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Development of a Noise Prediction Model Based on Advanced Fuzzy Approaches in Typical Industrial Workrooms

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ABSTRACT

Background: Noise prediction is considered to be the best method for evaluating cost-preventative noise controls in industrial workrooms. One of the most important issues is the development of accurate models for analysis of the complex relationships among acoustic features affecting noise level in workrooms. In this study, advanced fuzzy approaches were employed to develop relatively accurate models for predicting noise in noisy industrial workrooms.

Methods: The data were collected from 60 industrial embroidery workrooms in the Khorasan Province, East of Iran. The main acoustic and embroidery process features that influence the noise were used to develop prediction models using MATLAB software. Multiple regression technique was also employed and its results were compared with those of fuzzy approaches.

Results: Prediction errors of all prediction models based on fuzzy approaches were within the acceptable level (lower than one dB). However, Neuro-fuzzy model (RMSE=0.53dB and R^2=0.88) could slightly improve the accuracy of noise prediction compared with generate fuzzy model. Moreover, fuzzy approaches provided more accurate predictions than did regression technique.

Conclusions: The developed models based on fuzzy approaches as useful prediction tools give professionals the opportunity to have an optimum decision about the effectiveness of acoustic treatment scenarios in embroidery workrooms.

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Introduction

Exposure to excessive noise, as the most important physical pollutant in industrial workrooms causes hearing loss, interfere with communication, disturb sleep, reduce performance and provoke annoyance response and change in social behavior of workers[1]. Prediction of noise, especially in the feasibility design of the industrial processes can be mostly economical because, planning costs should be kept as low as possible[2]. In addition, occupational health professionals can use noise prediction models to evaluate the pre-and post–prevention controls in terms of cost-benefit and efficacy and moreover, estimate noise level in any part of workrooms. Therefore, it is possible to compare this value with noise exposure limit in order to evaluate various solutions of noise control programs[3,4]. A number of models have been developed for predicting the noise level in enclosed workrooms, ranging from simple empirical models to some more complicated and laborious models such as ray tracing[5, 6]. However, development of laborious models is complicated and needs computer and acoustics expertise and time-consuming calculations so that they are frequently employed in special cases. On the other hand, comparison of simple room acoustic models applied to industrial workrooms showed that empirical models with high validity and applicability are rare [7]. The classic model of noise prediction was proposed by Sabine titled diffuse field theory based on the assumption that the distribution of sound energy within the room is homogeneous, and that sound absorptions is uniformly distributed. Mainly due to its simplicity, Sabine's equation is normally used even though the real situations of workrooms seldom comply with its preconditions. The literature indicated acousticians are not altogether satisfied with the existing equations, thus it is still an open issue for finding solutions better fitted to noise control applications[8, 9].

In this area, one of the most important issues is assigning more accurate models which can analyze the complex relationships among different features affecting noise in enclosed workrooms. Presently, artificial intelligence approach is assigned as an alternative statistical technique[10].This approach is recognized as a new method for modelling in different parts of sciences. During the last decades; artificial intelligence included fuzzy set and neural networks have offered an interesting opportunity for analyzing the non-linear and vague information located in the complex phenomena of the actual world[11]. The results of applying fuzzy approach to the development of noise control model and acoustic comfort optimization in industrial workrooms suggest that the fuzzy approach can be utilized for analyzing very complex processes and be successfully applied to highly nonlinear systems [12,13]. In order to have two abilities of learning and interpretability in a unique system, integrating neural networks and fuzzy approaches, and forming neuro-fuzzy systems, have been suggested[14]. Considering the growing interest in developing empirical noise prediction models with high level of validity and applicability, applying artificial intelligence can be helpful and efficient.

In this study, the application of advanced fuzzy approaches as generate fuzzy inference system (GENFIS) and adaptive neuro-fuzzy inference system (ANFIS) for developing a noise prediction models in terms of real situation of the industrial embroidery workrooms was investigated. In addition, multiple regression technique was employed and its results were compared with those of fuzzy models.

Methods

Flowchart for developing noise prediction model based on the advanced fuzzy approaches is presented in Figure 1.

