www.czasopisma.pan.pl PAN www.journals.pan.pl
Archives of Acoustics Vol. **46**, No. 4, pp. 677–683 (2021), doi: 10.24425/aoa.2021.139644

Research Paper

Work Efficiency Prediction of Persons Working in Traffic Noise Environment Using Adaptive Neuro Fuzzy Inference System (ANFIS) Models

Manoj YADAV*, Bhaven TANDEL

Civil Engineering Department, S. V. National Institute of Technology
Surat, India; e-mail: bnt@ced.svnit.ac.in
*Corresponding Author e-mail: yadavmanoj2212@gmail.com
Orchid ID: 0000-0003-1560-7027

(*received April 14, 2020; accepted October 5, 2021*)

A study was carried to assess the effect of traffic noise pollution on the work efficiency of shopkeepers in Indian urban areas. For this, an extensive literature survey was done on previous research done on similar topics. It was found that personal characteristics, noise levels in an area, working conditions of shopkeepers, type of task they are performing are the most significant factors to study effects on work efficiency. Noise monitoring, as well as a questionnaire survey, was done in Surat city to collect desired data. A total of 17 parameters were considered for assessing work efficiency under the influence of traffic noise. It is recommended that not more than 6 parameters should be considered for ANFIS modeling hence, before opting for the ANFIS modeling, most affecting parameters to work efficiency under the influence of traffic noise, was chosen by Structural Equation Model (SEM). As a result of the SEM model, two ANFIS prediction models were developed to predict the effect on work efficiency under the influence of traffic noise. R squared for model 1, for training data was 0.829 and for testing data, it was 0.727 and R squared for model 2 for training data was 0.828 and for testing data, it was 0.728. These two models can be used satisfactorily for predicting work efficiency under traffic noise environment for open shutter shopkeepers in tier II Indian cities.

Keywords: traffic noise; noise exposure; social questionnaire survey; human work efficiency; ANFIS prediction model.

1. Introduction

Present urban road traffic conditions are very different than it was in the last two decades due to increase in population and rapid urbanization (Yadav, Tandel, 2019). Especially in developing countries like India, the number of vehicles is increasing day by day irrespective of the capacity of road availability (Tandel, Macwan, 2017). Due to this, in recent years road traffic noise and its adverse and complex effects on human beings are increasing (Banerjee, 2012). These effects are both psychological and physiological in nature (Ivošević *et al.*, 2018). This paper is focused on one major physio-psychological effect of noise pollution which is effect of noise on work efficiency. The relation of cognitive work efficiency and noise exposure is very complicated to measure with a linear scale as it involves not only the workplace noise exposure, but also a person's socioeconomic status and his/her personal characteristics (Eriksson *et al.*, 2013; Hancock, Vasmatzidis, 1998; Zaheeruddin, 2006). Also, environmental conditions like ambient temperature and humidity in which a person is working can also affect work efficiency when combining with noise exposure (Singh *et al.*, 2007; Bell, 1980).

To predict the exact nature of the effect on work efficiency by noise pollution, one must consider all possible variables in which a person is working (Yadav, Tandel, 2019). A study was conducted in Surat city in the state of Gujarat, India for analyzing the effect of noise pollution on roadside shopkeepers. The study area chosen was one of the most important commercial areas of Surat city, consisting of narrow lanes and a very high number of open shutter shop keepers working the whole day. The people working here are exposed to the noise level of more than 77 dBA for more than 12 hours daily (Yadav, Tandel, 2019) which is clearly above permissible noise pollution standards in India (CPCB, 2002). Also, a questionnaire survey consisting of 24 questions was carried out on 700 individuals to understand the personal characteristics of people working in the area and their attitude towards road traffic noise in which they work daily. Due to very huge and complex data, the developing prediction model for work efficiency is very difficult (Recio *et al.*, 2016) with a high number of input variables (Azadeh *et al.*, 2015). So, for the elimination of unwanted variables and weakly correlated variables, two statistical methods were used namely exploratory factor analysis (EFA) (Norris, Lecavalier, 2010) and structural equation modeling (SEM). Both statistical methods in the combine are widely used when one is handling more than 20 variables at a time to understand its inter-correlation as well as correlation with output (Thompson, 2004; Liu *et al.*, 2018).

