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Noise effects in skill discretion and modeling

Ahmed Hameed Kaleel, Abdnoor Jameel Shaheed Al-hamadani, kareem jawad kadhim

Department of Aeronautical Engineering, University of Baghdad, Baghdad- Iraq.

*Corresponding Author Email: a.h.alobaidi@coeng.uobaghdad.edu.iq

ABSTRACT: Diesel generators is widely used in Iraq for the purpose of maintaining electric power demand. Large number of operators engaged in this work encounters high level of noise generated by back pack type diesel generators used for this purpose. High level of noise exposure gives different kinds of ill effect on human operators. Exact nature of deteriorated work performance is not known., in present research , quastionaire was adsministered 86 repondents in Baghdad city were exposured to wide range of noise level (80-110) dB(A) with different ages and they have different skill discretion levels. Noise levels A-weigthed decibles dB(A) were measured over 8 weeks two times aday during the 2019 summer using a sound level meter.For predicting the work efficiency deterioration fuzzy tool has been used in present research. It has been established that a fuzzy computing system will help in identification and analysis of fuzzy models fuzzy system offers a convenient way of representing the relationships between the inputs and outputs of a system in the form of IF-THEN rules.The paper presents a fuzzy model for predicting the effects of noise pollution on operators performance as a function of noise level, skill discretion and age of the operators.

KEYWORDS: Age, skill discretion, operators performance, neuro- fuzzy model, noise pollution.

INTRODUCTION

In adequate and erratic power supplies mean small business use electric generators for alternative power, electricity which is one of the benefits of industrialization has become major priority, due to the unavailability and unreliability of electricity in Iraq Noise has many ill effects on living as well as non-living things. The adverse effects of noise may include noise induced hearing loss; sleep disruption, speech interference, annoyance and reduction in human work efficiency. In assessing noise induced effects the global criterion is "human health" [1]. The effects of noise pollution on human performance have been thoroughly studied and reported in the literature by various researchers, World Health Organization (WHO) and other related agencies, of the world from time to time [1-4]. It has been found that the impact of noise on work efficiency depends to a large extent on the type of tasks The complex tasks gets significantly affected at lower noise levels while simple tasks remains unaffected at very high noise levels. In addition, the duration of noise exposure is an important factor in determining the work efficiency. In the above studies, the inferences drawn about the noise work efficiency relationship are based on the actual surveys and no mathematical formalism is given in support of their results. This underlines the need to model the cause-effect relationships in the context of noise-work efficiency linkage. Since this relationship, in general, is quite complex and Nonlinear in nature, an accurate mathematical representation is rather difficult. Moreover, the parameters involved in this relationship are imprecise and uncertain, which cannot be dealt by conventional techniques. In order to deal with such situations, a fuzzy model approach based on fuzzy logic, is considered to be the most appropriate [5].

Significant background noise may negatively affect performance in a number of ways. In some cases, the noise may directly affect one's ability to perform a task but there are also many ways in which noise can disturb task performance indirectly [6]. Noise is also recognized as a serious health problem in our modern societies [3,7]. The effects of noise on human physical and mental performance can be divided into effects on nonauditory task performance and effects on auditory task performance (e.g. interference with speech communication, etc.). Among nonauditory deleterious effects of noise, sleep disturbances are clearly studied and documented [4,8]. On the other hand, in humans, direct effects of noise on various cognitive abilities such as long-term memory, mental arithmetic activity, visual tasks, etc. have been demonstrated [9-11]. The level of noise necessary to produce adverse effects greatly depends upon the type of task [12]. Simple tasks remain unaffected at noise level as high as 115 dB or above, while more complex tasks get disrupted even at much lower levels. Frequency and temporal characteristics also play an important role. High frequency sound is more disruptive than low frequency sound; an intermittent noise can affect performance more adversely than continuous noise of equivalent energy. Long term exposure to noise causes noise-induced hearing loss. Obvious reason for the same is damage to sensors in the inner ear. The effect is in terms of reduced sensitivity to certain frequencies of noise. Initially reduced sensitivity usually occurs in the region of 4 kHz. As the condition becomes more severe, sensitivity is further reduced. Much research has been carried out to determine cutoff noise levels below which operators can be exposed to an eight-hour day without increased risk of hearing loss. The concept of a maximum daily noise dose can be used for the purpose of correct assessment of noise induced effects for both auditory and non-auditory type of effect. A practical approach to assessing the noise health hazard is to use the index dB (A) Leq [13]. OSHA has specified 90 dB (A) as the maximum permissible exposure to continuous noise for an eight-hour shift. Indirect effects on workers' health could include physiological responses (changes in heart rate, blood pressure, adrenalin production, etc.). However, it is difficult to relate these changes directly to harmful effects on the body. Psychological responses to noise can also produce effects on mental health and emotional state especially if the noise adds to an already stressful environment. In, addition, noise also effects work efficiency. The effects on work efficiency may have serious implications for industrial workers and other occupants. Indirect effects of noise are often difficult to demonstrate and also to quantify in practice. Guidelines on their effects are therefore difficult to formulate. However, attempts can be made to assess through subjective or objective methods.

