Research Article

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Emotional artificial neural network (EANN)-based prediction model of maximum A-weighted noise pressure level

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Abstract: Noise is considered one of the most critical environmental issues because it endangers the health of living organisms. For this reason, up-to-date knowledge seeks to find the causes of noise in various industries and thus prevent it as much as possible. Considering the development of railway lines in underdeveloped countries, identifying and modeling the causes of vibrations and noise of rail transportation is of particular importance. The evaluation of railway performance cannot be imagined without measuring and managing noise. This study tried to model the maximum A-weighted noise pressure level with the information obtained from field measurements by Emotional artificial neural network (EANN) models and compare the results with linear and logarithmic regression models. The results showed the high efficiency of EANN models in noise prediction so that the prediction accuracy of 95.6% was reported. The results also showed that in noise prediction based on the neural network-based model, the independent variables of train speed and distance from the center of the route are essential in predicting.

Keywords: Emotional artificial neural network, noise prediction, railway, rail Transportation

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1 Introduction

The uncontrolled population growth combined with the industrial development and technology of metropolitan areas brings many problems for urban dwellers, of which environmental pollution is one of the most important. Noise pollution as one of the most important environmental pollutants in creating such problems in large cities has played a significant role. Noise pollution is directly related to technology (especially industrial technology), in other words, along with the growth and development of technology, the problem of noise pollution also becomes more widespread and causes more problems. The problem of this type of pollution in most industrialized countries is considered as one of the most important environmental issues. In a way that even in metropolitan management, the interior architecture of health centers, educational-research, residential-commercial as well as the design of industrial machinery has received special attention. The most common sources of noise pollution in the urban environment are the railway system and airports. If the noise of these systems does not exceed a certain level, it will have adverse and sometimes irreversible psychological effects on the people living around these sound sources. Therefore, the noise caused by the movement of trains in urban areas is one of the hazards that can always endanger human health.Therefore, the noise caused by the movement of trains in urban areas is one of the hazards that can always endanger human health. In the field of noise pollution caused by train traffic in urban areas, many studies have been done, which shows the importance of this source of pollution as one of the problems of urban life.

As mentioned earlier, noise has harmful effects in three areas: mental, safety, and health [1]. According to studies, railway noise is more annoying and destructive than road traffic noise [2]. One of the most important effects in the rail transport sector is its effects on staff health and passenger sleep [3, 4]. For this reason, the study of noise and its amount in railways and rail transport and ways to reduce it is of great importance. The main reasons for noise propagation in railways are wheel wear with rails, traction noise and auxiliary systems at low speeds, and aerodynamic noise at speeds above 200 km/h [5]. In addition to stopping time, braking, and acceleration, train noise is also transmitted by maneuvering activities usually performed locally [6].

In designing highways, ordinary roads and evaluating existing or anticipated changes, traffic noise prediction models greatly help designers. Logically, the above definition is applicable in railway design. Undoubtedly, railway traffic noise prediction models can play a decisive role in assessing and monitoring the impact of noise on railway development projects [6]. The railway traffic noise is recognized as a complex system due to the interaction of different spatio-temporal factors. Both distributed and lumped models can simulate the railway traffic noise through different approaches. In practice, conceptual/physical-based models require enormous volume of data and calculations. On the other hand, black box models have recently become a popular choice

Artificial neural network (ANN) is one of the black box modeling methods that has been used in recent decades [7, 8]. For example, Cammarata and colleagues developed a post-diffusion neural network in 1995 to predict maximum A-weighted noise pressure level (L_{Aeq}) by measuring noise in Italy [9]. They compared neural network predictions with several conventional models. Hamoda also developed the general regression neural network (GRNN) and the back-propagation neural network (BPNN) in 2008 to predict the structure of construction noise to assess environmental impacts [10]. The results showed that the predictions of the GRNN are more accurate than the BPNN. These results show the ability of neural networks to predict the structure of noise.

Nassiri *et al.* (2007) developed an equation that calculates the L_{Amax} of the Tehran-Karaj local train (4GE diesel model) [5]. The proposed model form is derived from the L_{Amax} prediction equations for single locomotive trains. This model is provided in the US Federal Transportation Manual and in the French Rail Noise Prediction Model. Givargis and Karimi (2009) developed three mathematical, statistical, and neural models to compare the L_{Amax} of the Tehran-Karaj express train [6]. The results of these three models were satisfactory without statistically significant differences. However, the authors emphasize that more work is needed to develop and evaluate complex heterogeneous models.

