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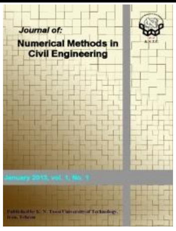

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Prediction of reduced sound wave intensity in floor systems using machine learning methods

Hamid Mohammadnezhad*, Fardin Jafari, Nahad Sedighi*****

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Abstract:

Sound insulation of building elements such as floors plays a vital role in noise control in buildings. When the incident sound wave hits the floor surface, part of it passes through the floor in the form of airborne and percussion and the other part is reflected or absorbed by the floor material. In the latter case, the measurement of sound wave energy variation is difficult and time-consuming and requires simulation or on-site tests. Hence, estimating sound reduction has always been considered by experts and engineers in the field of building engineering. In the present study, using Artificial Neural Network (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS), and linear regression, the sound reduction is estimated in floor materials in buildings with acceptable results. The required data for machine learning methods were obtained by simulation of different floor systems with varying material and thickness in the INSUL software. From the 252 data, 80% were randomly selected and used as training data for modeling and training the networks, and the other 20% was employed as test data to investigate the accuracy of the defined models. The results showed that ANFIS with correlation coefficients of 0.982 and 0.974, respectively for train and test data, is a better and more accurate tool compared to ANN and linear regression for estimating the sound reduction in common building floor systems.

1. Introduction

Prediction of sound insulation of buildings is an important factor that has been neglected over the recent decades [1]. Nevertheless, the current density of urban space and conversion of traditional houses into residential complexes have increased the importance of sound insulation [2]. Since people spend considerable time indoors, indoor sound level is of particular importance [3, 4]. Sound is directly related to the calmness of residents and their sleep disorders, and some of the mental disorders that are of environmental origin are caused by the emitted sounds [5-7]. The incompatibility of sound level in buildings with the predicted insulation levels has caused some disruptions and resulted in the dissatisfaction of residents in residential complexes [8]; this is due to the fact that the number of input and output parameters is so great that it makes it difficult to predict [2] [9, 10]. Regarding interior acoustics, background sound and the sound from adjacent spaces are two potential factors that should be adequately understood. Sound usually enters or exits the interior spaces of a given building through surrounding walls (facades) and openings (windows) [11-13]. Meanwhile, the factors considered in adjacent spaces are the sound transmitted through partitions and the floor in each story [13]. Colliding with partitions (wall and floor), sound could have three kinds of behavior based on the partitions' materials; A part of it is reflected, another part is absorbed, and the rest passes through the partitions [14, 15]. In this regard, in the construction industry, the opinion that walls and floors are the most crucial barrier to sound penetration has led to paying particular attention to their materials. There are even standards for sound insulation. Nonetheless, certain elements cannot be standardized using the systematic methods for sound penetration prediction, which has contributed to the idea of using artificial

**Corresponding author: Faculty of Civil, Water & Environmental Engineering, Shahid Beheshti University, Tehran, Iran. Email: h_mohammadnezhad@sbu.ac.ir*

***Graduate MSc student, Department of Art and Architecture, Islamic Azad University Science and Research Branch Tehran, Iran*

**** MSc student, Faculty of Civil, Water & Environmental Engineering, Shahid Beheshti University, Tehran, Iran*

intelligence for sound reduction estimation in different countries [16].

In recent years, Machine learning, as one of the soft computing techniques, has become one of the main areas of research in engineering fields, especially civil engineering [17] [18, 19]. Artificial Neural Network (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS), and linear regression are among the powerful and efficient methods of machine learning that have been used by researchers in predicting and modeling complex systems due to their high capability.

Over the last decade, comprehensive research has been conducted in various fields of sound insulation in buildings, including the studies by Schiavi et al. [20] and Cao et al. [21]. However, regarding the use of artificial intelligence for estimating the sound reduction in building walls, research has been conducted by a group of researchers whose results are as follows: N. Garag et al. worked on estimating sound insulation of sandwich panel walls using an artificial neural network model. In this study, 283 data with a topology of 1-14-13 were used to estimate sound reduction. They achieved regression coefficients of 0.98 and 0.92 for training and test data, respectively [2]. Moreover, Sedighi et al. utilized ANFIS to estimate sound insulation of building materials. They compared it to linear regression using 441 data, which estimated sound frequency reduction by ANFIS and linear regression representing regression coefficients of 0.978 and 0.7 for training data and 0.971 and 0.733 for test data [22]. In another study, Jafari et al. estimated sound insulation of walls with building materials using ANN and linear regression and 441 data with correlation coefficients 0.962 and 0.948 respectively for training and test data [23]. Bienvenido-Huertas et al. used an artificial neural network to assess thermal transmittance in walls based on the thermometric method data [24].

