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Development of an Empirical Acoustic Model for Predicting Reverberation Time in Typical Industrial Workrooms Using Artificial Neural Networks, Mohsen Aliabadi, Rostam Golmohammadi, Abdolreza Ohadi, Muharram Mansoorizadeh, Hassan Khotanlou and Mohammad Saber Sarrafzadeh, Acta Acustica **vol. 100** (Number 6), 2014, pp. 1090-1097

DOI
https://doi.org/10.3813/AAA.918788

Acta Acustica united with Acustica
Vol. 100 (2014) 1090 – 1097

DOI 10.3813/AAA.918788

Development of an Empirical Acoustic Model for Predicting Reverberation Time in Typical Industrial Workrooms Using Artificial Neural Networks

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Summary

In noisy workrooms, acoustic treatments may be very costly and subject to different limitations. Reverberation time prediction can be employed for discovering acoustic treatments opportunities so that, more acceptable conditions are obtained. Using artificial neural networks, this study aims to develop an empirical model for predicting the reverberation time in industrial embroidery workrooms. Geometrical model was also employed and its results were compared with those of neural networks. The main acoustic features and reverberation times were determined in the studied workrooms. Different structures of networks were developed and finally, the networks with one hidden layer along with five neurons were found to be the best model for predicting reverberation time (RMSE = 0.17(s) and $R^2 = 0.77$). The relative errors of the networks and the geometrical models for a new case of workroom were 6% and 4.7%, respectively. Although networks are empirical in nature, the results confirmed the potential of this approach for minimizing the uncertainties in acoustics' modeling. The developed model gives professionals the opportunity to have an optimum decision about the effectiveness of acoustic treatment scenarios in embroidery workrooms.

PACS no. 43.50.-x, 43.55.-n

1. Introduction

Noise is one of the most common occupational health hazards in workrooms. In recent years, attention has been paid to such noticeable issues of room acoustics as modeling of noise propagation in industrial workrooms [1]. Noise level in workrooms is composed of the sound directly emitted by machines and of the sound reflected by the internal surfaces of workrooms. Some workrooms are, therefore, much noisier than the others, even with similar noise sources. One of the most important methods for noise control is reducing the reverberant noise level within enclosed workrooms. Noise can be reduced by applying suitable acoustic structural materials or by placing acoustic-absorbing surfaces in workrooms. However, this is only effective, if the reverberant field significantly affects the noise level of the workrooms. As the final results of acoustic treatments of existing workrooms depends basically upon the initial conditions, acoustic experts shall perform an analysis before designing for remedies in noisy workrooms using suitable acoustic parameter [2].

One of the important parameters describing the acoustic characterization of workrooms is the reverberation time (RT) [3, 4]. Because acoustic modifications may be extremely costly and subject to restrictions, RT predictions are needed for different room acoustic configurations so that optimum acoustic conditions can be gained [5]. During the past century several empirical and theoretical equations for predicting RT were developed based on the assumption of homogeneous distribution of sound energy within the room, which leads to the uniform distribution of sound absorptions [6, 7]. The literature on room acoustics indicated acoustic professionals are not altogether satisfied with the existing equations; hence, this issue is still open for further studies which might develop solutions that better describe workroom acoustic characterizations. In this regards, Eyring showed Sabine's equation is invalid when there is noticeable absorption in the enclosed room and that this equation should be used for live rooms and also confirmed reverberation time depends upon the room shape [8, 9].

Received 6 July 2013,
accepted 20 May 2014.

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In regard to determine the share of the workroom acoustic characteristics, it is necessary to measure and predict reverberation time within closed workrooms [1]. In this way, the optimum reverberation times based on the workrooms volume in order to design low-noise workrooms have been recommended in the ISO standard methods. Though reverberation time is frequently used in noise control measures as an acoustic design criterion, no detailed comparison of models for RT prediction in industrial workrooms was found [10]. Comparisons have been performed in auditorium, classrooms and concert halls, but their results might not be applicable to workrooms [10]. More recent acoustic prediction models are geometrical ones which exhibit higher validity and acceptability compared with empirical models. However, development of these models is complicated and needs computer and acoustics expertise and entails time- consuming calculations, hence they are employed just in special cases [11, 12].