The artificial intelligence approaches applied for noise modeling in the previous papers, particularly the classical ANN method which is the most popular artificial intelligence method used for noise modeling, are sometimes confront with different shortcomings such as incapability to offer probabilistic forecasting, low generalization ability, underestimation, overfitting in fore-casting, and the need to apply external data pre-processing methods (such as wavelet transform) outside the framework of the model due to insufficient data samples for model training or non-stationary data samples with high seasonal variations.

It is obvious that to recognize the noise, a reliable and appropriate model must be achieved. By analyzing the model, it is possible to identify the noise and the factors involved in it and reduce these factors as much as possible. Considering the shortcomings mentioned in the previous paragraph about classical ANN method, the authors have motivated to use the Emotional ANN (EANN) model which is an advanced ANN approach combining ANN with artificial emotions. In this paper, after stating the importance of studying noise prediction models, the study area is introduced according to sampling, and in the next stage, statistical analysis is performed.

2 Materials and method

2.1 Sampling

Trans-siberian railway (located in Russia) was selected as the test area since it possesses all of the features to satisfy the requirements of ISO 3095 (a flat site, free of sound-reflecting objects and free of sound-absorbing covering). The Bruel and Kjaer-2230, sound level meter, was installed alternately at the height of 1.5 meters and at distances of 25, 35, 45, 55, and 65 meters from the axis of symmetry. At each of these points, L_{Amax} values for ten passing trains (a total of 50 samples) were measured. The train speed was calculated by using the measured pass-by time of the train from buffer to buffer and the length of the train. Table 1 shows these data.

Table 1: The specifications of the samples

Samples	Sampling stations	Distance from the centre of the track (m)	Train speed (km/h)	Measured L_{Amax}
1	1	25	61.2	80.5
2	1	25	73.6	83.6
3	1	25	77.2	82.7
4	1	25	80.1	86.4
5	1	25	65.4	81.1
6	1	25	72.9	82.3
7	1	25	63.8	81.6
8	1	25	80.6	82.5
9	1	25	71.2	83.6
10	1	25	73.6	86.1
11	2	35	81.3	85.5
12	2	35	82.6	83.2
13	2	35	78.8	82.4
14	2	35	76.9	85.4
15	2	35	83.4	84.7
16	2	35	87.6	88.2
17	2	35	80.4	83.1
18	2	35	71.3	81.6
19	2	35	72.8	85.4
20	2	35	89.4	88.5
21	3	45	66.8	80.3
22	3	45	76.4	82.2
23	3	45	79.6	83.5
24	3	45	83.4	85.4
25	3	45	77.7	81.5
26	3	45	79.2	82.1
27	3	45	80.1	82.9
28	3	45	88.7	87.9
29	3	45	93.4	88.8
30	3	45	85.5	82.3
31	4	55	89.6	84.6
32	4	55	94.2	86.8
33	4	55	89.3	85.6
34	4	55	95.1	86.7
35	4	55	78.9	82.2
36	4	55	81.5	83.4
37	4	55	76.8	81.2
38	4	55	90.3	86.8
39	4	55	93.1	87.5
40	4	55	82.7	82.7
41	5	65	88.6	85.2
42	5	65	97.6	88.4
43	5	65	93.4	87.9
44	5	65	90.5	87.1
45	5	65	83.4	82.3
46	5	65	85.1	83.4
47	5	65	79.4	82.1
48	5	65	89.1	84.5
49	5	65	75.6	82.5
50	5	65	77.9	83.4

2.2 ANN model

Neural networks are generally nonlinear learning mathematical systems [11]. The way these networks work is modeled on how the human brain works. In fact, neural networks are a machine for building a model that can be simulated by hardware or software. Unlike digital computers, which require very explicit instructions, a neural network does not require pure mathematical models but, like humans, can learn from a number of specific examples [12, 13]. Each neural network goes through three stages of training, validation, and execution. In fact, neural networks can be used to solve problems that do not have precise mathematical relationships between inputs and outputs.

ANNs are a very large set of parallel processors called neurons that work in unison to solve problems and transmit information through synapses (electromagnetic connections). In these networks, if one cell is damaged, other cells can compensate for its absence and also participate in its reconstruction. These networks are able to learn. For example, by injecting tactile nerve cells, the cells learn not to go to the hot body, and with this algorithm, the system learns to correct its error [14]. Learning in these systems is adaptive; that is, using parables, the weight of the synapses changes in such a way that the system produces the correct response if new inputs are given. Learning to see neural networks is nothing more than adjusting the communication weights of neurons in exchange for different examples so that the network output converges to the desired output [15].

