most influence on the shear wave velocity values.
- Due to the problems of the down-hole test (high cost, being time-consuming, and the requirement for a specialized operator) as well as the accuracy of proposed models, they can be used for the initial estimation of V_S and consequently, to determine the dynamic moduli of fine-grained soils. Obtaining the input variables considered for these models is simply possible in all geotechnical studies.

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Persian Abstract

چکیده

پارامترهای دینامیکی مهمترین داده‌های ژئوتکنیکی برای درک رفتار محیط خاکی تحت بارهای دینامیکی و شناسایی پاسخ لرزه‌ای خاک می‌باشند. برای تعیین این پارامترها از چندین آزمایش ژئوفیزیکی آزمایشگاهی و برجا مانند آزمایش لرزه‌ای درون گمانه‌ای استفاده می‌شود. از آنجایی که این آزمایش پرهزینه و زمان بر است و آماده سازی گمانه‌های مناسب آسان نیست، نیاز است نتایج این آزمایش با کمک مدل‌ها و روابط تجربی تخمین زده شود. خروجی اصلی آزمایش لرزه‌ای درون گمانه‌ای سرعت موج برشی (Vs) خاک است که می‌توان از آن به صورت غیر مستقیم برای بدست آوردن مدول برشی دینامیکی خاک (Gs) استفاده کرد. رابطه بین خصوصیات فیزیکی و پارامترهای مکانیکی خاک از اصول شناخته شده مهندسی ژئوتکنیک است. در این مطالعه از نتایج ۱۹ آزمایش لرزه‌ای درون گمانه‌ای و داده‌های ژئوتکنیکی موجود در مناطق جنوبی شهر تهران به عنوان داده‌های ورودی یک سیستم استنتاج عصبی فازی تطبیقی (ANFIS) برای توسعه مدل‌هایی کاربردی به منظور پیش‌بینی سرعت موج برشی خاک های ریزدانه در تهران استفاده شده است؛ در نتیجه پیش پردازش و مدل سازی هوشمند صورت گرفته دو مدل جدید برای این مهم پیشنهاد شده است. متغیرهای مستقل اولین مدل پیشنهادی شامل درصد رطوبت، شاخص خمیری (PI)، حد روانی (LL)، عمق انجام آزمایش و توزیع اندازه ذرات خاک‌ها بوده است. در مدل دوم علاوه بر ورودی‌های ذکر شده از عدد آزمایش نفوذ استاندارد (N_{SPT}) نیز به عنوان متغیر مستقل استفاده شده است. ضرایب تعیین (R^2) مدل‌های پیشنهادی به ترتیب ۰/۷٤ و ۰/۸ برای کل داده‌های آموزش و آزمایش بوده است.