Neuro-Fuzzy computing provides the system identification and interpretability of fuzzy models and the learning capability of neural networks in a single system (Ghosh *et al.*, 2014). In the last decade, various neuro-fuzzy systems have been developed (Zaheeruddin, 2006). Among them, the adaptive neuro-fuzzy inference system (ANFIS) provides a systematic and directed approach for model building and gives the best possible design parameters in minimum time (Tiwari *et al.*, 2018). They have got wide acceptance for modeling many real-world problems. One such problem frequently encountered is the effects of noise pollution on human work efficiency. In the present work, ANFIS was adopted because of the advantages of both fuzzy computing and neural network computing. Fuzzy computing is essential as the data available is in linguistic form (Mallick *et al.*, 2009). Generally, when only a fuzzy computing technique is used for preparation of rule base, an expert advice or knowledge base is required (Khambete, Christian, 2014). Also, neural network trains the data needed to form fuzzy rules. Hence, ANFIS was used because it forms a fuzzy rule base using data collected (Aliabadi *et al.*, 2015). No expert advice is required, rules are formed using given input and output data pairs (Rashid, 2012).

2. Methodology

The methodology to carry out this research consists of two important phases. Phase one was to perform noise monitoring to validate that the primary source of noise in the area is road traffic (Yadav, Tandel, 2019). The second phase was to conduct a questionnaire survey to understand the attitude of shopkeepers working in the traffic noise environment and their awareness towards this problem. The questionnaire was designed in such a way that all possible variables which affect human cognitive work efficiency by noise pollution were included in questions as shown in Table 1. These variables were chosen on the basis of available literature (Pal, Bhattacharya, 2012; Banerjee, 2012; Zaheeruddin, Jain, 2008; Quartieri *et al.*, 2009). As it can be observed in Table 1, these variables are a combination of personal characteristics of a person, socio-economic status, environmental conditions in which a person works and most importantly prominent adverse effects of noise pollution. The questionnaire survey was conducted for the sample size of 700 people in the form of personal interviews. The survey was done in the local language "Gujarati", to ensure that people answering the questions understand the proper purpose of questions. To make it further simple and also suitable for statistical analysis as well as ANFIS modeling, answers were taken in the form of five-point "Likert's scale", in the form of "very less (1)", "less (2)", "moderate/medium (3)", "high (4)", and finally "very high (5)".

Table 1. List of observed linguistic variables (Yadav, Tandel, 2019).

Sr. no.	Observed linguistic variables
1	Headache due to noise pollution
2	Hearing problem on work due to noise
3	Interference in spoken communication due to noise
4	Annoyance due to noise
5	Loss of concentration due to noise
6	Stress due to noise
7	Feeling of exhaustion due to noise
8	Customer rush
9	Effect of temperature
10	Effect of humidity
11	Daily working hours
12	Age
13	Working Years (work experience in the area)
14	Education Level
15	Difficulty performing the task due to noise
16	Level of comfort when not working in noise
17	Job satisfaction

Now after these two phases of data collection, the goal was to construct a prediction model to predict work efficiency in road traffic noise environment with significant variables. The adaptive neuro-fuzzy inference system (ANFIS), is one of the best methods to build upon this kind of prediction model. It is recommended that not more than 6 parameters should be considered for ANFIS modeling (Zaheeruddin, Garima, 2006). Hence, before opting for the ANFIS modeling, significant parameters to work efficiency under the influence of traffic noise were chosen by Structural Equation Model (SEM). Integration of Structural equation modelling and exploratory factor analysis was identified as suitable method to study noise exposure effect on work performance efficiency (Yadav, Tandel, 2021). In the study all possible variables affecting work efficiency in the influence of noise pollution, found in literature were considered for analysis. They comprise of important noise pollution effects, environmental conditions in which an individual is working and personal characteristics of the individual. Primarily it was found that work efficiency of open shutter shopkeepers is affected by important noise pollution effects like headache, stress, annoyance, interference in spoken communication, exhaustion etc. It was also found that environmental conditions like temperature and humidity also have slight effect on work efficiency. So, it can be said that in high temperature conditions like in summer season work efficiency will be less as compared to in the winter season where temperatures will be less. Lastly it was observed that the personal characteristics like individuals age, working years and education is having least or negligible effect on work efficiency when working in traffic noise pollution. Hence, after the SEM, out of 17 variables 5 were chosen and 12 were discarded.