Description of model features

The data were collected from 60 industrial embroidery workrooms in Khorasan Province, East of Iran in 2012. Due to the nature of embroidery operations, the operators must be exposed to excessive noise with some risks of hearing loss. The main acoustical features were determined based on ISO 11690-3[4]. Because the geometrical shapes of all workrooms were similar (all rectangular), this parameter 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[15]. 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 values of noise absorption coefficient in the 250 Hz, 500 Hz, 1000 Hz and 2000 Hz octave bands was used[15]. The total equivalent sound absorption area of workrooms in square meter was calculated based on ISO 12354-6 standard[16]. The equivalent absorption area in regular shape room was determined as follows [16]:

$$A = \sum_{i=1}^{n} \alpha_{S,i} . S_i + \sum_{j=1}^{o} A_{obj,j} \qquad (1)$$

Where $\alpha_{s,i}$ is absorption coefficient of surface i, S_i is area of surface i, $A_{obj,j}$ is equivalent absorption area of object j, n is the number of surfaces i; o is the number of objects j.

Equivalent absorption surface area of objects located in workrooms mostly included embroidery machines surfaces was also approximately estimated based on ISO 12354-6 recommendations [16]. Average absorption coefficient of workroom ($\bar{\alpha}$) and room absorption constant(R) in square meter and reverberation time (RT) in second as important acoustic features were determined based on Sabine's theory according to equation 2,3 and 4, respectively [15]:

$$\bar{\alpha} = \frac{A}{S_t} \qquad (2)$$

$$R = \frac{A}{1-\bar{\alpha}} \qquad (3)$$

$$RT = \frac{0.16 \times V}{A} \qquad (4)$$

Where S_t is the total surface area of workroom in square meter, V is the volume of workroom in cubic meter and A is sound equivalent absorption area in square meter.

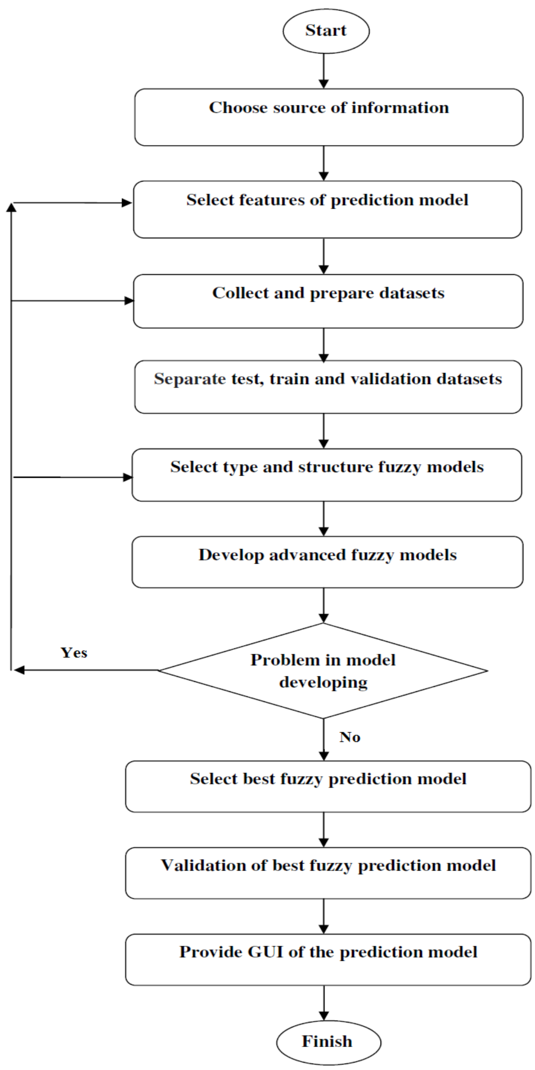

Figure 1: Flowchart for developing noise prediction model based on the advanced fuzzy approaches

Features of embroidery machinery included the type of machinery maker (MT), number of embroideries (NE), number of embroidery heads (NH), lifetime of embroidery machine (EL) and operation speed of embroidery (ES) were significant regarding noise emission. Furthermore, most important feature of used raw materials, which could affect the noise level of embroidery operations, was the type of fabric (FT). The varieties of fabrics used were recorded in terms of thickness decreasing in seven major classes, including three layered fabric, felted, duplex cotton, lee, manoplex cotton, satin and silk, based on the ordinal scale.