In this regards, one of the most important issues is applying alternative methods which can recognize the complex relationships among different variables which affect the reverberation time in enclosed workrooms. Artificial neural networks (ANNs) as one of the most important artificial intelligence techniques have innate capability in storing and to applying empirical data [13]. This technique is known to be an accurate approach in modeling various phenomena in basic, engineering and medical sciences with the ability to determine the complex relations among different variables and the capacity of using multiple learning algorithms data [13].

Neural networks can be a good tool for the analysis of such physical phenomena as sound propagation in enclosed room in which adequate data related to different variables are being collected while the mechanisms of interaction effects are complex and not fully understandable. Despite the increasing application of neural networks as a new approach for predicting acoustic performance of sound absorbents, active noise control and environmental acoustics, few studies about acoustic parameters of industrial workrooms have used this technique. Employing neural networks for predicting the sound speech level in classrooms and passenger cars, noise level in industrial workroom and reverberation time in auditoriums are some examples in this regard [14, 15, 16, 17]. Nannariello et al used neural networks as an alternative method of predicting the reverberation time for enclosures. The results indicated that there is a good basis for using trained neural networks to predict the reverberation time with accuracy of ±10% [16].

Therefore, it is necessary to develop applied techniques which can more accurately predict reverberation time in typical industrial workrooms and also can take important acoustic variables such as workroom shape, volume, and equivalent sound absorption surface into account. The noisy process of industrial embroidery in which patterns and designs are imprinted on cloth, is considered to be an important part of the textile industry. Using artificial neural networks as an alternative method, this study aims to present an empirical technique for predicting reverberation time in enclosed workroom of industrial embroidery. Geometrical model based on ray tracing was also employed and its results were compared with those of neural networks.

2. Materials and methods

In this study, the development of the empirical technique of RT prediction consisted of in three main phases. The first phase included choosing the specific area of application in the context of industrial noise, identifying features that might influence the reverberation time, collecting and analyzing data set, and finally, determining the main features. The second phase consisted of separating the data into train and test data sets, determining the type and the parameters of artificial neural networks structure and learning algorithm and training the networks. In the third phase, the test data set was employed to access the validity of the best networks based on the performance criteria. Consequently, geometrical model based on ray tracing was developed for a typical case of embroidery workroom. Performance of this model was then compared with that of neural networks.

2.1. Source of data

In order to eliminate the possible effect of such space-related variables as differences in geometrical shapes, development of the prediction model was carried out in the similar industrial processes. The industrial embroidery was chosen as the research field in the form of enclosed workrooms. The data were collected in 31 embroidery workrooms with similar processes and structures located in Khorasan province (East of Iran). Due to the nature of sewing operations, operators are exposed to high level of noise as a pollutant with some risks of hearing loss. High noise level in these workrooms and no complexity of process and similarity of workroom shapes were important factors for selecting this field. Based on these criteria, it is possible to control the numbers of features that influence the reverberation time.

2.2. Characterizing model features

2.2.1. Acoustical, structural features of workrooms

Main acoustical features were determined based on ISO 11690 [18]. The most important structural characteristics of workrooms were dimensions including length (L), width (W), height (H) and total surface area(S), volume (V) and geometrical shape. Because the geometrical shapes of all workrooms were similar (all rectangular), this parameters was not considered as a candidate feature. The structural materials of workrooms were recorded carefully and their sound absorption coefficient values were specified from valid resources and the local data [19, 20]. As the surface absorption coefficient is a function of the frequency of the incidence sound, noise reduction coefficient (NRC), which is defined as the average of noise absorption coefficients in the 250 Hz, 500 Hz, 1000 Hz and

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Table I. Descriptive statistics of the constructional and acoustic features in the embroidery workrooms.

Features type	Symbol	Unit	Minimum	Maximum	Mean	Std. Dev.
Constructional features						
Length	L	m	6.3	20	10.60	3.5
Width	W	m	3	11	5.2	1.9
Height	H	m	2 5	3.8	0.7	
Volume	V	m^3	60	660	214	112
Total surface	S	m^2	102.4	640	228	105.80
Acoustic features						
Average absorption coefficient	$\overline{\alpha}$	-	0.04	0.14	0.06	0.02
Equivalent absorption surface	A	m^2	6.06	25.07	12.17	4.34
Room absorption constant	R	m^2	6.4	29.06	12.9	4.8
Target feature						
Reverberation time	RT	s	0.39	1.67	0.96	0.34

2000 Hz octave bands was used [19]. The total equivalent sound absorption area of workrooms (in m^2) was calculated based on ISO standard [21]. The most important acoustic features i.e. average absorption coefficient of workroom ($\overline{\alpha}$), room absorption constant (R) (in m^2) and reverberation time (RT) (in second) were determined based on based on ISO standard [21].