As a result of the SEM model, work efficiency under influence of traffic noise can be predicted by calculating two parameters considered in the questionnaire survey namely, 'difficulty performing the task due to noise' and 'level of comfort felt when not working in the noisy area'. And these two parameters are a function of five variables namely, 'headache', 'stress', 'annoyance', 'loss of concentration' and 'interference in spoken communication'. Hence, two ANFIS models are developed to predict the outputs as 1. 'Difficulty in performing the task due to noise' and 2. 'Level of comfort felt when not working in the noisy area' which ultimately gives the effect of traffic noise pollution on the work efficiency.

3. Results and discussion

The purpose of constructing an adaptive neuro-fuzzy inference system model is to predict the human work performance efficiency of open shutter shopkeepers in the noisy area as a function of most affecting parameters obtained by the structural equation model. From the structural equation model, it is observed that the five most important factors influencing work efficiency of open shutter shopkeepers are headache, stress, annoyance, loss of concentration and interference in spoken communication which are five inputs for ANFIS model. On the other hand, the output "work efficiency" also depends on two parameters combining namely 'difficulty in performing the task due to noise' and 'level of comfort felt when not working in the noisy area'. As ANFIS is a multiple input single output system (MISO), two models for the prediction of work efficiency were constructed. For both models, the five inputs were the same i.e. headache, stress, annoyance, loss of concentration and interference in spoken communication. Whereas the output of the first model is 'difficulty in performing the task due to noise' and output of the second model is 'level of comfort felt when not working in the noisy area'. By assessing the outputs of these two models, work efficiency can be predicted. The implementation of model 1 and model 2 is explained below.

3.1. Implementation of model 1

Model 1 was implemented in the ANFIS toolbox of MATLAB R2014b software. The system is designed using a Sugino fuzzy inference system. It is five inputs and one output system as shown in Fig. 1. The inputs in the system are Headache, Stress, annoyance, loss of concentration and interference in spoken communication and output in the system is 'Difficulty performing the task due to noise'. The input parameters are represented by fuzzy sets (or linguistic variables). We have chosen gbell shaped membership functions to characterize these fuzzy sets (Zaheeruddin, Garima, 2006). While designing the system, from a total of 700 data pairs, 400 were used for data training, 200 were used for data testing and 100 were used for data checking (validation). After loading data into the system the ANFIS structure is generated which is given in Fig. 2. A total number of 243 rules are formed, some of which are given in Fig. 3. The hybrid learning rule is used to train the model according to input/output data pairs. The model was trained for 10 epochs and it was observed that most of the learning was completed in the first 2 epochs as the root mean square error (RMSE) settles down to almost 0.544 at 2nd epoch. Figure 4 shows the training RMSE for the model.

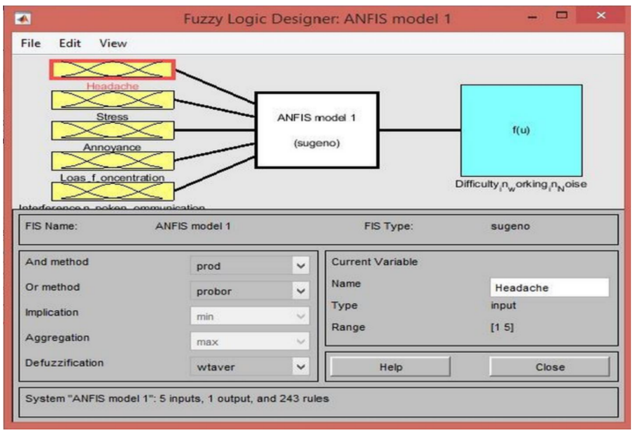

Fig. 1. ANFIS model 1 representation.