As with age effects, sensitivity to the high frequencies is lost first and the loss is irreversible. In audiometry, such loss is described as a permanent threshold shift. Audiometric testing consists of determination of the minimum intensity (the threshold) at which a person can detect sound at a particular frequency. As sensitivity to a particular frequency is lost as a result of age or damage, the intensity at which a stimulus can be detected increases. It is in this sense that hearing loss can be described as a threshold shift. Studies have shown age decrements in performance of sustained attention tasks [5]. In yet another study it was found that for young and older subjects, there was an age-related increase in the time required to allocate attention within the individual [14]. It was also found that in a dual task situation reaction time (RT) for the older subjects was greater than that observed in case of the younger ones, while studies reported that there was no significant age difference in situations where divided attention kind of task was involved [15,16]. Presence of vibrations in a working environment act as a stressor, leading to poor performance of humans, who have a pre-specified threshold of tolerance to vibration induced stresses. The areas in which performance of operator is generally affected are visual tasks, motor tasks and cognitive tasks. In case of grass trimmers noise of magnitude between 105 to 115 dB(A) was measured. Likely outcome of this level of noise exposure for 5 to 6 hours daily is decrement in cognitive as well as work efficiency of the workers involved in this profession. Keeping in view this fact present study was planned.

DESCRIPTION OF STUDY AREA

A 40 diesel generators are located at sectors 434 and 436 on Bagdad city in Iraq, 33°20'26.09" N latitude and 44°24'3.17" E longitude nearby federal Courthouse of Karkh each generate approximately 0.25 – 0.5 Mw with noise level 80-110 dB(A) Figure 1. The noise level was measured with the help of Cirrus sound level meter, model CR: 710B, UK. The instrument is sensitive to sound pressure between 20 and 20000 HZ was used to measure the noise level calibrated by microphone adapter. The range and sensitivity of the instrument is 30 dB(A) to 100 dB(A) for low sound pressure and 60 dB(A) to 130 dB(A) for high sound pressure with accuracy plus/minus three percent [17]. The noise level was recorded at distances of 1.5-3 meters on the base where the cumulative noise was expected from different sources or at workers, monitoring was done at a height of 1.5 meter and one meter away from the chest covering 20 locations for 30 minutes at an interval of 15 seconds. Prior to the actual experiment, the need to find out noise induced effects qualitatively among the operators was felt. Prior consent was taken from operators and a questionnaire was arranged for this purpose. it is self-administered questionnaire consists of 12-items. The operators were asked to respond to each and every item of questionnaire by giving subjective opinions from strongly disagrees to strongly agree. The items of the questionnaire were classified into two factors. The first factor is skill discretion, described by (possibility of learning new things, repetitive nature of the work, creative thinking at work, and high level of skill, time span of activities and developmental nature of job). The second factor is operator performance, described by (felt depressed, sleep was restless, enjoyed life, felt nervous while work, exceptionally tired in the morning and exhausted mentally and physically at the end of the day). Operator performance largely depends upon the type of task they perform e.g. simple task or complex task. In this study, workers were operating in the occupational environment under the impact of noise and heat both. According to a study, heat generally produces performance decrement at temperatures above (about) 26.7° to 29.4°C [18]. Heat stress interacts with an individual's existing state of arousal and may lead to performance increment or decrement; depending on an individual's existing state making the task complex. The average ages for young, medium, and old groups were 22.5, 43, and 56.6 years respectively. Eighty-six operators were questioned by the questionnaire forms. Only 75 operators matched the criteria of the present study. The remaining represented other kinds of task and hence their tasks were cancelled.

Figure 1. Geographical location of electricity generators

DATA ANALYSES

After data collections, data was analyzed and scores for each operator (noise level, age, skill discretion type and operator efficiency), input/output parameters were categorized. The values of scores were used to establish the rules for optimum model. Neural fuzzy model under reference used three input and one output parameters. Questionnaire answers graded the skill discretion type into three categories (simple, moderate, and complex). Noise levels prevalent in the industries were graded as (low, medium, high), while operator s were graded into three categories as (young, medium, and old age operators). Then noise levels and age are scaled from 40 dB(A) to 110 dB(A), and 15 to 65 years respectively, and skill discretion type scaled from (1) strongly disagree to (5) strongly agree. While the output (operator efficiency) classified as questionnaire answers weight (0%=strongly disagree, 25%=disagree, 50%=neutral, 75%=agree, and 100% =strongly agree). Model was constructed according to questionnaire form responses.

NEURO-FUZZY COMPUTING

Neuro-fuzzy computing is a judicious integration of the merits of neural and fuzzy approaches. This incorporates the generic advantages of artificial neural networks like massive parallelism, robustness, and learning in data-rich environments into the system. The modeling of imprecise and qualitative knowledge as well as the transmission of uncertainty is possible though the use of fuzzy logic. Besides these generic advantages, the neuro-fuzzy approach also provides the corresponding application specific merits some of the neuro-fuzzy systems are popular by their shorts names [19,20]. For example ANFIS, DENFIS, SANFIS and FLEXNFIS, etc [21-24].

Our present model is based on adaptive neuro-fuzzy interface system (ANFS) an ANFIS is a fuzzy interface system implement in framework of adaptive neural networks. ANFIS either uses input/output data sets to construct a fuzzy interface system whose membership functions are tuned using a learning algorithm or an expert may be specify a fuzzy interface system and then the system is trained with the data pairs by an adaptive network . The conceptual diagram of ANFIS based on latter approach shown in Figure 2. Is consists of two major components namely fuzzy interface system and adaptive neural network. A fuzzy interface system has five functional blocks. A fuzzifier converts real numbers of input into fuzzy sets. This functional unit essentially transforms the crisp inputs into a degree of match with linguistic values. The database (or dictionary) contains the membership functions of fuzzy sets. The membership function provide flexibility to the fuzzy sets in modeling commonly used linguistic expressions such as "the noise level is low"or "person is young" A rule base consist of a set of linguistic statements of the form, if x is A then y is B, where A and B are labels of fuzzy sets on universes of discourse characterized by appropriate membership function of database.