2.2.2. Reverberation time measurement

Measuring the reverberation time is performed based on ISO standard in the studied workrooms [22]. Reverberation time is not identical in different locations in a room, so it is usually measured at several locations. The reverberation time based on interrupted noise method was measured for two positions of the sound source and for each of them in two positions of the microphone at center and at one corner of each workroom. The results were then averaged. For each location of the source- microphones, measurement of the reverberation time was repeated thrice. Measurement was also performed at representative low, mid and high frequency ranges in octave bands from 125 to 4000 Hz [22]. VA-Lab REV module which is developed by BSWA Technology Co. Ltd was employed for measuring RT. It supports the interrupted noise method which includes Omni directional sound source with sound power of 115 dB pink noise, and the 1/2" prepolarized free-field microphones. Descriptive statistics of the constructional and acoustic features in the studied workrooms was presented in Table I.

To process and select the final features of the proposed model, such statistical methods as correlation matrix were used. Length (L), width (W), volume (V), total surface (S), average absorption coefficient ($\overline{\alpha}$) and equivalent absorption surface (A) were found to be the most influential features and hence were included as the input features. Finally, measured reverberation time was considered as the target feature. Hence, the mean values of reverberation time at representative low, mid and high frequency ranges of the one octave-band frequencies from 125 to 4000 Hz was considered. Passero and Zannin [23] have also used the mean values of reverberation time in classrooms across 125 to 4000 Hz for developing prediction models.

2.3. Neural networks model development

Artificial neural networks consist of a number of interconnected neurons which are positioned in at least three layers, i.e. one input layer of source neurons, at least one hidden layer and an output layer of computational neurons. Generally, each neuron in the hidden layer of the networks can be considered as a simple processing element taking one or more input(s) and giving one and more output(s). In each neuron, a related weight is assigned to each input, through which the power of the input is adjusted. The neuron can, thereby, combine all the inputs and calculate an output, which is passed on. Following basic equations illustrate the structure of typical artificial neural networks [24].

$$y_1 = F(z_1), \tag{1}$$

$$z_i = \sum_{i=1}^{n} w_i x_i + b_i, \tag{2}$$

$$\sum_{i=1}^{n} w_i x_i = w_1 x_1 + w_2 x_2 + w_3 4 x_3 + \cdots + w_n x_n, \tag{3}$$

Where $x_1, x_2, \ldots x_n$ denote the measured value for input variables, $w_1, w_2, \ldots w_n$ are the weights, b_i is the bias, y_i is the output variable while Z_i represents the activation function. Nonlinearity can be considered as the main activation function of neural networks, the most typical of which is sigmoid function used as an activating one [24]. In this study, different structures of neural networks were developed using MATLAB software. Multilayer perceptron (MLP), used in the present study, can be regarded as the most widely accepted structure of neural networks, applied for modeling physical phenomena [24]. Regarding the interconnections within the neural networks structure, feed forward networks, were selected. Training the neural networks is the process of adjusting the weight of the neurons so that the networks output will converge to the

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Table II. Absorption coefficients of the structural materials in the studied workrooms.

Material description	63 Hz	125 Hz	250 Hz	500 Hz	1000 Hz	2000 Hz	4000 Hz	8000 Hz
Ceramic tile	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02
Acoustic mineral tile	0.39	0.39	0.63	0.57	0.58	0.50	0.38	0.38
Gypsum	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Solid wooden panel	0.14	0.14	0.10	0.06	0.08	0.10	0.10	0.10
Glass, large	0.18	0.18	0.05	0.04	0.03	0.02	0.02	0.02

desired output. In this study, the training process was performed based on the supervised learning method using error back propagation learning algorithm. The network receives a set of inputs and their corresponding output examples during the learning process; hence, the relationships between the inputs and the output were determined. The networks process the inputs and compare theirs resulting output against the expected output. Then, errors are propagated backward through the structure, leading the networks to gradually modify the weights until the desired output is created [25].