This research was designed to develop an algorithm using an artificial neural network and ANFIS. The algorithm could be used to obtain a correct prediction of the amount of noise reduction in story floors in the early stages of design. The results were compared to those of linear regression.

1.1. Theoretical review

Sound could be simply defined as a vibration that propagates in a transmission medium as an acoustic wave or as a stimulus of the auditory sense. The frequency range of audible sound waves is between 20 and 20,000 Hz [25]. In contrast, soundproofing prevents the transmission of sound to the adjacent space. In other words, the sound energy transmitted to the adjacent space is reduced. In building acoustics, two types of soundproofing against airborne and percussion sounds are investigated [26-28], each of which has its own characteristics. Some basic definitions related to sound are discussed in the following.

1.2. Analytical calculation

The analytical calculation was carried out on the traditional commercial wall, based on the equations reported in [28]. R-value is obtained by the following equation [29]:

$$R = -10\log\left(10^{-0.1R_f} + 10^{-0.1R_r}\right) \tag{1}$$

where R, R_f and R_r are the sound reduction index, sound's forced transmission, and sound's resonant transmission, respectively.

The sound reduction index for resonant transmission only, R_r, is calculated as:

$$R_r = R_0 - 10\log\left(\frac{c^2\sigma_{res}^2}{2\eta_{tot}sf} * \frac{\Delta N}{\Delta f}\right) \tag{2}$$

where R_0, c, σ_{res}, η, t, s, f and $\frac{\Delta N}{\Delta f}$ are obtained with the mass law for normal incidence, sound vibration, the radiation efficiency of resonant vibrations at random incidence, internal damping, transmission coefficient, sound intensity, octave band or one-third octave band frequency, and modal density in the plate, respectively.

In addition, the sound reduction index for forced transmission only, R_f, is calculated according to Eq. 3:

$$R_f = R_0 - 10\log\left(\left(1-\left(\frac{f11}{f}\right)^2\right)^2 * \left(1 - \left(\left(\frac{c}{c_c}\right)^2 + \left(\frac{f_c}{f}\right)^2\right)^{-1}\right)^2 + \eta_{tot}^2\right) - 10\log\left(2\sigma_{for}\right) \tag{3}$$

where f_c and σ_{for} are the critical frequency and radiation efficiency of forced vibrations at a random incidence, respectively, and R_0 is the sound reduction index calculated with the mass law for normal incidence based on Eq. 4:

$$R_0 = 10\log\left[1 + \left(\frac{2\pi f m}{2\rho_0 c_0}\right)^2\right] \tag{4}$$

where ρ_0, c_0, and m are the density of air, phase velocity of sound in air, and mass per unit area, respectively.

1.3 Software simulation

The INSUL 9.0.22 software was used to simulate the case study floors. The input values required by this software are the density, internal loss factor, elastic modulus of the materials, and geometrical dimensions of the floor. In the INSUL software, the sound reduction index of a single leaf wall is calculated according to the mass law for diffuse incidence of the critical frequency in order to take into account the effect of the panel size based on Eq. 5 [29, 30]:

$$R_0 = 10\log_{10}\left(\frac{1}{t}\right) \tag{5}$$

where t is the transmission coefficient.
Moreover, the value of the transmission index t is calculated based on Eq. 6 [30]:

$$t = \left(\frac{2\rho_0}{mk(1-\mu^{-4})}\right)^2 \Big[ln\Big(k\sqrt{A} + 0.16 - U\left(\frac{L_X}{L_Y}\right) + \frac{1}{4\mu^6} + [(2\mu^2 - 1)(\mu^2+1)^2 \ln(\mu^2 - 1) + (2\mu^2+1)(\mu^2+1)^2 \ln(\mu^2 + 1) - 4\mu^2 - 8\mu^2 ln\mu]\Big)\Big] \tag{6}$$

where K, ln, μ, U, L_X, L_Y, and m are the wavenumber, sound pressure levels, dynamic viscosity, acoustic transmission, element length, element wide, and mass, respectively.

2. Methods

2.1. Floor's modeling

The required data in this study were obtained through modeling of frequently used floors in the Iranian construction industry using the INSUL software.
The INSUL software is developed for sound insulation and impact noise predictions of walls, slabs, and windows. The predictions are based on analytical calculations, and the software can predict the transmission loss in third-octave bands and the weighted sound reduction index. It models materials using a well-known elastic plate theory, including allowances for thick panel effects. The INSUL calculations are in accordance with EN 12354-3:2000 "Building Acoustics - Estimation of acoustic performance of buildings from the performance of elements - Part 3: Airborne sound insulation against outdoor sound" [30, 31].
Four types of floors, namely brick, steel deck, concrete, and lightweight concrete with thicknesses of 250, 300, and 350 mm, were modeled in the software. In all the models, two layers of the materials with thicknesses of 80 mm were used for covering the floor, and a layer with a thickness of 10 mm was fixed below them. The thickness of the floors increased only in their core. The INSUL software output data showed that as the floor thickness increased, the sound insulation declined. They also indicated that in the frequency of 63 Hz, lightweight concrete with 52 dB and heavyweight concrete with 49 dB have the highest and lowest sound reduction, respectively. The sound insulation diagrams in the floors modeled with different cores are shown in Figs. 1-4.