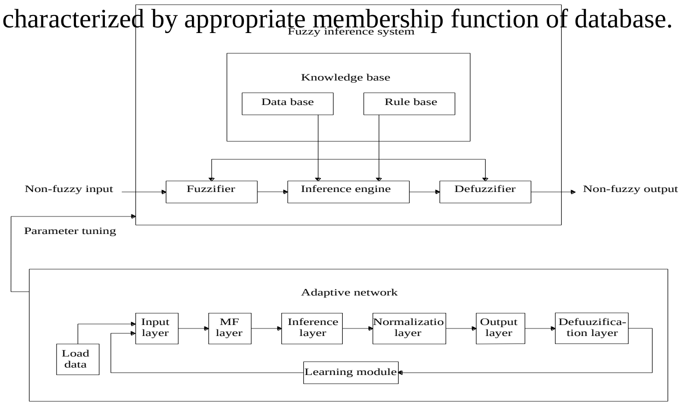


Figure 2. Conceptual diagram of ANFIS

An interface engine performs the interface operations on the rules to infer the output by a fuzzy reasoning method. Defuzzifier converts the fuzzy outputs obtained by interface engine into a non-fuzzy output real number domain. In order to incorporate the capability of learning from input/output data sets in fuzzy interface systems, a corresponding adaptive neural network is generated. An adaptive network is a multi-layer feed-forward network consisting of nodes and directional links through which nodes are connected. As shown in Figure 3. Layer 1 is the input layer, layer 2 describes the membership functions of each fuzzy input, layer 3 is interface layer and normalizing is performed in layer 4. Layer 5 gives the output and layer 6 is the defuzzification layer. The layers consist of fixed and adaptive nodes, each adaptive node has asset of parameters and performs a particular function (node function) on incoming signals. The learning model may consist of either back propagation or hybrid learning algorithm, the learning rules specifies how the parameter of adaptive node should be change to minimize a prescribed error measure [25]. The change in values of the parameters results in change in shape of membership functions associated with fuzzy interface system.

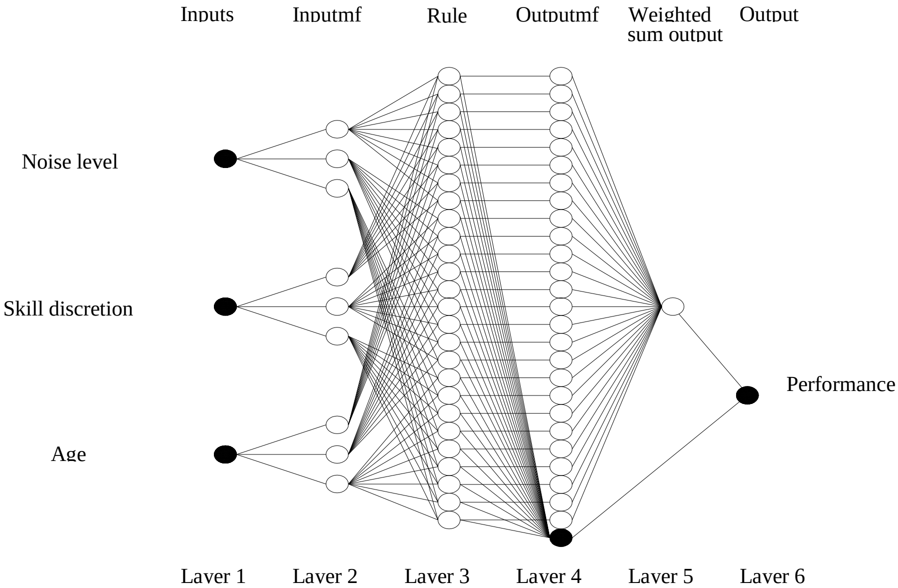


Figure 3. ANFIS structure of the model

System Modeling: The modeling process based on ANFIS can broadly be classified in three steps:

Step 1: System identification

The first step in system modeling is the identification inputs and outputs variables called the system's Takagi-Sugeno-Kang (TSK) model are formed, where antecedent are defined be a set of non-linear parameters and consequents are either linear combination of input variables and constant terms or may be constants, generally called, singletons [21,22].

Step 2: Determining the network structure

Once the input and output variables are identified, the neuro-fuzzy system is realized using a six-layered network as shown in Figure 3. The input, output and node functions of each layer are explained in the subsequent paragraphs.

Layer 1: Input layer

Each node in layer 1 represents the input variables of the model identified in step 1 this layer simply transmits these input variables to the fuzzification layer.

Layer 2: Fuzzification layer

The fuzzification layer describes the membership function of each input fuzzy set, membership functions are used to characterize fuzziness in fuzzy sets, the output of each node *i* in this layer is given by $\mu_{A_i}(x_i)$ where the symbol $\mu_A(x)$ is the membership function. Its value on the unit interval (0, 1) measure the degree to which elements *x* belongs to the fuzzy set *A*, x_i is the input to the node *i* and A_i is the linguistic label for each input variable associated with this node.