Cross-Validation is a statistical method of evaluating and comparing training algorithms by dividing data into two segments: one used to train a model and the other used to test the model. The basic form of cross-validation is k-fold cross-validation. In k-fold cross-validation the data is first partitioned into k equally sized segments or folds and then k experiments are conducted by using one fold for test and remaining $k-1$ folds as training data. In this study, five folds from the observations were produced to train and test the prediction model. Therefore, each fold included 20% of dataset. In this way, four folds of the dataset were used as as training set and one fold was used as test set. Subsequently, k iterations of training and test are performed. At each iteration, a different fold of the data is held-out for test and the remaining $k-1$ folds are used for training.

By default, MATLAB's Neural Networks package uses 15% of training data for validation. The training procedure and updating synaptic weights continues until there is no improvement on the validation set. Furthermore, MATLAB selects 15% of training set as the test set and reports the most current network's performance on this set for demo purposes.

Training the networks continues until a certain number of epochs are passed or the error variations of the networks in a mentioned epoch are minimized. Moreover, each variable was normalized by subtracting from its mean value and then dividing the result by its standard deviation so as to have zero mean value and unity variance for all variables. The best networks were then chosen using trial and error in terms of the number of hidden layers and their neurons. In our case, the networks with one hidden layer along with five neurons were found to be the best structure for the prediction purpose.

2.4. Geometrical model development

In this study, computer simulation of a typical case of embroidery workroom was performed using ODEON room acoustics software version 10 [26]. The calculation method is based on ray tracing algorithm [27, 28]. The room geometry in a 3D model of workroom shows three receiver positions, and a single point source position according to Figure 1.

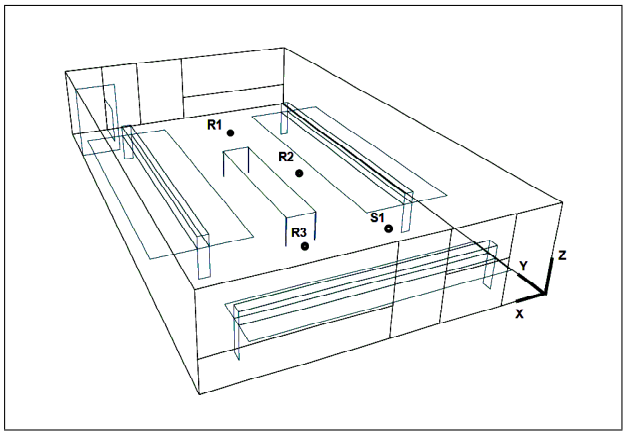


Figure 1. Location of sound source (S1) and microphones (R1, R2, R3) points in the 3D model of the embroidery workroom (S1: X=2m, Y=3m and Z=1.4m), (R1: X=4m,Y=14m and Z=1.4m), (R2: X=3m,Y=8.5m and Z=1.4m) , (R3: X=5m,Y=3m and Z=1.4m).

Length, width, and height of the studied workroom were 17 m, 10 m and 3 m, respectively. On the other hands, embroidery machines located in workroom have a length of 9.5 m, a width of 3 m and a height of 1.75 m.

The sound absorption characteristics of some structural materials in the workrooms extracted from material library for room were specified in Table II. ODEON describes two methods for calculating the global decay of rooms includes quick estimate and global estimate. Global estimate is the most precise methods which produce high quality results. In this regards, global estimate as a reliable method for estimating the reverberation time values was applied and its results were compared with the results of actual measurement of RT. In order to achieve this goal, a single decay for the whole workroom once the sound source is fixed was considered. However, in order to ensure the accuracy of prediction, some decay measurements were repeated as shown in Figure 1.

The program was run and the final values for the reverberation time were obtained. The number of early rays is normally best left for ODEON to decide. ODEON estimates a number of early rays to use in order to detect important early reflections based on the number and size of

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surfaces, the dimensions of the room. Finally, root mean square error (RMSE), coefficient of determination (R^2) and relative error (RE) were used in order to assess the performance of developed prediction techniques.