In a multilayer ANN model, each layer has its own specific weight matrix W, its own bias vector b, its own input n vector, and its own specific output vector a. Different layers can have different numbers of neurons. It is important to mention that the number of neurons to be used in the input layers and in the output one strictly depends on the number of inputs and outputs. Multilayer networks are more powerful than single-layer networks [16]. Figure 1 shows the structure of a multilayer ANN model.

Feed-forward neural network (FFNN) models are among the most commonly used neural network-based models that are extensively applied to model different processes. In FFNN, some adjusted weights are initialized depending on the data pattern and multiplied by the inputs, which are then summed up and passed through an activation function that handles the nonlinearity of the model to provide output. It should be noted that in the current study the Levenberg-Marquardt backpropagation algorithm was used for the training process of FFNN model.

2.3 EANN model

The FFNN model with three layers (hidden, input, and output layers), trained by the backpropagation algorithm, has indicated suitable efficiency in nonlinear modeling tasks.

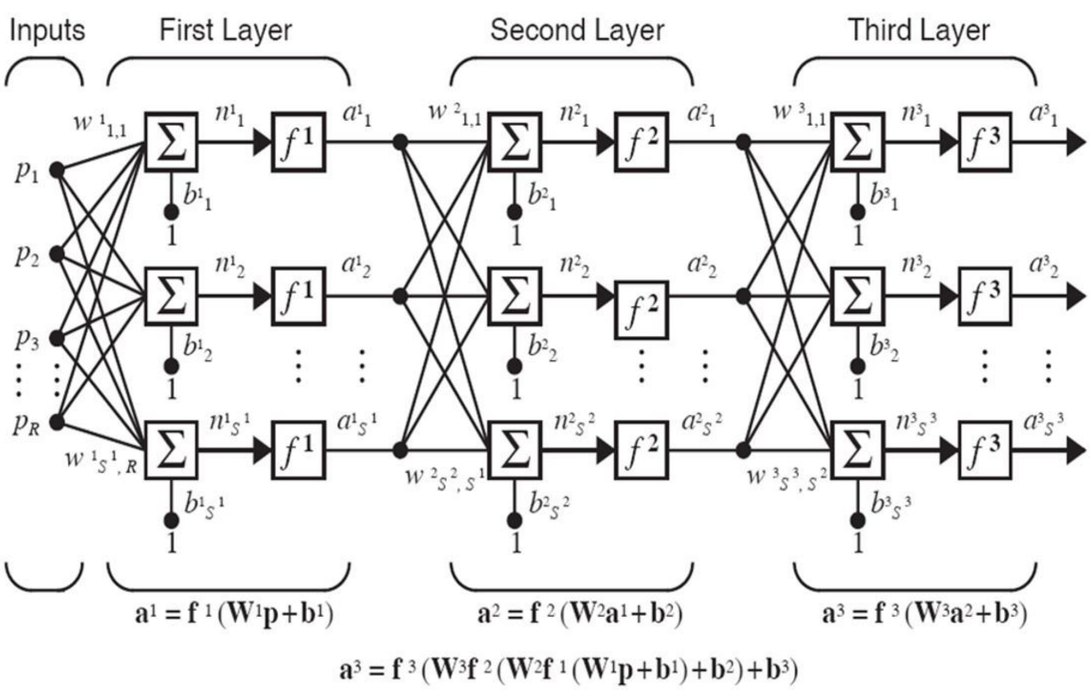

Figure 1: The structure of a multilayer ANN model

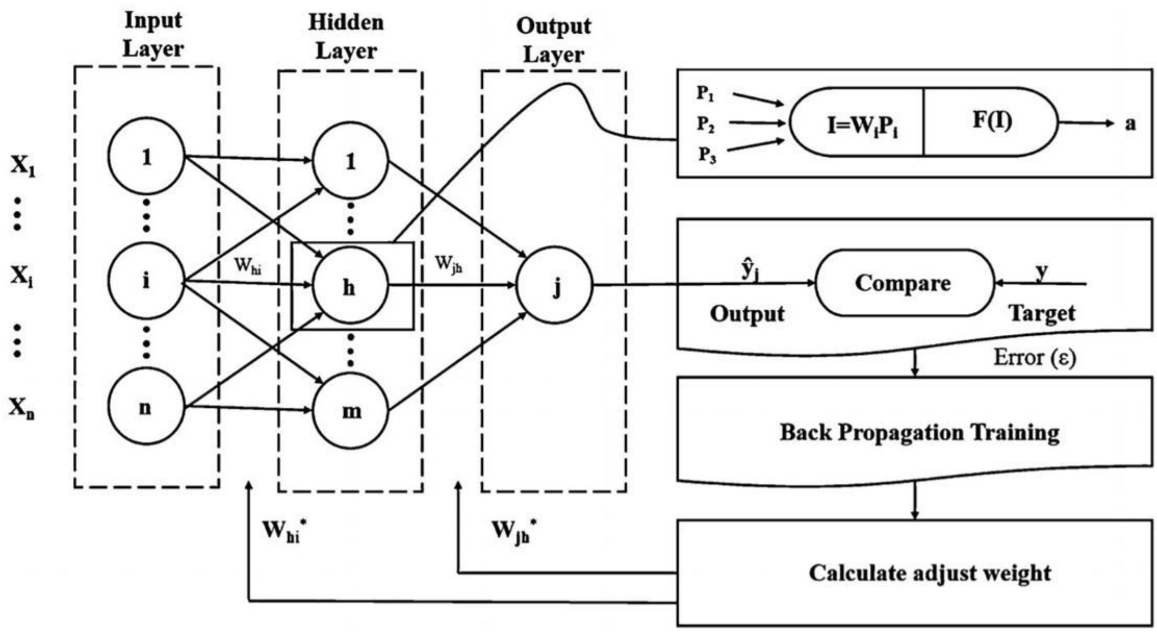

Figure 2: The three-layer FFNN model

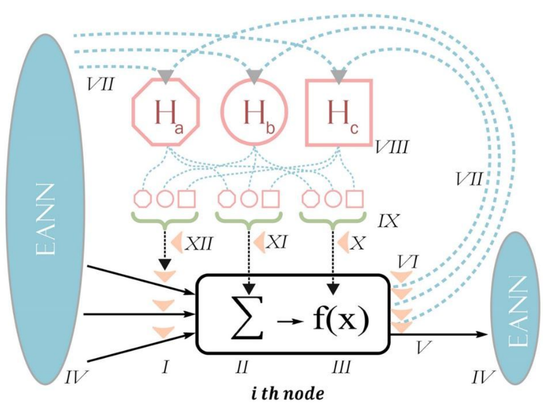

Figure 3: The EANN structure [19, 20]