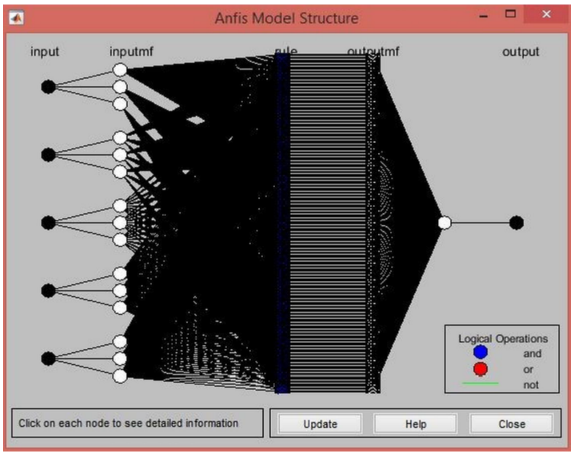

Fig. 2. ANFIS model 1 structure.

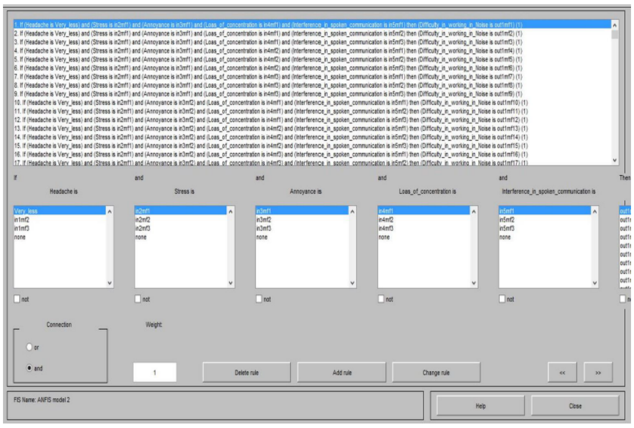

Fig. 3. ANFIS model 1 rule viewer.

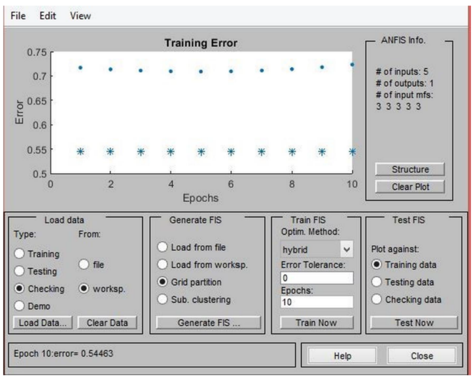

Fig. 4. ANFIS model 1 training error.

After training, model results were tested with training data and checking data by plotting input against training data and checking data. Figures 5 and 6 show the plots of predicted output against training data and predicted output against checking (validation data) respectively. The root mean square error in checking data was 0.711 as shown in Fig. 6. It was observed that in both plots most of the predicted output is matching with observed output. Very few data points are showing distance from their respective observed output data point. This is because of the fact that originally there

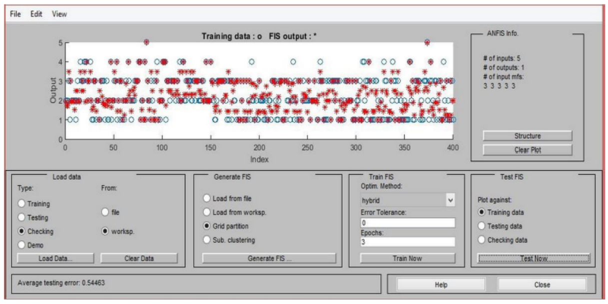

Fig. 5. The plot of predicted output against training data for model 1.