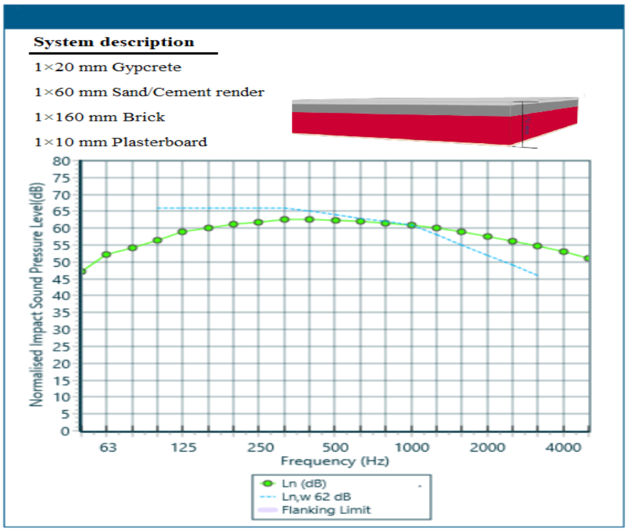


Fig. 1: Sound insulation in the floor with the brick core.

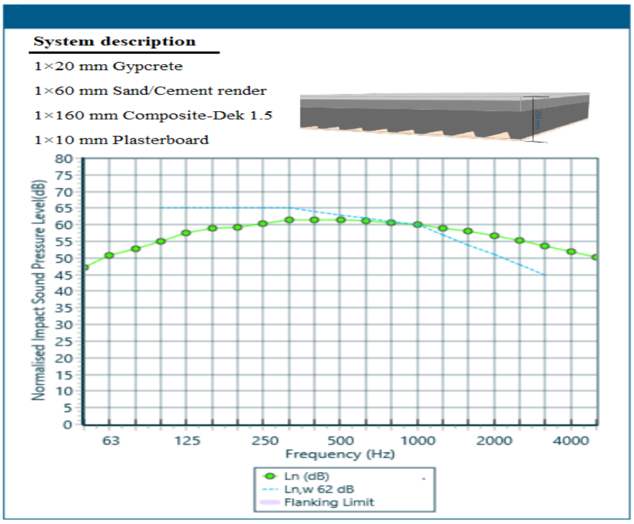


Fig. 2: Sound insulation in the floor with the composite deck core.

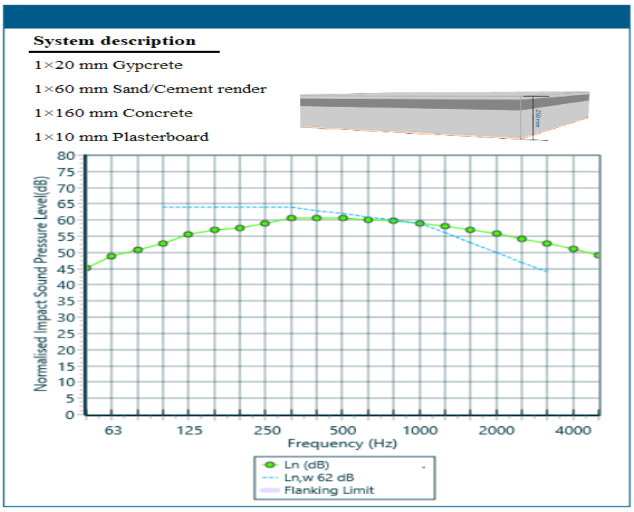


Fig. 3: Sound insulation in the floor with the heavyweight concrete core.

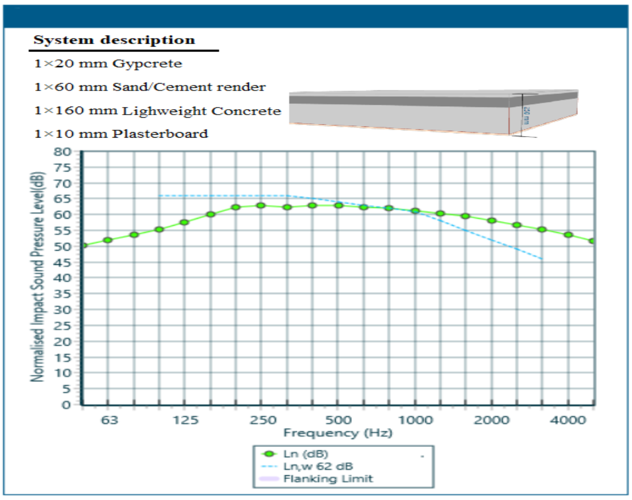


Fig. 4: Sound insulation in the floor with the lightweight concrete core.