Each node in this layer is an adaptive node that is the output of each node depends on the parameters pertaining to these nodes. Thus the membership function for *A* can be any appropriate parameterized membership function. The most commonly used membership functions are triangular, trapezoidal, Gaussian, and bell shaped. Any of these choices may be used, for specifying fuzzy sets as they are non-linear and smooth and their derivatives are continuous gradient methods can be used easily for optimizing their design parameters. Thus in this model, we have used bell shapes memberships functions. The bell or generalized bell (or gbell) shaped membership function is specified by a set of three fitting parameters {a,b,c} as:

$$\mu_A(x) = \frac{1}{1+\left[\left((x-c)/a\right)^2\right]^b} \tag{1}$$

The desired shape of gbell membership function can be obtained by proper selection of the parameters more specifically we can adjust *c* and *a* to vary the center and width of membership function, and *b* to control the slope at the crossover points. The parameter *b* gives gbell shaped membership function one more degree of freedom than the Gaussian membership function and allows adjusting the steepness at crossover points. The parameters in this layer are referred to as premise parameters.

Layer 3: inference layer

The third layer is inference layer. Each node in this layer is fixed node and represents the IF part of a fuzzy rule. This layer aggregates the membership grades using any fuzzy intersection operator which can perform fuzzy AND operation [26]. The intersection operator is commonly referred to as T-norm operators are min or product operators. For instance

IF x_1 is A_1 AND x_2 is A_2 AND x_3 is A_3 THEN y is $f(x_1, x_2, x_3)$ Where $f(x_1, x_2, x_3)$ is a linear functions of input variables or may be constant, the output of ith node is given as:

$$w_i = \mu_{A_1}(x_1) \times \mu_{A_2}(x_2) \times \mu_{A_3}(x_3) \tag{2}$$

Layer 4: normalization layer

The ith node of this layer is also a fixed node and calculates the ratio of the ith 'rules' firing strength in interference layer to the sum of all the rules firing strengths

$$\bar{w}_i = \frac{w_i}{w_1 + w_2 + \ldots + w_R} \tag{3}$$

Where i =1,2, , R and R is total number of rules. The outputs of this layer are called normalized firing strengths.

Layer 5: Output layer

This layer represents the THEN part (i.e., the consequent) of the fuzzy rule. The operation performed by the nodes in this layer is to generate the qualified consequent (either fuzzy or crisp) of each rule depending on firing strength. Every node i in this layer is an adaptive node. The output of the node is computed as:

$$O_i = \bar{w}_i f_i \tag{4}$$

Where $\overline{W}_i$ is normalized firing strength from layer 3 and f_i is a linear function of input variables of the form ($p_i x_1 + q_i x_2 + r_i$)where {p_i, q_i, r_i} is the parameter set of the node i, referred to as consequent parameters or f may be a constant if f_i is linear function of input variables then it is called first order Sugeno fuzzy model (as in our present model) and if f_i is a constant then it is called zero order Sugeno fuzzy model. This consequent can be linear function as long as it appropriately describes the output of the model within the fuzzy region specified by the antecedent of the rule. But in the present case, the relationship between input variables (noise level, , skill discretion, and age) and output (operators performance) is highly non-linear. In Sugeno model, consequent can be taken as singleton, i.e. real numbers without losing the performance of the system.

Layer 6: Defuzzification layer

This layer aggregate the qualified consequent to produce a crisp output. the single node in this layer is a fixed node. It computes the weighted average of output signals of the output layer as:

$$O = \sum_i O_i = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{5}$$

Step 3: Learning algorithm and parameter tuning

The ANFIS model fine-tunes the parameters of membership functions using either the back propagation learning algorithm is an error-based supervised learning algorithm. It employs an external reference signal, which acts like a teacher and generate an error signal by comparing the reference with the obtained response. Based on error signal, the network modifies the design parameters to improve the system performance. It uses gradient descent method to update the parameters. The input/output data pairs are often called as training data or learning patterns. They are clamped onto the network and functions are propagated to the output unit. The network output is compared with the desired output values. The error measure E^P, for P pattern at the output node in layer 6 may be given as:

$$E^P = \frac{1}{2}\left(T^P - O_6^P\right)^2 \tag{6}$$

Where T^P are the target or desired output and O_6^P the single node output of defuzzification layer in the network. Further the sum of squared errors for the entire training data set is:

$$E = \sum_P E^P = \frac{1}{2}\sum_P \left(T^P - O_6^P\right)^2 \tag{7}$$

The error measure with respect to node output in layer 6 is given by delta (δ):

$$\delta = \frac{\partial E}{\partial O_6} = -2\left(T - O_6\right) \tag{8}$$

This delta value gives the rate at which the output must be changed in order to minimize the error function, since the output of adaptive nodes of the given adaptive network depend on the design parameters so the design parameters must be updated accordingly. Now this delta value of the output unit must be propagated backward to the inner layers in order to distribute the error of output unit to all the layers connected to it and adjust the corresponding parameters the delta value for the layer 5 is given as:

$$\frac{\partial E}{\partial O_5} = \frac{\partial E}{\partial O_6}\frac{\partial O_6}{\partial O_5} \tag{9}$$

Similarly, for any *k*th layer, the delta value may be calculated using the chain rule as:

$$\frac{\partial E}{\partial O_K} = \frac{\partial E}{\partial O_{K+1}}\frac{\partial O_{K+1}}{\partial O_K} \tag{10}$$

Now if α is a set of design parameters of the given adaptive network then

$$\frac{\partial E}{\partial \alpha} = \sum_{\alpha \in P}\frac{\partial E}{\partial O^I}\frac{\partial O^I}{\partial \alpha} \tag{11}$$

Where P is the set of adaptive nodes whose output depends on α thus update for the parameter α is given by:

$$\Delta\alpha = -\eta\frac{\partial E}{\partial \alpha} \tag{12}$$

Where η is the learning rate and may be calculated as:

$$\eta = \frac{K}{\sqrt{\sum_\alpha \left(\partial E/\partial \alpha\right)^2}} \tag{13}$$