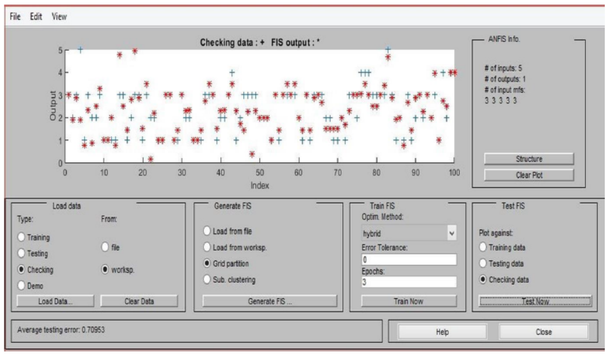

Fig. 6. The plot of predicted output against checking data (validation) for model 1.

were 17 parameters that were considered for modeling from which 5 were selected by the structural equation model, as they were showing high co-relation to the desired output.

So, parameters that were not considered in the ANFIS model also have very little impact on the desired output which explains the RSME which settled at 0.711. The correlation coefficient R squared was also calculated for assessing model validity. R squared for training data was 0.829 and for testing data, it was 0.727. R squared more than 0.7 shows a good correlation between observed and predicted outputs.

The output of model 1 is presented in Fig. 7. As shown in Fig. 7, five inputs are visible as headache,

Fig. 7. The output of the model 1.

stress, annoyance, loss of concentration and interference in spoken communication and output in the system is 'difficulty performing the task due to noise'. As per need, we can change the input values for five inputs, the respective output will be calculated.

3.2. Implementation of model 2

Model 2 was implemented in the ANFIS toolbox of MATLAB R2014b software. The system is designed using a Sugino fuzzy inference system. It is five inputs and one output system as shown in Fig. 8. The inputs in the system are headache, stress, annoyance, loss of concentration and interference in spoken communication and output in the system is 'level of comfort when not working in the noisy area'. The input parameters are represented by fuzzy sets (or linguistic variables). We have chosen gbell shaped membership functions to characterize these fuzzy sets (Zaheeruddin, Garima, 2006). While designing the system, from a total of 700 data pairs, 400 were used for data training, 200 were used for data testing, and 100 were used for data checking (validation). After loading data into the system, the ANFIS structure is generated which is given in Fig. 9. A total number of 243 rules are formed, some of which are given in Fig. 10. The hybrid learning rule is used to train the model according to input/output data pairs. The model was trained for 10 epochs and

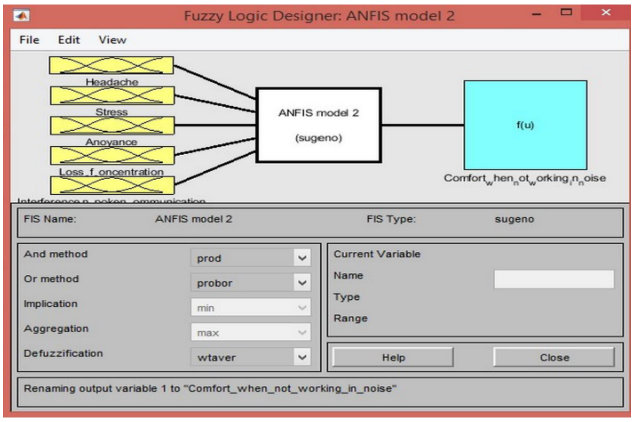

Fig. 8. ANFIS model 2 representation.

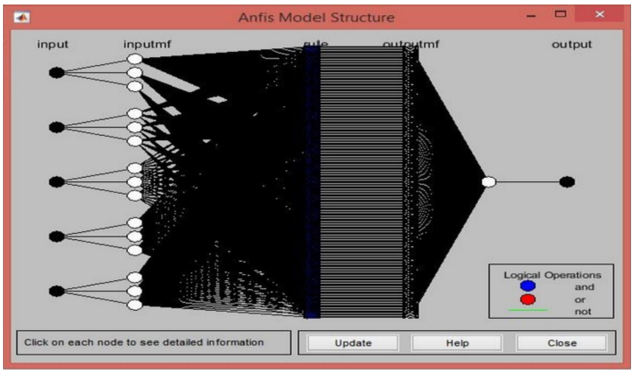

Fig. 9. ANFIS model 2 structure.