Noise level in workstation of embroidery operator in each workroom as reference point was considered as a target feature in the prediction techniques. This point was the same place in the whole workrooms. Measuring equivalent noise level (L_{eq}) for short time in workstations was performed based on ISO 9612 using calibrated and integrated sound level meter Norsonic type132 [17]. Despite the uniformity of structural and acoustical features of each workroom, some new observations appeared in the workrooms by varying features of embroidery process and re-measuring noise level. Hence, the number of possibility recorded observations became 100. To process and select the final features of noise prediction models, statistical methods such as correlation matrix were employed. Finally, nine features were recognized as final input features to develop the noise prediction models. Descriptive statistics of constructional features of embroidery workrooms are listed in Table 1. Descriptive statistics of the final structural, acoustical and embroidery processes features in the workrooms are listed in Table 2.

Table 1: Descriptive statistics of constructional features of embroidery workrooms

Features type, symbol	Min	Max	Mean	SD
Length (m), L	5.70	20.00	10.40	4.05
Width (m), W	2.70	11.00	4.94	1.84
Height (m), H	2.00	5.00	3.58	0.71
Volume (m^3), V	52.50	660.00	188.00	129.25
Total surface (m^2), S	89.40	640.00	207.00	119.40

Table 2: Descriptive statistics of final features of workrooms for developing noise prediction models

Features type, symbol	Min	Max	Mean	SD
Average absorption coefficient,α	0.04	0.14	0.06	0.02
Room absorption constant (m^2), R	4.10	26.09	12.25	6.11
Reverberation time (s), RT	0.94	4.21	2.70	0.89
Number of embroideries, NE	1.00	4.00	1.24	0.53
Number of embroidery heads,NH	6.00	40.00	14.31	5.70
Embroidery lifetime (yr), EL	1.00	20.00	11.40	5.34
Embroidery speed (spm), ES	690.00	850.00	747.00	39.24
Fabric type [a], FT	1.00	7.00	-	-
Machine maker type [b], MT	1.00	2.00	-	-
Noise level (dB), L_{Aeq}	79.40	88.70	85.20	1.96

[a] This feature was based on ordinal scale
[b] These features were based on nominal scale

Development of advanced fuzzy models

Generate fuzzy inference systems are the most important advanced fuzzy models that can be built from data using grid partition, subtractive clustering and FCM clustering. GENFIS 2 generates a sugeno-type FIS structure using subtractive clustering and requires separate sets of input and output data as input arguments [18]. Due to the fact that there was not any clear thought about how many clusters could be exist in the dataset, subtractive clustering, a fast algorithm for estimating the total of clusters and the cluster centers in the dataset, was employed. After this step, the clusters' information was applied for determining the initial number of rules and antecedent membership function used for constructing the fuzzy inference system (FIS). The initial FIS was generated using the MATLAB fuzzy logic toolbox function GENFIS2[18].

When there is only one output, GENFIS2 can be used to generate an initial FIS for ANFIS training. GENFIS2 accomplishes this by extracting a set of rules that models the data behaviour. The rule extraction method first uses the subclust function to determine the number of rules and antecedent membership functions and then uses linear least square estimation to determine each rule s consequent equations. This function returns a FIS structure that contains a set of fuzzy rules to cover the feature space. The subtractive clustering at first, cluster the data to separable sets based on radius defined by user. These clusters are used to extract rules refined by least square estimation.

In this way, approximately 80% of dataset was randomly selected and used to train networks and 20% of dataset to test and validation of the FIS equally.

Adaptive neuro-fuzzy inference system is a systematic approach for modelling and providing the best possible design specifications in a short time[19]. Accordingly, in the final step, ANFIS was applied to generate the best FIS system. ANFIS utilizes the result from GENFIS2 to begin optimization and uses a combined learning algorithm to enhance parameters of sugeno-type fuzzy inference systems. It assigns a combination of the least-squares method and the back propagation gradient descent method for training FIS membership function parameters to copy a given training data set. Finally, root mean square error (RMSE) and coefficient of determination (R^2) as the commonly-used criteria were employed for evaluating the performance of the developed models.

Results

Noise levels of embroidery workrooms were approximately within the range of 80 to 90 dB. Therefore, some embroidery workrooms have excessive noise compared with the occupational exposure limit equal to 85 dB for 8 h. Descriptive statistics of the main features in the workrooms as shown in Table 2 stated that the values of RT in some workrooms were higher than the recommended limit value [20]. In these reverberant workrooms, by adding more noise absorption material on internal surfaces of workrooms, noise reflections and consequently, noise level is reduced.