On the other hand, an EANN model is the improved version of conventional ANN-based models, including an emotional system that emits artificial hormones to modulate the operation of each neuron, and in a feedback loop, the hormonal parameters are also adjusted by inputs and output of the neuron [17–19]. The schematic of an inner neuron from FFNN and EANN has been showed in Figures 2 and 3.

By comparing these two Figures (Figures 2 and 3), it is deduced that in contrast to the FFNN in which the information flows only in the forward direction, a neuron of EANN can reversibly get and give information from inputs and outputs and also can provide hormones (*e.g.*, Hc, Hb, and Ha) [21–24]. The output of ith neuron in an EANN with three hormonal glands of Ha; Hb and Hc can be computed as:

$$Y_i = \underbrace{\Big(\gamma_i + \sum_h \partial_{i,h} H_h\Big)}_{1} \times f\Bigg(\sum_j \Big[\underbrace{\Big(\beta_i + \sum_h \chi_{i,h} H_h\Big)}_{2} \times \underbrace{\Big(\alpha_{i,j} + \sum_h \Phi_{i,j,k} H_h\Big) X_{i,j}\Big)}_{3} + \underbrace{\Big(\mu_i + \sum_h \psi_{i,h} H_h\Big)\Big]}_{4}\Bigg) \qquad (1)$$

As the artificial hormones calculated as:

$$H_h = \sum_i H_{i.h} \quad (h = a,\ b,\ c) \qquad (2)$$

In Eq. (1), the implemented weight to the target (f) is depicted by (1). It incorporates the permanent neural influence such as the dynamic hormonal weight of $\sum_h \partial_{i,h} H_h$. The implemented weight to the gathering (net) function is given by Term (2), the employed weight to the $X_{i,j}$ (an input from *j* the node of the former layer) is confirmed by Term (3), and the preference of the summation purpose is indicated by Term (4).