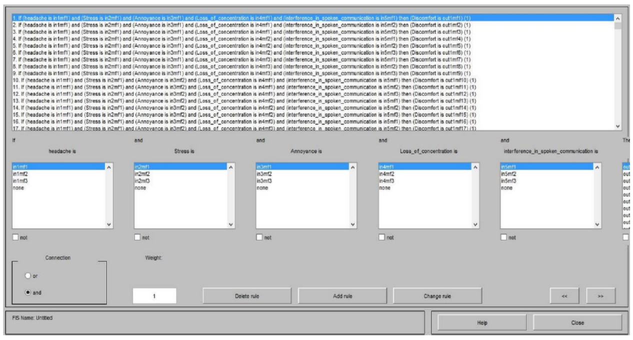

Fig. 10. ANFIS model 2 rule viewer.

it was observed that most of the learning was completed in the first 2 epochs as the root mean square error (RMSE) settles down to almost 0.33 at 2nd epoch. Figure 11 shows the training RMSE for the model.

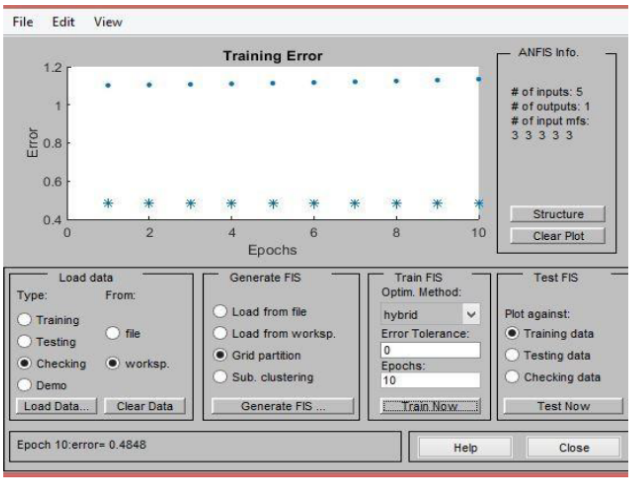

Fig. 11. ANFIS model 2 training error.

After training, model results were tested with training data and checking data by plotting input against training data and checking data. Figures 12 and 13 show the plots of predicted output against training data and predicted output against checking (validation data) respectively. The root mean square error in

Fig. 12. The plot of predicted output against training data for model 2.

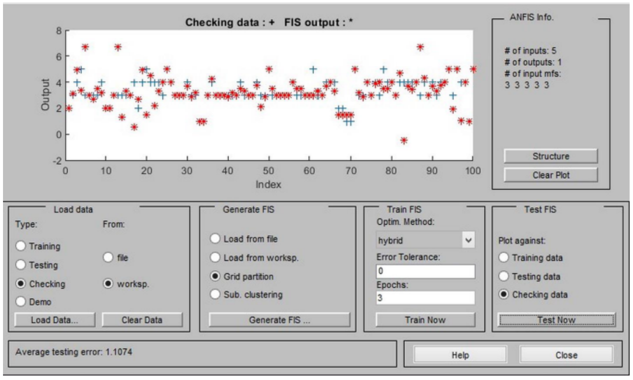

Fig. 13. The plot of predicted output against checking data (validation) for model 2.

checking data was 1.107 as shown in Fig. 13. It was observed that in both plots most of the predicted output is matching with observed output. Very few data points are showing distance from their respective observed output data point. This is because of the fact that originally there were 17 parameters that were considered for modeling from which 5 were selected by the structural equation model, as they were showing high co-relation to the desired output.

So, parameters that were not considered in the ANFIS model also have very little impact on the desired output which explains the RSME which settled at 1.1074. The correlation coefficient R squared was also calculated for assessing model validity. R squared for training data was 0.828 and for testing data, it was 0.728. R squared more than 0.7 shows a good correlation between observed and predicted outputs.

The output of model 2 is presented in Fig. 14. As shown in Fig. 14, five inputs are visible as headache, stress, annoyance, loss of concentration and interference in spoken communication and output in the system is 'level of comfort when not working in the noisy area'. As per need, we can change the input values for five inputs, the respective output will be calculated.