3. Models for estimating dependent variables

In this study, ANN, ANFIS, and linear regression models were used to estimate sound frequency reduction (R_{db}). The corresponding results were compared to determine the model with the highest efficiency and accuracy.

3.1. Data used in the estimation models

Three independent parameters for determining sound frequency reduction were introduced as three inputs in the form of training and test data to optimize the studied models. These independent data listed are M as wall materials, T as floor thickness, and f as sound frequency, and the dependent data is R_{db}.

Tables 1 and 2 represent the statistical characteristics of the data, including the minimum, maximum, mean, and standard deviation of the training and test data sets, respectively.

Table. 1: Statistical specifications of the train data

	Train data			
	max	min	ave	s.d
Materials	3.00	0.00	2.90	0.50
Thickness	35.00	25.00	29.90	4.06
Frequency	5000.00	50.00	1059.78	1346.57
R_{db}	63.00	43.00	56.56	4.40

Table. 2: Statistical specifications of the test data

	Test data			
	max	min	ave	s.d
Materials	3.00	0.00	1.62	1.13
Thickness	35.00	25.00	29.33	4.12
Frequency	5000.00	63.00	1410.52	1455.93
R_{db}	63.00	46.00	55.08	4.22

3.2. Artificial Neural Network (ANN)

An artificial neural network consists of three layers: input, output, and processing. Each layer contains a group of nerve cells (neurons) normally associated with all the neurons in other layers unless the user restricts the relationship between the neurons; meanwhile, the neurons in each layer have no relationships with the other neurons in the same layer [23].

A neuron is the smallest unit of information processing that forms the basis of the function of neural networks. A neural network is a set of neurons that, in different layers, form a special architecture based on the relationships among neurons in different layers. A neuron could be a nonlinear mathematical function; accordingly, a neural network made up of a community of these neurons can also be a completely complex and nonlinear system. In the neural network, each neuron operates independently, and the overall behavior of the network is the result of the behavior of multiple neurons. In other words, neurons correct each other in the process of cooperation [19].

One of the most widely used methods for iteration in neural networks is forward backpropagation. The structure of this method is shown in Fig. 5. In this method, we have two stages in each round (in each iteration). The first stage is feedforward, which is done by multiplying input data by weights and then summing them by deviation. Ultimately, at the first stage, we come to an output that is probably different from the actual one. Herein, through loss function, we determined how much error the feedforward stage had. Once we understood how much error the algorithm had regarding weights and deviations, we moved on to the second stage in one iteration. At this stage, we could go back and adjust weights and deviations; in other words, we changed weights and deviations in a way that in the next iteration, they produced results closer to the actual output with less error. This iteration (feedforward and backpropagation) is done until the network output for all the training data reaches its closest actual value (the value we have by training data). Thus, the algorithm was learned and could specify values by observing the characteristics of some data [2].

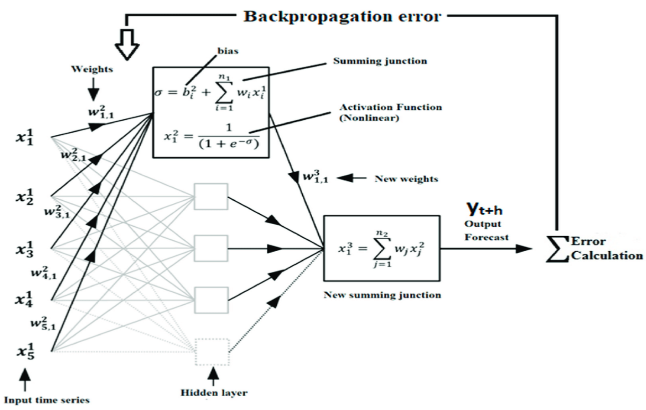


Fig. 5: Structure of the forward backpropagation algorithm.[2]

The forward backpropagation algorithm is employed to prepare the network in ANN. Input data is given to the network in three numbers. In this algorithm, ten hidden layers are used, and in the first layer, ten neurons are used. The 3-10-1-1 topology was used to train and estimate the data. Figure 6 depicts the topology used in the ANN method in this study.