3. Results

3.1. Performance of neural networks

The empirical technique for prediction of reverberation time was developed using artificial neural networks. The results showed that prediction error of the networks structure with one hidden layer along with five neurons was within the acceptable level with prediction error (RMSE) equal to 0.17(s) and $R^2 = 0.77$ for test data set. Performance of the artificial neural networks based on RMSE and R^2 was illustrated in Table III. Number of training epochs which have the lowest error was equal to 144. The performance of the trained networks based on number of epochs was shown in Figure 2. The results confirmed training error rapidly falls below 10^{-4} and then its improvement is smooth.

To attain the networks with optimal performance, model structure and learning algorithm were chosen in accordance with the nature of the phenomenon of study. In addition, the best networks were chosen using trial and error in terms of the number of hidden layers and their neurons. As expected, prediction errors for training data with RMSE = 0.009(s) were lower than prediction errors for unseen data with RMSE = 0.17(s).

The scatter plots of the measured values of reverberation time versus the predicted values by the neural networks for test data set were presented in Figure 3. In general, prediction errors in the training phase were lower than those in the test phase.

3.2. Case study

The main purpose for developing prediction model using neural networks was application of this model for analyzing a new case of embroidery workroom. In order to test this application in practice, one of the noisy embroidery workrooms was selected. In this regards, reverberation time in the embroidery workroom described in Figure 1 was predicted by the developed neural networks and the results were compared with ODEON prediction.

The results of computer simulation using ODEON software for predicting reverberation time in the typical embroidery workroom were recorded. Global reverberation times estimation was performed based on one point source and an overall gain equal to 70 dB. The number of rays determined by ODEON was 39056. Reverberation times based on RT20 derived from the global decay curves were shown in Figure 4. The measured and the predicted RT spectrums by ODEON for the typical embroidery workroom were shown in Figure 5.

Reverberation time in the mentioned embroidery workroom was also predicted by the developed neural networks. Note that, for the new case of workroom, the acoustic and structural features used in the geometrical model were considered to be identical with the developed neural networks. RT values predicted by the different prediction models in the case of new embroidery workroom were shown in Table IV. Relative errors of the different prediction techniques were shown in Table V.

ISO 3382 specifies two main levels of measurement accuracy for reverberation time included survey and engineering levels. The relative errors of the developed prediction techniques can be compared with the accuracy equal to 5% for the engineering method and 10% for survey method [22].

As shown in Table V, the prediction error of the developed neural networks was 6% which was slightly upper than accuracy threshold for the engineering method and lower than accuracy threshold for survey method. On the

Table III. Prediction performance of the artificial neural networks in the train and the test phases.

Train		Test	
RMSE (s)	R^2	RMSE (s)	R^2
0.009	0.99	0.17	0.77

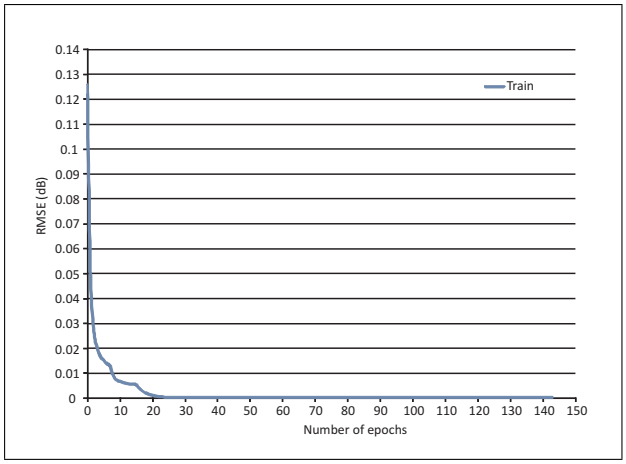


Figure 2. The performance of the trained networks based on number of epochs.

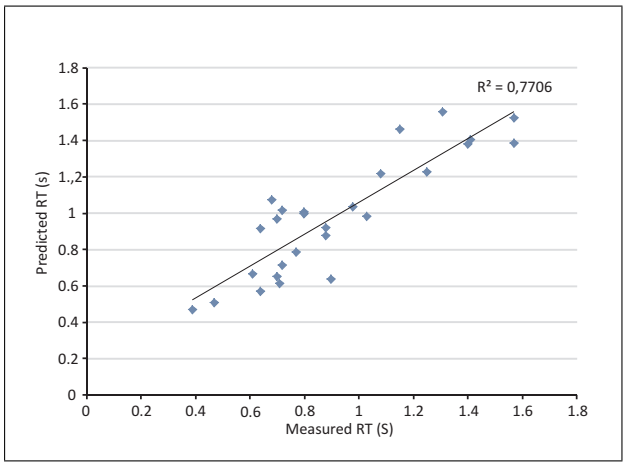


Figure 3. The scatter plots of the measured values of RT versus the predicted values by the neural networks.