Fig. 14. The output of the model 2.

4. Conclusion

Exploring traffic noise and its psychological effects on human is difficult task due to its complex and uncertain relationships in study parameters. This research focused on modelling the performance of work efficiency of shopkeepers exposed to high level of traffic noise. A 12-hour day time noise and traffic survey were carried on 5 stretches (10 locations) of urban area of Surat city, India. This survey validated the hypothesis that road traffic is the major source of noise, to which these open shutter shopkeepers are exposed to.

700 respondents (shopkeepers) gave then responses in the questionnaire survey conducted in local Gujarati language. Out of the 17 linguistic variables, 5 significant variables were selected by means of exploratory factor analysis (EFA) and structural equation modelling (SEM). These five significant variables are "headache", "stress", "annoyance", "loss of concentration", and "interference in spoken communication". Two prediction models were tested by ANFIS tool MATLAB R2014a which are:

(1) difficulty in performing task due to noise, and
(2) level of comfort felt when not working in the noisy area.

Both the models have given satisfactory results with good R squared value (0.727 for model 1 and 0.728 for model 2). Significantly less value of root mean squared error in both the prediction models indicate that five significant variables selected from initial seventeen linguistic variables by exploratory factor analysis (EFA) and structural equation modeling (SEM) have strong correlation with the predicted output i.e. work efficiency of shopkeepers. These developed models can satisfactorily predict effect on human work efficiency under traffic noise environment for open shutter shopkeepers.

The limitation of this study of predicting work efficiency of roadside shopkeepers of tier II Indian cities can be extended and elaborated to all upper and lower tier cities of India viz. tier I and tier III cities.

References

1. Aliabadi M., Golmohammadi R., Khotanlou H., Mansoorizadeh M., Salarpour A. (2015), Artificial neural networks and advanced fuzzy techniques for predicting noise level in the industrial embroidery workrooms, *Applied Artificial Intelligence*, **29**(8): 766–785, doi: 10.1080/08839514.2015.1071090.

2. Azadeh A., Saberi M., Rouzbahman M., Valianpour F. (2015), A neuro-fuzzy algorithm for assessment of health, safety, environment and ergonomics

in a large petrochemical plant, *Journal of Loss Prevention in the Process Industries*, **34**: 100–114, doi: 10.1016/j.jlp.2015.01.008.