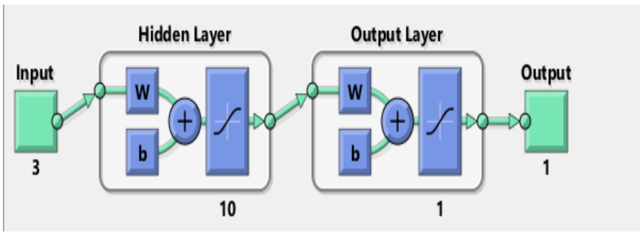


Fig. 6: Topology used in the ANN method.

3.3. ANFIS Model

The ANFIS model is derived from a comparative fuzzy neural network. Using any input in the data, the network creates a fuzzy inference system by creating a function that enables its fuzzy systems to learn from the data in modeling. The system integrates nerve networks and logical concepts in one way; accordingly, the network can use both facilities in just one format. Its system compatibility is in accordance with fuzzy rules, which can learn to approximate nonlinear functions. If the system has input x and y and the output is f, and if the rules are as follows [32]:

Rule if x is A_1 and y is B_1, then $f = p_1x + q_1y + r_1$

Rule if x is A_2 and y is B_2, then $f = p_2x + q_2y + r_2$

Additionally, if an average non-fuzzy builder is used to make a non-fuzzy mechanism, the output will be as in Eqs. 7-9 [22, 23] [32]:

$$f = \frac{w_1 f_1 + w_{2f_2}}{w_1 + w_2} = \overline{w_1}\, f_1 + \overline{w_2}\, f_2 \tag{7}$$

$$\overline{w_1} = \frac{w_1}{w_1 + w_2} \tag{8}$$

$$\overline{w_2} = \frac{w_2}{w_2 + w_1} \tag{9}$$

Figure 7 shows the structure of the ANFIS model used in this study.

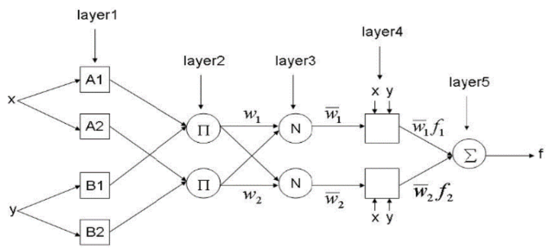


Fig. 7: Structure of the ANFIS model in this research.[22]

In layer 1, our functions pass through the membership functions based on Eqs. 10 and 11 [24,25]:

$$O_{1,i} = \mu A(x), for\ i = 1,2 \tag{10}$$

$$O_{1,i} = \mu B(x), for\ i = 1,2 \tag{11}$$

For each function, such as f, appropriate membership functions, such as the Gaussian function (Eq. 12), are chosen. In this formula, a_i, b_i, and c_i are the parameters of the initial layer.

$$\mu A(x) = \frac{1}{1 + \left|\frac{x - c_i}{a_i}\right|^{2bi}} \tag{12}$$

The output of layer 2 is the multiplication of the input signals, which is equivalent to the following rule [29] :

$$O_{2,i} = w_i = \mu A_i(x)\mu B_i(y) \quad , i = 1,2 \tag{13}$$

The output of layer 3 is the normalized form of the previous layer based on Eq. 14:

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2} \quad , i = 1,2 \tag{14}$$

Equation 15 shows the output of layer 4, which is the normalized pre-layer multiplication in the output or the same basic function, f.

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i) \tag{15}$$

The output of layer 5 is the whole system output based on Eq. 16:

$$O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{16}$$

Initially, the dimensionless ratios created were randomly divided into two groups of training data (93 mix designs) and experimental data (15 mix designs) in order to optimize the ANFIS network [32-34]. These data were normalized via Eq. 17 to avoid fast network saturation in the Takagi-Sugeno fuzzy inference method in the range of 0.1 to 0.9.

$$x\,(i) = 0.1 + 0.8 \times (x_{max} - x_i)/(x_{max} - x_{min}) \tag{17}$$

To achieve the optimal ANFIS network, various networks using variable parameters, such as the number of the intermediate layers and topology, were taught and tested. Among them, the optimal network with the 1-1-27-27-9-3 topology and in four hidden layers was selected. Other surveys were performed using the ANFIS optimal selected network [32-34]. Figure 8 shows the topology of the ANFIS model used in this study. The relationship between reduced sound intensity and independent data in the ANFIS model is shown in Fig. 9.

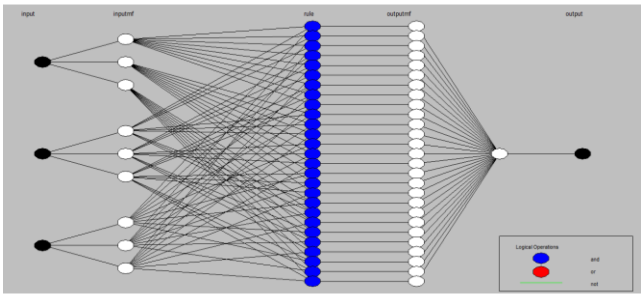


Fig. 8: Topology used for estimating reduced sound intensity.