The distribution of the overall hormonal level of EANN (*i.e.*, H_h) between the hormones must be verified by, and circumstances, the i^{th} node output (Y_i) provide hormonal feedback of $H_{i,h}$ to the network as follows:

$$H_{i,h} = glandity_{i,h} \times Y_i \qquad (3)$$

Where the glandity parameter can be calibrated in the training phase of the EANN model to find the appropriate hormone size for the glands.

2.4 Evaluation criteria

In order to evaluate the accuracy performance of the models, the root mean square error (RMSE) criteria (Eq. (4)) and the correlation coefficient (R) (Eq. (5)) are used [25]:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2} \tag{4}$$

$$R = \frac{\sum_{i=1}^{n}\left(O_i - \bar{O}\right)\left(P_i - \bar{P}\right)}{\sum_{i=1}^{n}\left(O_i - \bar{O}\right)^2 * \sum_{i=1}^{n}\left(P_i - \bar{P}\right)^2} \tag{5}$$

In these equations, $\boldsymbol{O_i}$ and $\bar{O}$ are the observed values and the mean of these values, respectively. Also $\boldsymbol{P_i}$ and $\bar{P}$ are the computational values, respectively, and the mean of these values, respectively. It should be noted that the n parameter is the number of data.

3 Results and discussion

According to recent studies, in this paper, data set was divided into two parts for AI models as training and verification; the first division as 75% of total data used as the training set and the rest 25% data was used for the verification purpose. In other words, in predicting the FFNN and EANN models, out of 50 samples, 37 were selected as training samples, and 13 items were selected as test samples of the model. Also, it should be mentioned that the higher values of maximum and standard deviation were considered in the training data set, due to the fact that the AI model can present accurate predictions for unseen data if their interpolator systems are familiar with same patterns. This means that training and test datasets were not selected completely randomly and a series of monitoring was considered for dividing datasets. For example, it was tried to put the maximum and minimum data in the training samples.

To speed up training systems, the inputs and output data were normalized before entering into the training step. Eq. (6) was applied to normalize all the data between values of 0 and 1 in order to bring all the data into the same unit and range. In this way, all the inputs can receive similar attention in modeling the output. The data normalization eliminates overshadowing the impact of the data with lower values by those with higher values [26, 27].

$$V_{norm} = \frac{V - V_{min}}{V_{max} - V_{min}} \tag{6}$$

Where V_{norm} is the normalized data value, V is the observed value, V_{max} and V_{min} are the maximum and minimum data values, respectively.

In the current study, the hidden neuron number is assumed up to 4 times of the input layer, and then the best number of the hidden neuron is selected by trial and error. The results of FFNN and EANN models are demonstrated in Table 2.

Table 2: The results of FFNN and EANN models

FFNN model	Train	RMSE	0.033
		R	0.915
		Training Time	0:00:00.03
	Test	RMSE	0.078
		R	0.893
EANN model	Train	RMSE	0.018
		R	0.956
		Training Time	0:00:00.09
	Test	RMSE	0.049
		R	0.908

As shown in Table 1, the EANN model is better than the FFNN model in both training and test, so that the EANN could outperform the FFNN model up to 45% and 37% in terms of training and test efficiency criteria, respectively.

Figure 4 shows that in the EANN and FFNN models, the independent variables of train speed (Km/h), sampling station, and distance from the center of the route (Km) are important in predicting, respectively. In other words, in the neural network-based models, the most effective independent variable in predicting L_{Amax} is train speed (Km/h), and distance from the center of the track (Km) has less effect on L_{Amax} prediction compared to the other three variables. As a result, the neural network-based models use all independent variables to predict the dependent variable. It

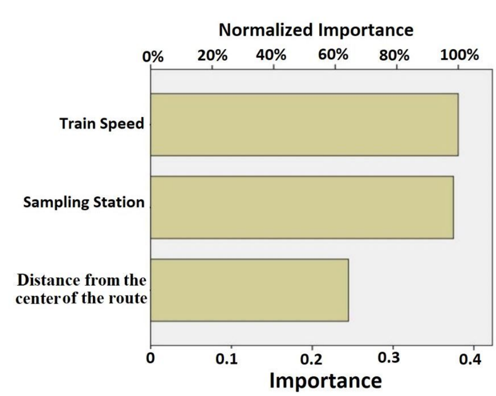

Figure 4: The importance of each of the effective factors in noise

should also be noted, given that it is strongly recommended to normalize the data (because the data normalization can effectively increase the training rate and performance of FFNN and EANN models), data were normalized before predicting L_{Amax} using FFNN and EANN models.