Where '*k*' is the step size. The value of *k* must be properly chosen as the change in value of *k* influences the rate of convergence.Thus the design parameters are tuned according to the real input/output data pairs for the system. the change in value of parameter results in change in shape of membership functions initially defined by an expert. the new membership functions thus obtained after training gives a more realistic model of the system the back propagation algorithm though widely used for training neural networks may suffer from some problems. The back propagation algorithm is never assured of finding the global minimum. The error surface may have many local minima so it may get stuck during the learning process on flat or near flat regions of the error surface. This makes progress slow and uncertain. Another efficient learning algorithm, which can be used for training the network, is hybrid-learning rule. Hybrid learning rule is a combination of least square estimator (LSE) and gradient descent method (used in back propagation algorithm). It converges faster and gives more interpretable results. The training is done in two passes. In forward pass, when training data is supplied at the input layer, the functional signals go forward to calculate each node output. The non-linear or premise parameters in layer 2 remain fixed in this pass. Thus the overall output can be expressed as the linear combination of consequents parameters. These consequents parameters can be identified using least square estimator (LSE) method. The output of layer 6 is compared with the actual output and the error measure can be calculated as in equations 6-7. In backward pass, error rate prorogates backward from output end toward the input end and non-linear parameters in layer 2 are update using the gradient descent method [equations (8-13)]as discussed in back propagation algorithm. Since the conquest parameters are optimally identified using LSE under the condition that the premise parameters are fixed, the hybrid algorithm converges much faster as it reduces the search space dimensions of the original pure back propagation algorithm.

Implementation

We have implemented our model using ANFIS [27]. The system is first designed using Sugeno fuzzy interference system. It is three inputs–one output systems. The input variables are the noise level, skill discretion, and age and the performance is taken as the output variable.The input parameters are represented by fuzzy sets (or linguistics variables). We have chosen gbell shaped membership functions to characterize these fuzzy sets. The membership functions for input variables are shown in Figure 4. The membership functions are then aggregated using T-norm product to construct fuzzy IF-THEN rules that have a fuzzy antecedent part and constant consequent. The total number for rules is 27. Some of the rules are given below:

R6: IF noise level is low AND skill discretion is moderate AND age is old THEN performance is approximately 75%.

R18: IF noise level is medium AND skill discretion is complex AND age is old THEN performance is approximately 25%.

R22: IF noise level is high AND skill discretion is moderate AND age is young THEN performance is approximately 50%.

After construction of fuzzy inference system, the model parameters are optimized using ANFIS. The network structure consists of 78 nodes. The total number of fitting parameters is 54, of which 27 are premise and 27 are consequent parameters. A hybrid learning rule is used to train the model according to input/output data pairs. The data pairs were obtained from steam power plant workers using questionnaire it was established for this purpose, out of the total 75 input/output data sets 60 (80%) data pairs were used for training the model. the model was trained for 250 epochs with error step size of 0.01 (automatically selected by the ANFIS) and error tolerance 0%. to validate the model 15(20%) data sets were used testing purpose.

RESULT AND DISCUSSION

The model was trained for 250 epochs and it was observed that the most of the learning was completed in the first 180 epochs as the root mean square error (RMSE) settles down to almost 0.09% at 180th epoch. Figure 5a shows the training RMSE curve for the model after training the fuzzy inference system. It is found that the shape of membership function is slightly modified. And data tested as shown in Figure 5b for model validity. This is because of the close agreement between the knowledge provided by the expert and input/output data pairs. Hence, the impact of the noise level on diesel generator operators performance is represented in the form of graphs in Figure 6 with the ages as parameters for different types of skill discretion.

The diesel generator operators performance down to the noise level of 70 dB(A)is almost negligible for all ages irrespective of types of skill discretion assuming effects of 25% reduction in work efficiency as negligible Figure 6(a) show diesel generator operators performance versus noise level with "simple"(0-2) skill discretion for 'young', 'medium', and 'old' ages. The diesel generator operators performance reduced to almost 30 and 42% at 95 dB (A) and above noise level s for 'medium' and 'old' ages but the 'young' age 'affected' slightly 70%. From Figure 6(b) it is to be observed that the diesel generator operators performance is not affected (only 72%) at 80 dB (A) for 'young' age whereas for 'medium' and 'old' ages the operators performance is 50 and 40% respectively at the same noise levels for 'moderate' types of skill discretion. However, diesel generator operators performance is almost 49, 40, and 18% for ‘young’, 'medium' and 'old' ages, respectively at 95 dB(A) and above noise levels.

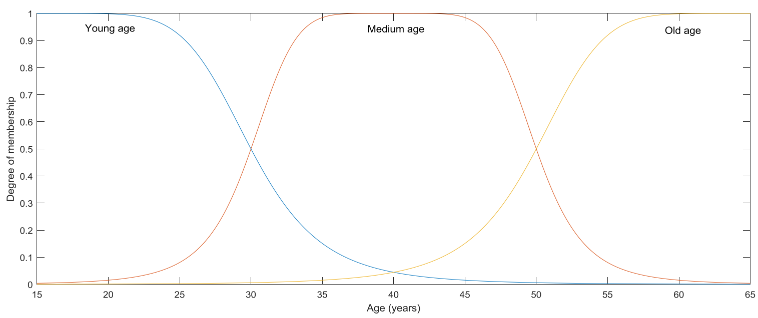
Figure 6c depicts the diesel generator operators performance with noise level at 'complex' types of skill discretion for 'young', 'medium', and 'old' ages. it is evident from this figure that the diesel generator operators performance is slightly effected up to the noise level of 80 dB(A) for 'young' and 'medium' age group of operators while it is highly about 35% for 'old' ages operators performance start reducing after 90 dB(A) even for 'young' and 'medium' ages. At 95 dB(A), diesel generator operators performance reduced to 15%, 12% and 11% for 'young', 'medium' and 'old' ages, respectively There is significant reduction in the diesel generator operators performance after 100 dB(A) for all ages. When noise level is in the interval of 100-110 dB(A), it is 13% for 'young', 10% for 'medium' , and 9% for 'old' ages , respectively.