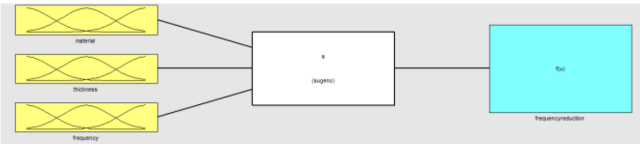


Fig. 9: Relationship between reduced sound intensity and independent data.

3.4. Regression Analysis

Linear and nonlinear regression analyses could be considered as the study of the relationship between dependent and independent variables, in which the function-dependent relationships between the dependent variable y and the independent variables x_1, x_2, ..., and X_P are suggested. These relationships are mainly used for purposes like finding the degree of importance of independent variables with certain techniques, such as stepwise and forward, the process of changing the variables associated with each of the independent variables, and also estimating the values of the dependent variable. The relationship is expressed in the form of an equation connecting dependent and independent variables. If we consider the multiple linear regression equation in the form of Eq. 18 [35]:

$$y = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_p x_{pi} + u_i \quad {}_{1 \le i \le n} \tag{18}$$

where β_0 is constant, β_1, β_2,…, β_p are called the model regression parameters, i is observation number, and u is a random disturbance. It is assumed that in the range of the studied observations, Eq. 18 provides an acceptable approximation to the actual relationship between dependent and independent variables. It is also assumed that for every fixed amount of xi, u is the random quantity independently distributed with a zero mean. All the assumptions are checked in the final step of forecasting. Parameters β_i are estimated via the method of least squares, which involves minimizing the sum of the residuals S (β_0, β_1, β_2, …, β_p) based on Eq. 19:

$$S(\beta_0, \beta_1, \dots, \beta_p) = \sum_{i=1}^{n} u_i^2 \tag{19}$$

The values of β_i that minimize Eq. 19 are given by solving the following system of equations:

$$S_{1i} b_1 + S_{2i} b_2 + \cdots + S_{pi} b_p = S_{yi} \quad , i = 1,2, \dots, p \tag{20}$$

where p is the number of independent variables and S_{ij}, Sy_i, and b_0 defined as in Eqs. 21-23 [32, 35]:

$$S_{ij} = \sum_{k=1}^{n} (x_{ik} - \bar{x}_i)(x_{jk} - \bar{x}_j), \quad i, j = 1,2,3, \dots, p \tag{21}$$

$$S_{yi} = \sum_{k=1}^{n} (y_k - \bar{y})(x_{ik} - \bar{x}_i), \quad i = 1,2,3, \dots, p \tag{22}$$

$$b_0 = \bar{y} - \sum_{i=1}^{n} b_i \bar{x}_i \tag{23}$$

Hence, the estimated value can be obtained based on Eq. 24:

$$\hat{y}_i = b_0 + b_1 x_{1i} + b_2 x_{2i} + \cdots + b_p x_{pi} \quad , \mathrm{i} = 1,2,3, \dots, \mathrm{p} \tag{24}$$

If $e_i = y_i - \hat{y}_i$ is the difference between the observations and the estimated values and $e_{is}=e_i/s$ is the standardized standard deviation error, it could be shown that in a suitable model, it has a normal distribution with a zero mean and standard deviation of one. According to the Student's t-distribution test, it also varies in the range of (-2, + 2). In most cases, nonlinear regressions can be converted to linear regressions by changing the appropriate variables (both independent and dependent variables). The calculations of this type of regression follow the principles of linear regression [36, 37]. The stepwise method was used in the present study. In this method, independent variables enter regression equations one by one, and if they do not play a significant role in the regression, they are eliminated. The linear regression model provides Eq. 25 for estimating the data. The values of the linear regression relation coefficients are presented in table 3.

$$R_{db} = a_0 + a_1 M + a_2 T + a_3 f \tag{25}$$

Table. 3: Values of linear regression relation coefficients.

a_0	a_1	a_2	a_3
62.217	0.136	-0.373	-0.001

4. Evaluation criteria

The optimal model among different models was selected based on some statistical criteria. Table 4 shows the symbols used in the evaluation criteria in this study.

The optimal model was selected based on a higher R^2 and AAE index and lower RMSE index than the other models.