Prediction errors of all different structures of advanced fuzzy models were in the acceptable level with RMSE lower than one dB for unseen dataset. However, ANFIS could slightly improve the accuracy of noise prediction compared with GENFIS. The comparison of all different structures of developed empirical models was done based on RMSE and R^2 (Table 3). Due to performance nature of FIS model, prediction errors in the train phase of the developed FIS models were significantly low.

Table 3: Comparison of developed noise prediction models in the train and the test phases

Model developing phase	Train		Test	
Evaluation criteria (dB)	RMSE	R^2	RMSE	R^2
Generate fuzzy inference systems	0.00	1.00	0.55	0.87
Adaptive neuro-fuzzy inference system	0.01	0.99	0.53	0.88
Multiple linear regression	0.99	0.74	1.24	0.61

To attain the simpler noise prediction models to derive ready to use empirical formulations, multiple regressions were employed. Multiple linear regression (MLR) equation for predicting sound pressure level (Y) in dB was formulated as follows.

$$Y = 85.311 - 0.409(MT) - 0.121(NE) + 0.725(NH) + 0.333(EL) + 0.380(FT) + 0.785(ES) - 0.007(RT) + 0.154(\propto) - 0.552(R) \tag{5}$$

Where MT is type of machinery maker, NE is number of embroideries, NH is number of embroidery heads, EL is lifetime of embroidery machine, ES is operation speed of embroidery, RT is reverberation time in second, $\bar{\alpha}$ is average absorption coefficient of workroom and R is room absorption constant in square meter units.

Note that, all the dependent features defined in these equations are normalized. The results showed that advanced fuzzy models compared with multiple regression technique, were more accurate in noise prediction. Comparison between the measured values of noise level versus predicted values by GENFIS is presented in Figure 2. The scatter plots of the measured versus the predicted noise using ANFIS for the test data are presented in Figure 3.

The Gaussian membership function as shown in Figure 4 related to embroidery speed was the best membership function for the input features, because of its simplicity and precision in determining the value of the input features. Figure 5 shows that the typical 3D illustration for embroidery speed in terms of stitches per minute (SPM) and number of embroidery heads along with the output features based on the GENFIS prediction model. This result confirmed that increase the embroidery speed and number of heads lead to an increase in noise level of workrooms. However, the embroidery speed feature was more effective than the number of heads.

The developed models can predict the effectiveness of the different noise controls on the noise of embroidery workrooms. Naturally, acoustics analysis of the typical embroidery workrooms based on the developed models can facilitate using the graphical user interface (GUI). Provision of graphical user interface based on artificial intelligence model which is able to predict noise of embroidery workrooms as a simple practical tool was performed according to Figure 6. The provided MATLAB package involved GUI for predicting noise level can be run on any computer with current windows. Instruction for using noise prediction model is achievable through help section of the developed GUI. For employing GUI, firstly, the values of qualitative and quantitative features of the workrooms and embroidery processes must be entered in the specified locations. In the next step, acoustic features are calculated based on formulas, automatically. Finally, noise level of studied workroom is predicted by using calculate button.

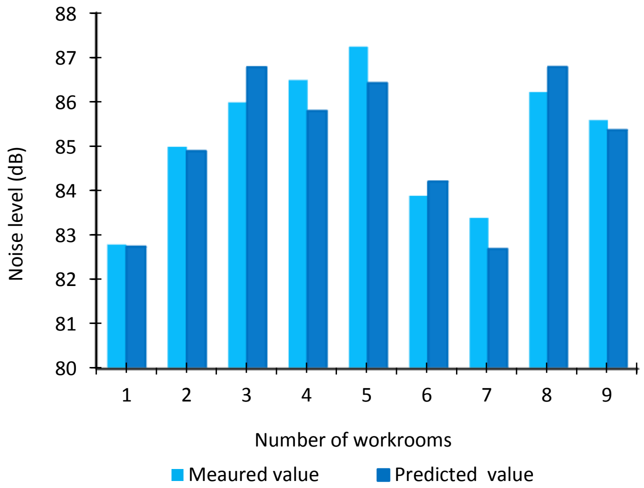

Figure 2: Comparison between the measured and the predicted noise using generate fuzzy inference systems for the test data