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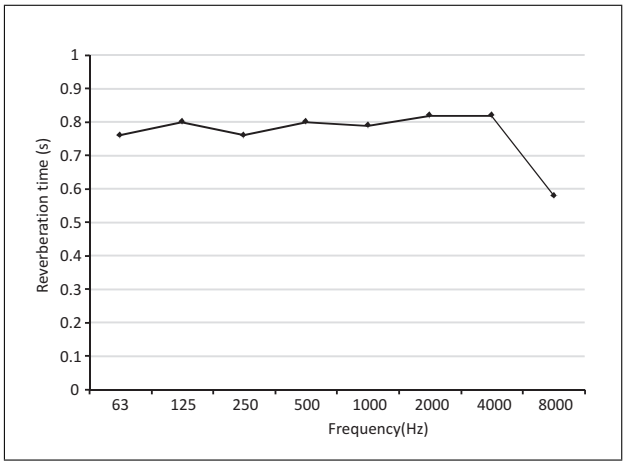


Figure 4. The reverberation times (RT20) derived from the global decay curves.

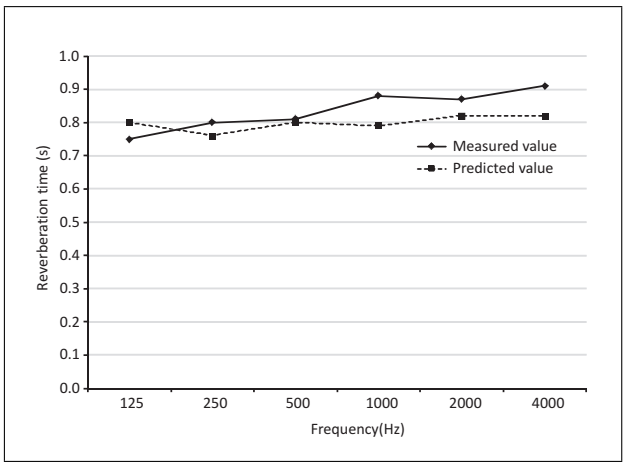


Figure 5. The measured RT spectrum compared with the predicted RT spectrum by ODEON.

other hands, the prediction error of the Odeon was 4.7% which was lower than both accuracy thresholds.

The results showed that the errors of the developed neural networks and geometrical model were comparable with the ISO recommendation values. Prediction accuracy of the neural networks and the geometrical model for predicting RT in the case study were relatively consistent. However, prediction accuracy of Sabine equation was not satisfactory.

4. Discussion

Accurate prediction technique for reverberation time is considered to be an important tool for evaluating acoustic characteristics of industrial workrooms. Empirical techniques can be considered as more practical and quicker methods than other mentioned approaches especially for acoustic and occupational health experts. Hence, artificial intelligence method was employed as a new approach for predicting the reverberation time in the field of industrial acoustics' modeling. The results confirmed that neural networks could accurately predict the reverberation time in

Table IV. Predicted RT values by the prediction models in the case of new embroidery workroom. L = 17 m, W = 10 m, S = 482 m^2, V = 455 m^3, $\overline{\alpha} = 0.12$, A = 58 m^2.

Measured RT (s)	ANNs	ODEON	Sabine
0.84	0.89	0.8	1.25

Table V. Relative errors of the techniques for prediction of reverberation time in the case of new embroidery workroom.

Prediction techniques	RE (%)
Neural networks	6
ODEON	4.7
Sabine	49
Neural networks vs. ODEON	10.1

terms of acoustic parameters of parallelepiped embroidery workrooms with a prediction error equal to 0.17(s). Although the developed neural networks model achieved an acceptable level of validity in predicting RT, the domain of application is restricted to the studied fields. The results confirmed the high capability of artificial neural networks in improving the performance of acoustics prediction techniques compared with current empirical techniques developed using classical methods such as regression techniques [7]. Similar results were found by Nannariello and Fricke [16] who employed neural networks as an alternative method for predicting RT in classrooms with accuracy lower than 10%.