Equations 26-28 define the mathematical form of these statistical criteria:

$$R = \frac{\sum(X-\bar{X})(Y-\bar{Y})}{\sqrt{(\sum(X-\bar{X})^2\sum(Y-\bar{Y})^2}} \quad (26)$$

$$AAE = \frac{\sum(X-Y)}{X} * 100 \quad (27)$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(X-Y)^2}{n}} \quad (28)$$

where N is the number of data.

Table. 4: Symbols used in the evaluation criteria

Symbo l	Name	Symbol	Name
R	correlation coefficient	$\bar{X}$	mean estimated reduced sound intensity
R^2	regression coefficient	$\bar{Y}$	mean measured reduced sound intensity
AAE/N	mean percentage error	X	measured reduced sound intensity
RMSE	root-mean-square error	Y	estimated reduced sound intensity

Table 5 presents the statistical specifications of the measured and estimated frequency reduction using ANN, ANFIS, and linear regression.

Table. 5: Statistical specifications of the models

Train data

Model	ANFIS	ANN	LR
R	0.982	0.985	0.405
R^2	0.965	0.971	0.164
AAE/n	1.310	1.160	11.080
Max AAE	3.862	7.419	28.123
RMSE	0.917	0.774	46.089
Max e_{is}	0.657	0.387	2.214
Min e_{is}	-0.560	-0.433	-2.068

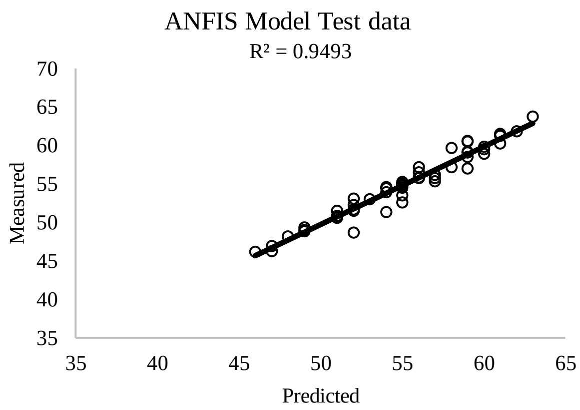
Test data

Model	ANFIS	ANN	LR
R	0.974	0.948	0.629
R^2	0.949	0.898	0.395
AAE/n	1.279	1.975	9.326
Max AAE	6.863	11.141	16.661
RMSE	1.032	2.883	35.524
Max e_{is}	0.310	0.385	0.971
Min e_{is}	-1.371	-0.790	-2.391

The values of the statistical index for ANN and ANFIS show an appropriate and excellent correlation between the independent and dependent data.

As the results in Table 5 show, the model used in ANFIS had high accuracy and estimated reduced sound intensity with less error than the other models.

Figures 10 and 11 show the regression coefficient of the test and training data for ANFIS and ANN. As shown in the diagrams, the ANFIS model estimated the results of the test data with further accuracy and higher correlation.



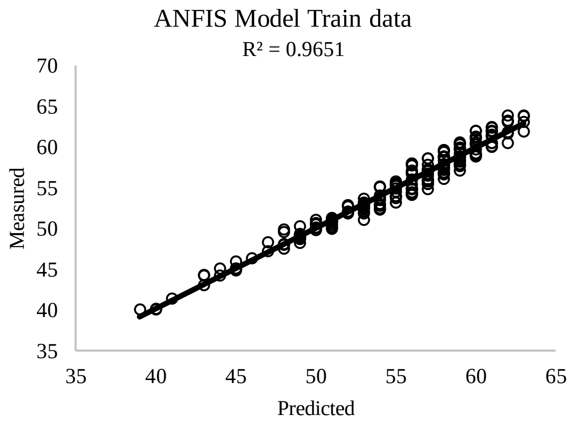
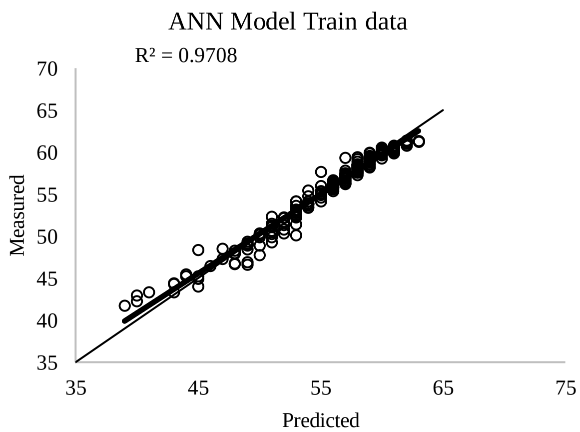