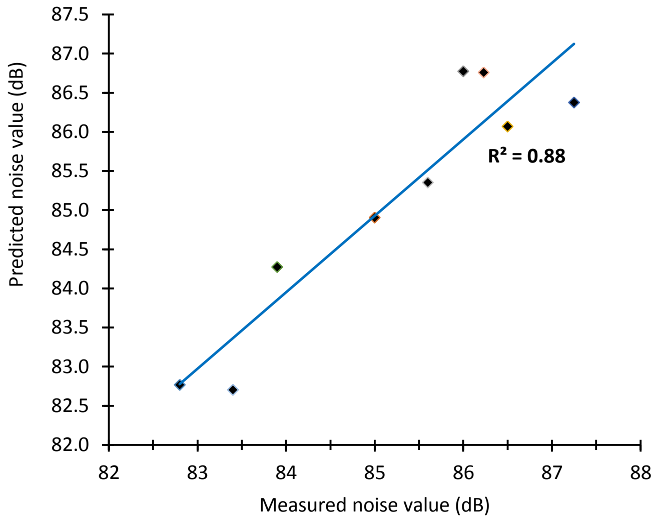

Figure 3: The scatter plots of the measured versus the predicted noise using adaptive neuro-fuzzy inference system for the test data

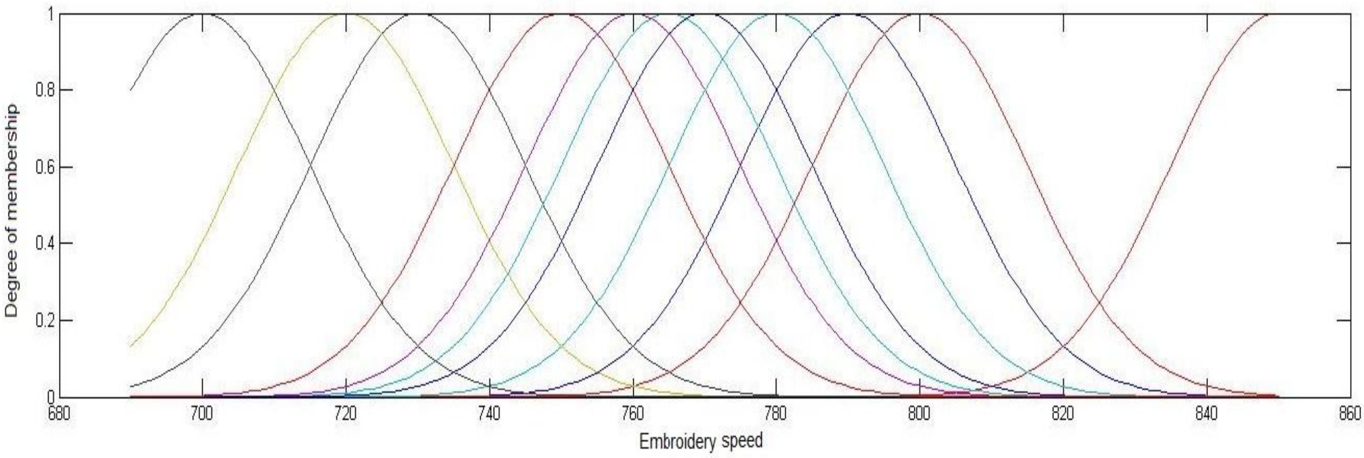

Figure 4: Membership functions related to embroidery speed in terms of stitches per minute (SPM)

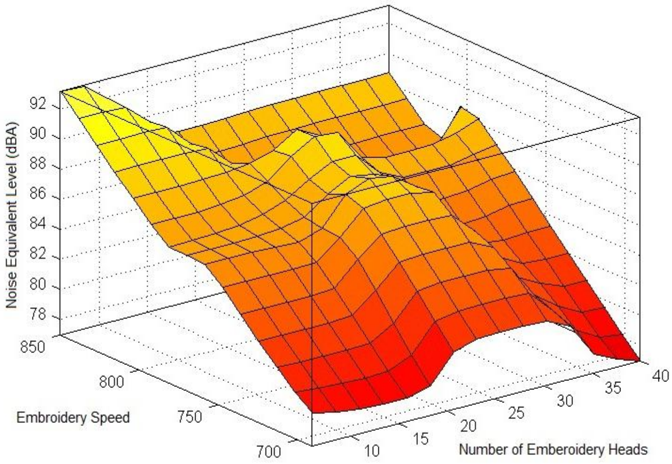

Figure 5: Output in the form of 3D representation with embroidery speed and number of embroidery heads