Higher prediction performance of the developed neural networks compared with the results of other studies can be due to the characteristics of our studies cases, i.e. relatively simple industrial workrooms. Note that, in this study, the main factor that negatively affects the performance of MLP neural networks in predicting reverberation time was the low number of observations collected from embroidery workrooms for training the networks. To solve this problem, random noise was added to the original observations in order to create additional training data [29]. The results confirmed that reverberation time calculated by the classical equation was not consistent with the measured reverberation time. In real conditions, the diffusion of sound can be uneven and very different from the simple assumption of a diffuse sound field, and the sound absorption can be very unevenly distributed over surfaces. This means that reverberation time cannot be accurately calculated by the classical equation of Sabine in real workrooms. Other empirical studies have shown the same results with regard to the performance of the Sabine's RT values confirming that this equation, offers a rough estimation in octave bands of parameters such reverberation time [8, 30, 23]. In another study, Nannariello and Fricke [16] showed that the correlation between measured and predicted RT by Sabine equation was 0.69.

Besides neural networks, geometrical acoustic method (as another tool for predicting RT) was used to generate simulated acoustic data. Relative error of the devel-

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oped geometrical model for the typical case of embroidery workroom was approximately 5%. Moreover, Astolfi *et al.* [31] showed that the relative error lower than 10% by geometrical model for predicting RT in classrooms. Due to the nature of this modeling approach, geometrical methods generally have an acceptable degree of accuracy for prediction of different acoustic parameters [32]. This model has to be sufficiently accurate in order to be used for proper evaluation of various acoustic treatments of more complex room cases. The results of the comparison of measured versus predicted RT spectrum by the geometrical method showed that the maximum absolute error was up to 0.1(s) in some frequencies. Similar results were found by Passero *et al.* [23] subject to predict reverberation time spectrum using geometrical model.

However, there were some errors reported by room acoustic simulation including inappropriate calculation parameters, imprecise selection of values attributed to the coefficients of absorption of materials [33]. For this reason, relative errors even up to 23% was also reported by Bistafa and Bradley [34] based on developed geometrical models.

Note that, application of geometrical model for occupational health experts is difficult and requires computer and acoustics expertise. Due to budget constraint, it is not possible to access the ODEON software in many industrial workrooms. An important disadvantage of the geometrical model is its limited generalization. The created geometrical model for a specific room is not applicable to other rooms since the model is defined by the room's special structure and arrangement [35]. Therefore, each individual room must be defined and simulated separately. On the other side, the developed empirical method can be used for similar cases. Its primary advantage is its simplicity and generalization.

Although neural networks are empirical in nature, the degree of accuracy of the developed prediction technique compared with that of the geometrical model demonstrated the high capability of this approach for modeling complex phenomena. Artificial networks approaches can be regarded as a good tool for minimizing the uncertainties in the field of industrial acoustics' modeling.

Finally, the developed prediction techniques can be allowed evaluating different acoustic treatment scenarios in order to achieve the optimum noise reduction in workrooms. In order to design low-noise workrooms, some specific reverberation time values have been recommended based on the volume of workrooms [36]. Acoustic characteristics of most of the studied embroidery workrooms were within the recommended limits. Due to the use of typical hard constructional materials on internal surfaces, RT values were relatively high in some of workrooms. By treating ceiling, wall or even floor surfaces using sound-absorbing materials, it is possible to improve the acoustic performance of these workrooms and to reduce the share of reflected noise level. Therefore, in this type of noisy embroidery workrooms, reverberation times based on different scenarios for treatment of workroom surfaces can be predicted using developed prediction model. However, this study can more improve through extension of the database of neural networks by adding more workrooms with different shapes and structures and acoustic features.

5. Conclusions

Empirical models are more practical and quicker methods than other mentioned models for acoustic and occupational health experts. The accuracy of neural network model as an easy to use method for predicting RT in embroidery workrooms with RMSE = 0.17(s) was within the acceptable level according to the international acoustics standard. It was demonstrated that artificial intelligence model can be regarded as a good tool for minimizing the uncertainties in the field of industrial acoustics compared with the conventional empirical methods. However, the domain of developed model is restricted to the studied fields. Provision of graphical user interface (GUI) based on the developed neural networks model can be facilitated prediction of reverberation time in any case of embroidery workroom by experts.

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