An alternative representation to Figure 6a-c discussed above is shown in Figure 7a-c, in which the diesel generator operators performance with noise level for 'simple', 'moderate' and 'complex' types of skill discretion at deferent ages is presented the following inference are readily down:

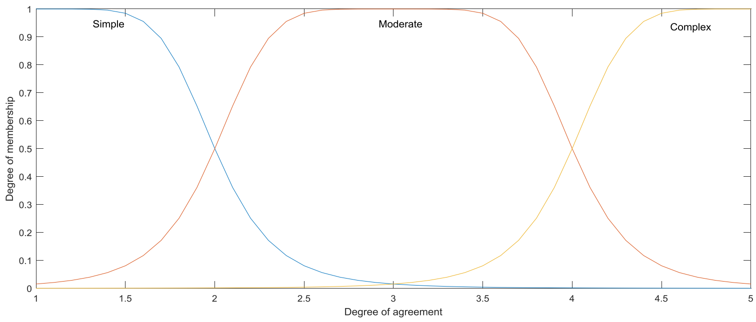
1. If age is 'young' as shown in Figure 7a the diesel generator operators performance reduces to 60% for 'simple' and 50% for 'moderate' types of skill discretion while it reduces to 29%for 'complex' types of skill discretion at 90 dB(A) above noise levels.
2. In case of 'medium' age, the diesel generator operators performance is reduced to 50%, 47%, and 27% at 90 dB(A) for 'simple', 'moderate' and 'complex' types of skill discretion respectively, as is evident from Figure 7b.
3. For 'old' ages, the reduction in diesel generator operators performance occurs even at much lower noise levels as can be observed from Figure 7c it is 35%, 12%, and 10% at 90 dB(A) for 'simple', 'moderate' and 'complex' types of skill discretion, respectively.

To validate the model, we have compared some of our model results with deduction based on the criterion of safe exposure limit recommended for industrial workers. The Recommended Exposure Limit (REL) for workers engaged in occupation such as engineering controls, administrative controls, and/or work practices is 85 dB(A) for 8 h duration (National Institute for Occupational Safety and Health. DHEW ((NIOSH) (1996)) [28]. DHEW ((NIOSH) (1972)) [29]. Also recommended a ceiling limit of 115 dB(A). Exposure to noise levels greater than 115 dB (A) would not be permitted regardless of the duration of the exposure time. There is almost no (zero per cent) reduction in work efficiency when a person is exposed to the maximum permissible limit of 85 dB (A) for eight hours and maximum (100%) reduction in work efficiency for a noise exposure of 105-115 dB(A) for eight hours.

(a)



(b)



(c)

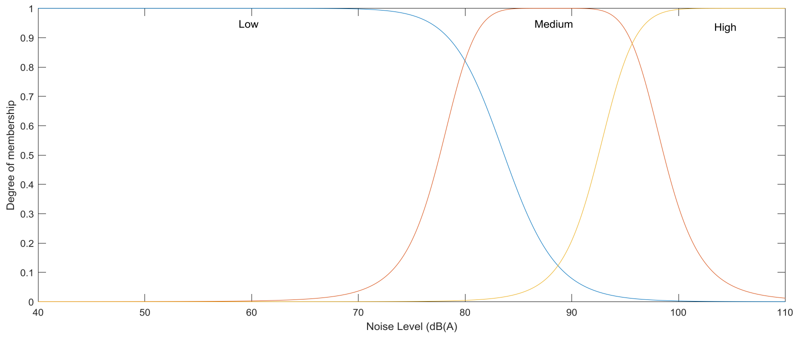
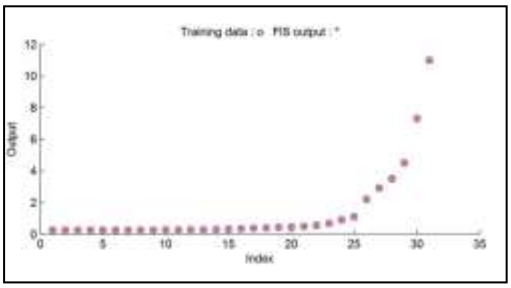


Figure 4. (a) Membership functions of noise level, (b) Membership functions of skill discretion, and (c) Membership functions of age

(a) (b)



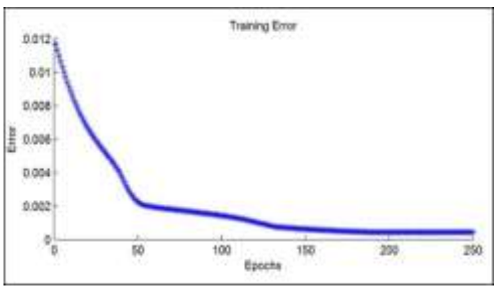
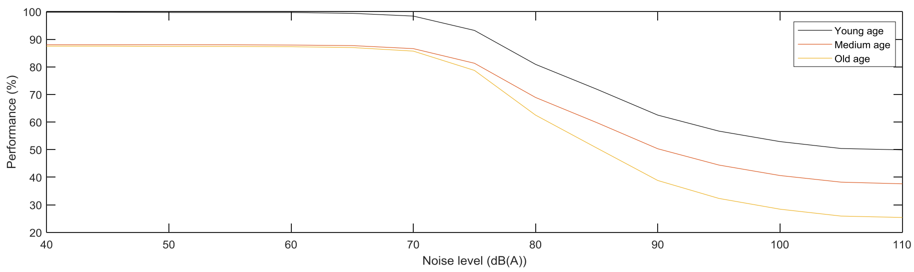