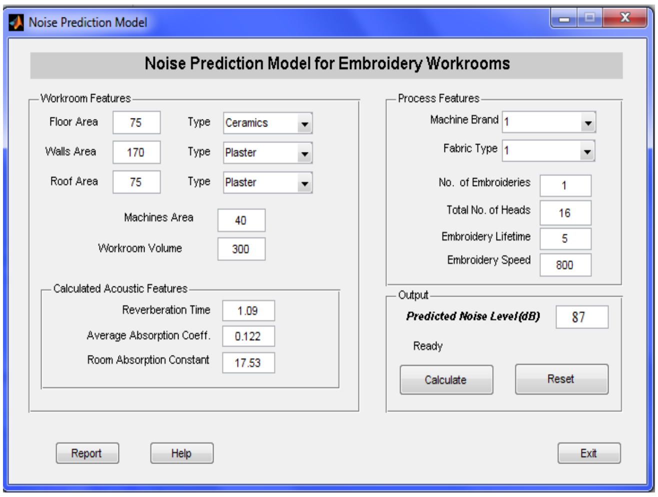

Figure 6: Graphical user interface as simple noise prediction tool for embroidery workrooms.

Discussion

Highly accurate noise prediction models are an important tool for evaluating cost- effective noise control measures in industrial workrooms. Empirical models are more practical and quicker methods than other mentioned models for acoustic and occupational health experts. Artificial intelligence models are simple to apply and have generated a great deal of interest in engineering. By considering the successfully application of this approach in complex engineering problems, in this study, artificial intelligence approaches were employed as alternative approach in the field of acoustics' modelling to predict the noise level in closed workrooms.

Results showed that fuzzy models could accurately predict the noise level in terms of acoustical parameters of workrooms and technical characteristics of real noise sources (embroidery machines). The prediction errors of noise by the developed GENFIS and ANFIS prediction models were lower than the subjective difference threshold for sound pressure level ±1dB mentioned in ISO 3382 [20]. The prediction errors of developed models were at an acceptable level compared with similar study that used artificial intelligence to predict the sound level in lecture rooms[21]. Developed model based on multiple regressions cannot provide accurate noise predictions, because this approach is restricted to human capabilities. However, simple equation extracted from regression model is considered to be main feature of this approach.

The results confirmed the high capabilities of fuzzy approaches in improving the performance of acoustics prediction models compared with those of current empirical models developed using conventional methods such as regression techniques in typical workrooms [6]. Therefore, the developed empirical models based on fuzzy approaches can suitably predict the effectiveness of different scenarios (various solutions for noise control) on the noise level of embroidery workrooms. Although our model achieved an acceptable level of validity in predicting noise level, the domain of application is restricted to studied fields.

The conventional method for constructing FIS is based on human's capabilities and expert knowledge [22]. Therefore, this approach cannot be useful if the phenomenon is very complex as is the case in noise pollution of enclosed workroom. Presently, automatic approaches for constructing the FIS such as GENFIS and ANFIS are considered as advanced methods for removing these limitations in a short amount of time.

Workroom acoustic treatments can be relatively costly and subject to different limitations especially in the utilization phase [25]. In this study, the radius parameters were optimized by genetic algorithm. After clustering and refining the clusters based on least square estimation, the remaining clusters used to extract optimized rules. The numbers of final clusters and rules were equal to 65.

ANFIS prediction model had minimum prediction error compared with other developed methods. This result can be due to the best learning performance of ANFIS. In addition, comfort of implementation, speed and accuracy of learning, robustness of generalization capabilities, superior interpretation facilities through fuzzy rules and ease of incorporation of both linguistic and numeric knowledge for problem solving are other advantages of ANFIS method [23,24]. It is noted that, the codes of the programs written in this research can be reached through the author's email for public.

Conclusions

Prediction of noise level is crucial when analyzing different acoustic measures so that, more acceptable acoustic situations can be finally obtained. The accuracies of fuzzy models for predicting the noise in industrial embroidery workrooms were within the acceptable level according to the international acoustics standard. Artificial intelligence models can be regarded as a good tool for minimizing the uncertainties in the field of industrial acoustics compared with the conventional methods. The developed prediction models can be considered as useful tools for occupational health and acoustics professionals in order to design, implement and evaluate various noise controls in the noisy embroidery workrooms.