Fig. 10: Regression coefficient of the estimated and measured data via ANFIS.6



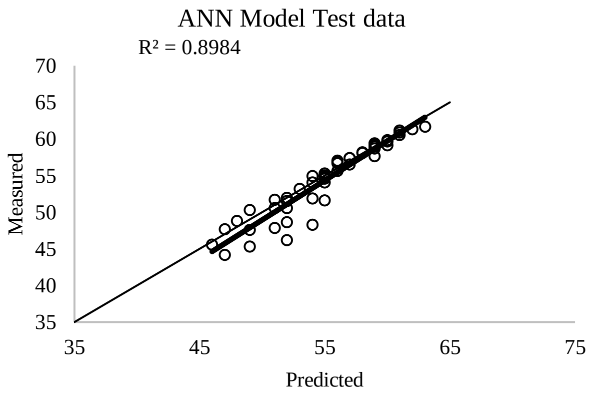


Fig. 11: Regression coefficient of the estimated and measured data via ANN.

If $e_i = y_i - \hat{y}_i$ is the difference between the measured and the estimated values and $e_{is}=e_i/s$ is the standardized error value with standard deviation (s), it could be assumed that in a suitable model, e_i has a normal distribution with a zero mean and standard deviation equal to one. Furthermore, e_{is} will be in the range of -2 to +2 based on the Student's t-distribution [32].

In both ANN and ANFIS models, the mean squared error indicated the fit of the model. Figure 12 shows the e_{is} values for the estimated data.

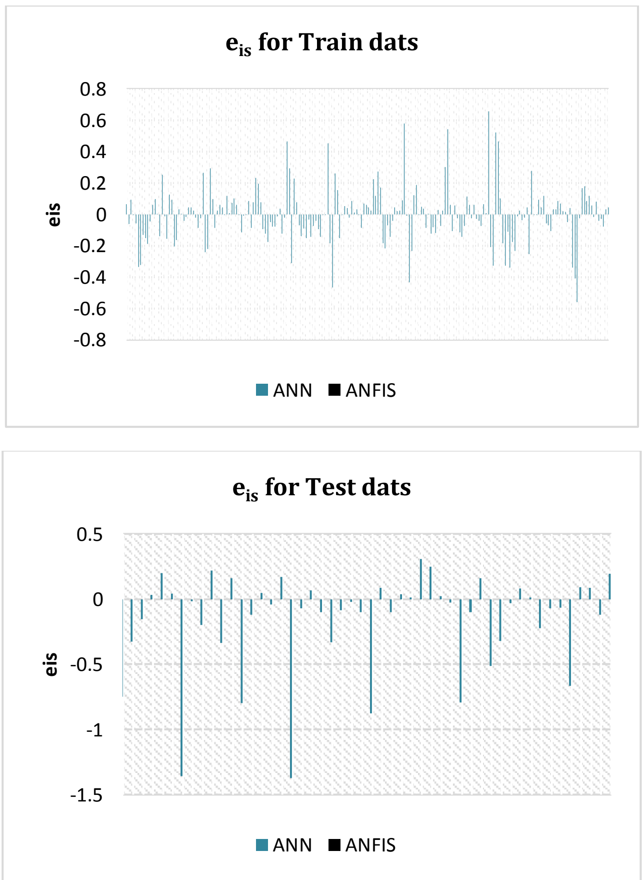


Fig. 12: e_{is} value for the train and test data in ANN and ANFIS

As shown, all the estimated values are in the range of -2 to +2.

5. Conclusion

One of the most important factors in choosing floor materials is their sound insulation. The sound reduction could be a function of the floor materials, floor thickness, and frequency of the produced sound wave. Hence, measuring sound reduction in floor systems is difficult, complex, and time-consuming. Therefore, using models to estimate sound reduction is important. In this study, the initial data were obtained through the simulation of floors via the INSUL software in four types of floor systems used in common structures in Iran with thicknesses of 250, 300, and 350 mm. It should also be noted that the number of finishing layers in all the models was the same in type and thickness, but materials and core thickness were designed differently in each of the models. The performed analyses implied that with the increase in thickness of the floors, an inverse effect is observed on their sound insulation. Based on the INSUL simulation results, 252 data were obtained and used to train and test ANN, ANFIS, and linear regression models. In order to evaluate the accuracy of the artificial neural network model, we obtained correlation coefficients of 0.985 and 0.948 for the training and test data, respectively. Similarly, these coefficients were 0.982 and 0.974 for the ANFIS and 0.163 and 0.395 for linear regression models. The results related to the regression coefficient indicated better estimation capability of the artificial neural network than that of ANFIS in the training data. Moreover, the ANFIS model had a much better performance than the artificial neural network in the test data. On the other hand, by investigating the mean percentage relative error and root-mean-square error, we observed that the ANFIS model had less error than the proposed ANN model.

The present study revealed that ANN and ANFIS could be tools with appropriate accuracy for predicting sound reduction, which could be highly beneficial in the initial steps of designing a house.

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