3. Banerjee D. (2012), Research on road traffic noise and human health in India: review of literature from 1991 to current, *Noise & Health*, **14**(58): 113–118, doi: 10.4103/1463-1741.97255.
4. Bell P. (1980), Effects of heat, noise, and provocation on retaliatory evaluative behavior, *Journal of Social Psychology*, **110**(1): 97–100, doi: 10.1080/00224545.1980.9924227.
5. Central Pollution Control Board, New Delhi, India (2002), *Ambient Air Quality Standards in Respect of Noise*.
6. Eriksson C., Nilsson M.E., Pershagen G. (2013), *Environmental noise and health – Current knowledge and research needs*, Swedish Environmetal Protection Agency Report 6553, Stockholm.
7. Ghosh S., Biswas S., Sarkar D., Sarkar P.P. (2014), A novel neuro-fuzzy classification technique for data mining, *Egyptian Informatics Journal*, **15**(3): 129–147, doi: 10.1016/j.eij.2014.08.001.
8. Hancock P.A., Vasmatzidis I. (1998), Human occupational and performance limits under stress: The thermal environment as a prototypical example, *Ergonomics*, **41**(8): 1169–1191, doi: 10.1080/001401398186469.
9. Ivošević J., Bucak T., Andraši P. (2018), Effects of interior aircraft noise on pilot performance, *Applied Acoustics*, **139**: 8–13, doi: 10.1016/j.apacoust.2018.04.006.
10. Khambete A.K., Christian R.A. (2014), Predicting efficiency of treatment plant by multi parameter aggregated index, *Journal of Environmental Research and Development*, **8**(3): 530–539.
11. Liu W., Zhao T., Zhou W., Tang J. (2018), Safety risk factors of metro tunnel construction in China: An integrated study with EFA and SEM, *Safety Science*, **105**: 98–113, doi: 10.1016/j.ssci.2018.01.009.
12. Mallick Z., Kaleel A.H., Siddiqui A.N. (2009), An expert system for predicting the effects of noise pollution on grass trimming task using fuzzy modeling, *International Journal of Applied Environmental Sciences*, **4**(4): 389–403.
13. Norris M., Lecavalier L. (2010), Evaluating the use of exploratory factor analysis in developmental disability psychological research, *Journal of Autism and Developmental Disorders*, **40**(1): 8–20, doi: 10.1007/s10803-009-0816-2.
14. Pal D., Bhattacharya D. (2012), Effect of road traffic noise pollution on human work efficiency in government offices, private organizations, and commercial business centres in Agartala City using fuzzy expert system: A case study, *Advances in Fuzzy Systems*, **2012**: Article ID 828593, doi: 10.1155/2012/828593.
15. Quartieri J., Mastorakis N.E., Guarnaccia C., Troisi A., D'Ambrosio S., Iannone G. (2009), Road intersections noise impact on urban environment quality, [in:] *Recent Advances in Applied and Theoretical Mechanics. Proceedings of the 5th WSEAS International Conference on Applied and Theoretical Mechanics(MECHANICS'09)*, Puerto de la Cruz, Tenerife, Spain, pp. 162–171), WSEAS Press.
16. Rashid T. (2012), Fuzzy logic and neuro fuzzy models for direct current motors, *International Journal of Engineering Inventions*, **1**(7): 68–75.
17. Recio A., Linares C., Banegas J.R., Díaz J. (2016), Road traffic noise effects on cardiovascular, respiratory, and metabolic health: An integrative model of biological mechanisms, *Environmental Research*, **146**: 359–370, doi: 10.1016/j.envres.2015.12.036.
18. Singh R., Ho L.J., Tan H.L., Bell P.A. (2007), Attitudes, personal evaluations, cognitive evaluation and interpersonal attraction: On the direct, indirect and reverse-causal effects, *British Journal of Social Psychology*, **46**: 19–42, doi: 10.1348/014466606X104417.
19. Tandel B., Macwan J.E.M. (2017), Road traffic noise exposure and hearing impairment among traffic policemen in Surat, Western India, *Journal of The Institution of Engineers (India), Series A*, **98**: 101–105, doi: 10.1007/s40030-017-0210-6.
20. Thompson B. (2004), *Exploratory and Confirmatory Factor Analysis: Understanding Concepts and Applications*, American Psychological Association, Washington DC.
21. Tiwari S., Babbar R., Kaur G. (2018), Performance evaluation of two ANFIS models for predicting water quality index of River Satluj (India), *Advances in Civil Engineering*, **2018**: Article ID 8971079, doi: 10.1155/2018/8971079.
22. Yadav M., Tandel B. (2019), Exposure effect study of traffic noise on roadside shopkeepers in Surat City, *Indian Journal of Environmental Protection*, **39**: 1038–1045.
23. Yadav M., Tandel B. (2021), Structural equation model-based selection and strength Co-relation of variables for work performance efficiency under traffic noise exposure, *Archives of Acoustics*, **46**(1): 155–166, doi: 10.24425/aoa.2021.136569.
24. Zaheeruddin (2006), Modelling of noise-induced annoyance: a neuro-fuzzy approach, *2006 IEEE International Conference on Industrial Technology*, 2006, pp. 2686–2691, doi: 10.1109/ICIT.2006.372676.
25. Zaheeruddin, Garima (2006), A neuro-fuzzy approach for prediction of human work efficiency in noisy environment, *Applied Soft Computing*, **6**(3): 283–294, doi: 10.1016/j.asoc.2005.02.001.
26. Zaheeruddin, Jain V.K. (2008), An expert system for predicting the effects of speech interference due to noise pollution on humans using fuzzy approach, *Expert Systems with Applications*, **35**, 1978–1988, doi: 10.1016/j.eswa.2007.08.104.