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Conflict of interest statement

The authors have no conflict of interests to declare.

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References

1. Kovacevic M, Belojevic G. Tooth abrasion in workers exposed to noise in the Montenegrin textile industry. *Ind Health*. 2006;44:481-485.

2. Lewis DN. Application of indoor noise prediction in the real world. *J Acoust Soc Am*. 2002;112:2267-2268.

3. Keranen J, Hongisto V. Comparison of simple room acoustic models used for industrial spaces. *ActaAcust*.2010;96:179-194.

4. lSO 11690-3. Acoustics - Recommended practice for the design of low-noise workplaces containing machinery – part 3: Sound propagation and noise prediction in workrooms. Geneva: International Standard Organization; 1997.

5. Elorza DO. Room acoustics modelling using the ray tracing method: implementation and evaluation [PhD thesis]. Finland: University of Turku; 2005.

6. Heerema N, Hodgson M. Empirical models for predicting noise levels, reverberation times and fitting densities in industrial workrooms. *Appl Acoust*.1999;57:51-60.

7. Hodgson M. When is diffuse-field theory applicable. *Appl Acoust*. 1996;49:197-207.

8. Hodgson M. Experimental evaluation of simplified models for predicting noise levels in industrial workrooms. *J Acoust Soc Am*. 1998; 103:1933-1939.

9. Hodgson M.Ray-tracing evaluation of empirical models for predicting noise in industrial workshops. *ApplAcoust*. 2003;64:1033-1048.

10. Morzynski L, Makarewicz G. Application of neural networks in active noise reduction systems. *Int J Occup Saf Ergon*. 2003;9(3):257-270.

11. Konar A.*Artificial intelligence and soft computing behavioural and cognitive modelling of the human brain.* Washington DC: CRC Press; 2000.

12. Aluclu I, Dalgic A, Toprak ZF. A fuzzy logic-based model for noise control at industrial workplaces. *Appl Ergon*. 2008;39:368-378.

13. Zaheerudin VK. An expert system for predicting the effects of speech interference due to noise pollution on humans using fuzzy approach. *Expert Syst Appl*. 2008;35:1978-1988.

14. Yilmaz I, Kaynar O. Multiple regression, ANN (RBF, MLP) and ANFIS models for prediction of swell potential of clayey soils. *Expert Syst Appl*. 2011;38:5958-5966.

15. Barron RF. *Industrial noise control and acoustics*. New York: Marcel Dekker Inc; 2001.

16. ISO EN 12354-6, Building Acoustics - Estimation of acoustic performance of buildings from the performance of elements - Part 6: Sound absorption in enclosed spaces. Geneva: International Standard Organization; 2003.

17. EN ISO 9612. Acoustics-Determination of occupational noise exposure engineering method. Geneva: International Standard Organization; 2009.

18. Lotfizadeh A, Berkeley CA. Fuzzy logic toolbox for use with MATLAB user's guide. 2nd ed. Natick: MathWorks Inc; 2001.

19. Riahi-Madvar H, Ayyoubzadeh SA, Khadangi E, Ebadzadeh MM. An expert system for predicting longitudinal dispersion coefficient in natural streams by using ANFIS. *Expert Syst Appl*. 2009;36:8589-8596.

20. ISO 3382-1. Acoustics measurement of room acoustic parameters Part 1: performance spaces. Geneva: International Standard Organization; 2008.

21. Nannariello J, Hodgson M, Fricke F. Neural network prediction of speech levels in university classrooms. *Appl Acoust*. 2001:62:749-767.

22. Agboola AH, Gabriel AJ, Aliyu EO, Alese BK. Development of a fuzzy logic based rainfall prediction model. *Int J Eng Tech*. 2013;3(4):427-435.

23. Boyacioglu MA, Avci D. An adaptive network-based fuzzy inference system (ANFIS) for the prediction of stock market return: The case of the Istanbul Stock Exchange. *Expert Syst Appl*. 2010;37:7908-7912.

24. Carnevale C, Finzi G, Pisoni E, Volta M. Neuro-fuzzy and neural network systems for air quality control. *Atmos Environ*. 2009;43:4811-4821.

25. Arezes PM, Bernardo CA, Mateus OA. Measurement strategies for occupational noise exposure assessment: A comparison study in different industrial environments. *Int J Ind Ergon*. 2012;42:172-177.