Figure 5. (a) Training root mean squared error, (b) Data testing for model validity

(a)



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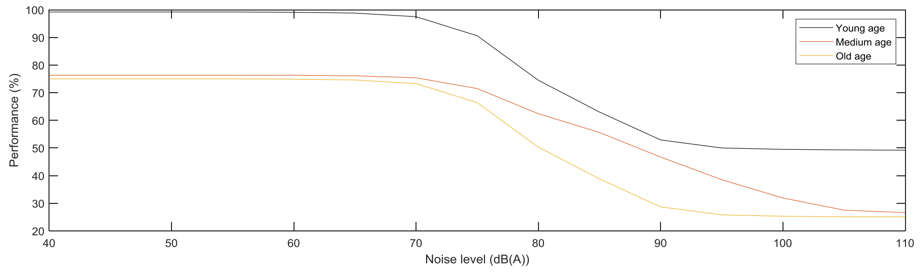

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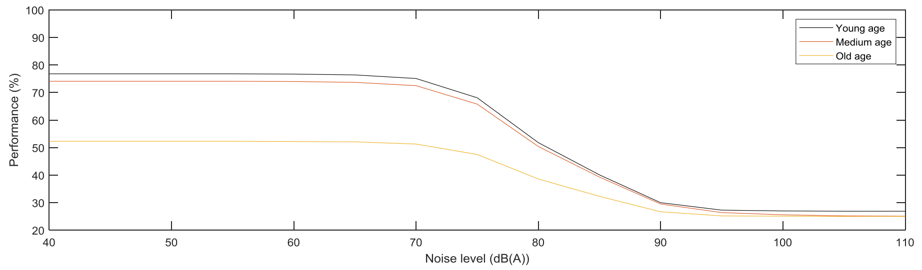
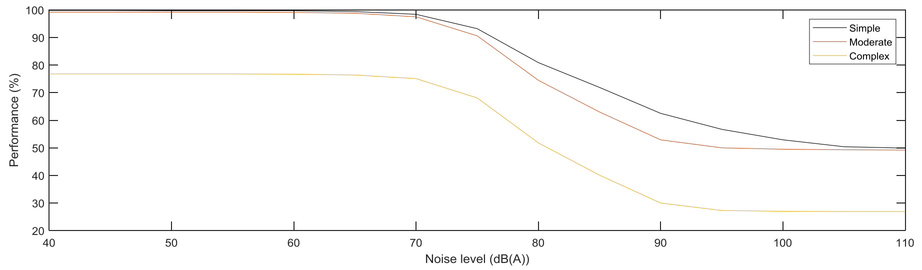
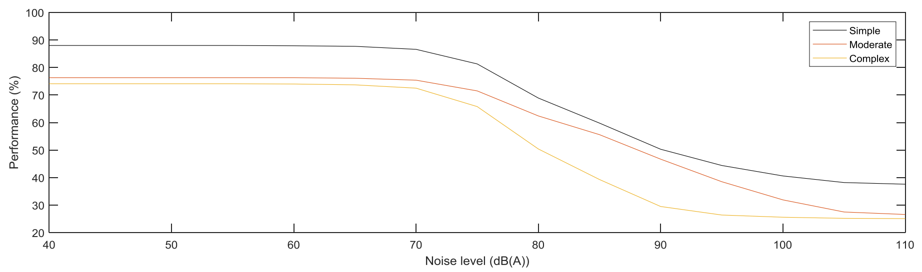


Figure 6. Diesel generator operators performance as a function of noise level, at: (a) simple, (b) moderate, and (c) complex, skill discretion for various ages respectively.

(a)



(b)



(c)

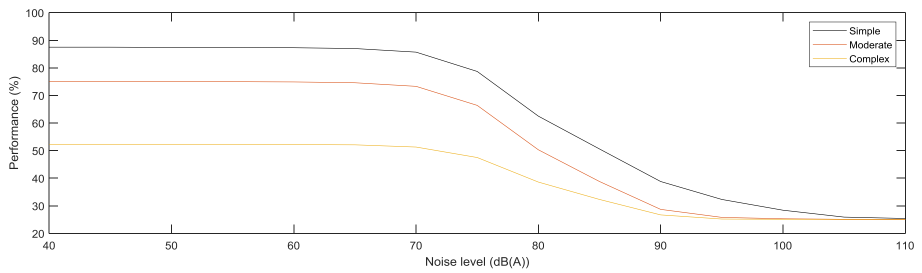


Figure 7. Diesel generator operators performance as a function of noise level of : (a) young, (b) medium, and (c) old, ages for various skill discretion respectively

CONCLUSION

The main thrust for the present work has been to develop a neuro-fuzzy model for the prediction of diesel generator operators performance as a function of noise level, skill discretion and age. It is evident from the graph that diesel generator operators performance, for the same types of skill discretion, depends to a large extent upon the noise level and age. It has also been verified that young age group of people are not affected even at very high noise level while old ages get significantly affected at much lower noise level. Also we concluded those diesel generator operators who has complex skill discreation are more sensitive to noise level compared with simple and moderate skill discreation . It is to be appreciated that the training done using ANFIS is computationally very efficient as the desired RMSE value is obtained in very less number of epochs. Moreover, minor changes are observed in the shape of the membership functions after training the model. This is because of close agreement between the knowledge provided by expert and input/output data pairs.