The fitted model, based on the first and second layers, is as follows:
First layer:

$$L_{Amax} = 0.62 + 0.95 \text{ Sampling station} + 0.28 \text{ Distance} - 0.11 \text{ Trainspeed}$$

Second layer:

$$L_{Amax} = 0.39 + 0.14 \text{ Sampling station} + 0.43 \text{ Distance} - 0.58 \text{ Trainspeed}$$

In order to compare the predicted model based on the neural network, in this section, we will predict the noise based on the regression model. Like the neural network-based models (FFNN and EANN), in the regression model, we assume that three independent variables of train speed (km/h), sampling station, and distance from the center of the route (km) are involved in predicting L_{Amax}.

According to Table 2, since the value of the significant level of Fisher statistic is equal to 0.000 and this value is less than the significant level of the test (<0.05), the model is approved. Also, according to Table 3, the model determination coefficient is equal to 0.826. 82.6% of the changes in LAmax with two variables of train speed (km/h) and distance from the center of the route (km) are expressed in the model, which is a reason to confirm the hypothesis. Also, the statistic value of the Watson camera is equal to 1.59. Because this value is in the range of 1.5 to 2.5, there is no reason for the correlation of errors. Therefore, the multiple linear regression model is as follows:

$$L_{Amax} = 82.18 - 0.17 \text{ Distance} + 0.099 \text{ Trainspeed}$$

In the following, the results of logarithmic regression are examined. According to the multiple regression output, the effective parameters of L_{Amax} are estimated based on the factors presented in Table 3. The logarithmic regression model is as follows:

$$Log\ (L_{Amax}) = 1.556 - 0.029 \text{ Sampling station} - 0.009 \text{ Distance} + 0.098 \text{ Trainspeed}$$

According to Table 4, since the value of the significant level of Fisher statistic is equal to 0.000 and this value is smaller than the significant level of the test (0.005), the model is approved. Also, according to Table 4, the independent variables of sampling station, distance from the center of the route (km), and train speed (km/h) is involved in predicting the L_{Amax} variable. As can be seen in this Table, the determination coefficient of the model is 0.889. That is, 88.9% of the changes in the L_{Amax} variable are expressed by the three variables of train speed (km/h) and distance from the center of the route (km) and the sampling station in the model, and this is a reason to confirm the hypothesis. Also, the value of the Watson camera statistic is 2.28 because this

Table 3: Linear regression results

Variable	Coefficients of variables	The standard deviation	τ Statistic	Level of significance of the test	Effective or not
Constant	82.18	0.920	87.502	0.000	effective
Distance (km)	−0.17	0.006	−21.060	0.000	effective
Train speed (km/h)	+0.099	0.012	8.514	0.000	effective
R = 0.826 RMSE = 0.079		Watson camera = 1.59		Level of significance = 0.00	

Table 4: Logarithmic regression results

Variable	Coefficients of variables	The standard deviation	τ Statistic	Level of significance of the test	Effective or not
Constant	1.556	0.028	46.128	0.000	effective
Sampling station	−0.029	0.014	−2.196	0.027	effective
Distance (km)	−0.009	0.024	−0.496	0.610	effective
Train speed (km/h)	0.098	0.008	12.462	0.000	effective
R = 0.889 RMSE = 0.053		Watson camera = 2.09		Level of significance = 0.00	

value is in the range of 1.5 to 2.5. As has been concluded in previous studies with comparing Tables 2, 3, and 4, it is obvious that the EANN model has better performance in predicting L_{Amax} than others (FFNN, Linear regression, and Logarithmic regression) [17].

4 Conclusions

The results show that in noise prediction based on the EANN model, independent variables of train speed (km/h), sampling station, and distance from the center of the route (km) are important in forecasting and the accuracy of this model, respectively. The prediction accuracy of this model is 95.6%. In the linear regression method, the variables of train speed and distance from the center of the route are effective in predicting noise. The prediction accuracy of this model is 82.6%. In the logarithmic regression, the independent variables of sampling station, distance from the center of the route, and train speed are involved in predicting the L_{Amax} variable. The prediction accuracy of this model is 0.889. Therefore, in this study, it was found that the EANN model offers more favorable results compared to FFNN, logarithmic regression, and linear regression models.

In future research, with the help of experimental design techniques, the causes of each type of noise can be identified and intensified. Experts believe that efforts can be made to reduce the noise caused by wheel and rail wear, and by analyzing the received noise, the type of possible errors such as wear or corrosion of wheels or rails can be determined.

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