REFERENCES

[1] I. Adams, “Comparison of synaptic changes in the precentral and postcentral cerebral cortex of aging humans a quantitative ultrastructural study”, Neurobiology Aging, Vol. 8, No. 3, Pp. 203-212, 1987.

[2] G. Bartzokis, M. Beckson, P.H. Lu, K.H. Nuechterlein, N. Edwards, and J. Mintz, “Age-related changes in frontal and temporal lobe volumes in men a magnetic resonance imaging study”, Arch Gen Psychiatry, Vol. 58, No. 5, Pp. 461- 465, 2001.

[3] A. Muzet, “The need for a specific noise measurement for population exposed to aircraft noise during night-time,” Noise Health, Vol. 4, Pp. 61-64, 2002.

[4] D. Ouis, “Annoyance from road traffic noise: a review”, J. Environ. Psychol., Vol. 21, Pp. 101-120, 2001.

[5] R. Parasuranam, L. Giambra, “Skill development in vigilance effects of event rate and age”, Psychology and Ageing, Vol. 6, Pp. 155-169, 1990.

[6] Webreference:http://www.butlertech.ie/products/pdfs/noise/cr710b.pdf. 402

[7] H. Ising, and B. Kruppa, “Health effects caused by noise evidence in the literature from the past 25 years”, Noise Health, Vol. 6, Pp. 5-13, 2004.

[8] S. Stansfeld, M. Haines, and B. Brown, “Noise and health in the urban environment,” Rev. Environ. Health., Vol. 15, Pp. 43-82, 2000.

[9] S.W.N. Cohen, “Nonauditory effects of noise on behavior and health,” J. Social Issues, Vol. 7, Pp. 36-70, 1981.

[10] G.R. Hockey, “Effects of loud noise on attentional selectivity,” Q. J. Exp. Psychol., Vol. 22, Pp. 28-36, 1970.

[11] H.J. Jerison, “Effects of noise on human performance,” J. Appl. Psychol., Vol. 43, Pp. 96-101, 1959.

[12] H.A. Suter, “Noise and its effects,” 1991. http.//www.noise.org/library/suter.htm.

[13] W. Burns, A.W. Robinson, “Hearing and Noise in Industry,” HMSO, London, 1970.

[14] D.J. Madden, “Selective and visual Search: Revision of an allocation model and application to age differences,” J. of Expr. Psychology, Human Perception and Performance, Vol. 18, Pp. 821-836, 1992.

[15] J.M. McDowd, and M. Craik, “Effects of ageing and task difficulty on divided attention performance,” J. of Expr Psychology, Human Perception and Performance, Vol. 2, Pp. 267-280, 1988.

[16] B.L. Sombereg, T.A. Salthouse, “Divided attention ability in young and old adults.” J. of Expr. Psychology., Human Perception and performance, Vol. 8, Pp. 651-663, 1982.

[17] Available from: http://www.butlertech.ie/products/pdfs/noise/cr710b.pdf

[18] D.E. Broadbent, “Decision and Stress”, London and NY: Academic Press, 1971.

[19] S. Mitra, and Y. Hayashi, “Neuro-fuzzy rule generation: survey in soft computing framework”, IEEE Trans Neural Network, Vol.11, Pp. 748-768, 2000.

[20] D. Kukolj, “Design of adaptive Takagi-Sugeno-Kang fuzzy models”, Applied Soft Computing, Vol. 2, Pp. 89-103, 2002.

[21] M. Sugeno, and G. Kang, “Structure identification of fuzzy models”, Fuzzy sets system, Vol.28, Pp. 15-33, 1988.

[22] T. Takagi, and M. Sugeno, “Fuzzy identification of systems and its applications to modeling and control”, IEEE Transactions on Systems, Man and Cybernetics, Vol.15, Pp. 116-132, 1985.

[23] G. Klir, B. and Yuan, “Fuzzy sets and fuzzy logic: theory and applications”, Prentice Hall, NJ, Englewood Cliffs, 1995.

[24] D. Rumelhart, G. Hinton, and R. Williams, “Learning internal representations by error propagation, in: Rumelhart DE, McClelland JL, editors”, Parallel distributed processing: Explorations in the microstructure of cognition. Cambridge: MTT press, Pp. 318-362, 1986.

[25] J. Jang, “ANFIS: adaptive-network based fuzzy”, Inference system, IEEE Transactions on Systems, Man and Cybernetics, Vol. 23, Pp. 665-685, 1993.

[26] Z. Mallick, A.H. Kaleel, and A.N. Siddiqui, “An expert System for Predicting the Effects of Noise Pollution on Grass Trimming Task Using Fuzzy Modeling”, International Journal of Applied Environmental Sciences, Vol. 4, No. 4, Pp. 389-403, 2009.

[27] Fuzzy logic toolbox for use with MATLAB@, the math works Inc, USA, 2000.

[28] National Institute for Occupational Safety and Health. DHEW (NIOSH). Criteria for a recommended standard: occupational noise exposure revised criteria 1996. (Online). Available from: http://www.nonoise.org/library/niosh/criteria.html. [cited in 1996].

[29] National Institute for Occupational Safety and Health DHEW (NIOSH) Criteria for a recommended standard: occupational exposure to noise revised. U.S Department of Health, Education, and Welfare, DHEW (NIOSH) publication No. HSM, Pp. 73-1101, 1972.