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PREDICTING AND MODELING THE EFFECTS OF TURBINES NOISE ON OPERATOR'S MENTAL TASK PERFORMANCE IN AL-DORA POWER PLANT

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Abstract

Noise has become one of the most critical environmental challenges. As one of noise kinds, the discomfort level of environmental noise can affect both personal quality of life and hearing sensitivity. An example is workplace noise pollution, which affects employees' regular functioning and profoundly impacts their mental, auditory health, and psychological well-being. In order to tackle these issues, the need for adaptive intelligent systems has significantly grown. This study aims to evolve a neuro-fuzzy model for predicting the effects of noise pollution on employee's work efficiency as a function of noise level and exposure time at Al-DORA Power Plant in Baghdad city. Participants' responses were used to develop a neural-fuzzy logic model based on artificial neural networks (ANN) and fuzzy inference systems (FIS). The model is performed using the fuzzy logic toolbox inherited from the MATLAB software. The measurements were carried out for duration of nine weeks, three times a day during summer, and the extensive noise level was up to 110 dB. Results in the trapezoidal-shaped membership form showed a discernible pattern or trend in the fluctuation of membership degree in relation to noise levels. The same trend could be seen for the exposure time. Furthermore, the results showed that the efficiency of the workers depends on the noise level and exposure duration. It has been confirmed that a medium noise level can influence workers' performance over a medium exposure time to a certain degree. Moreover, low noise levels can still affect the performance of workers who are exposed to noise for long durations. With this clear relationship between noise levels, exposure time, and mental work efficiency, organizations can implement certain strategies to optimize their acoustic environments.

Keywords: Noise pollution, mental performance, neuro-fuzzy logic modeling, ANN.

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1. Introduction

The rapid urbanization of human activities in densely populated areas has led to an increase in the need for electrical power. This increase in electrical power demand led to a rise in pollution levels. One of the main concerns in workplaces is the connection between noise and mental health. Regarding this, several studies have extensively explored the pollution and its harmful impact of power plant emissions on various diseases and the burden of early deaths [1]. Noise pollution, as a type pollution can affect the ability of employees to perform activities that require concentration.

This may result in wrong decisions, safety hazards, and a reduction in workers production, especially for those who works high level noise area such as power plants [2–4]. Besides the aforementioned effects, exposure to noise may lead to psychological disorders such as stress, anxiety, and mental dysfunction [5]. Only a few research studies have been performed on the effect of noise level on workers who work at steam and gas power plants. The available reported data showed that mental problems were higher among workers who work in power plant areas.

While noise can negatively impact human health, it can be mitigated using noise reduction control programs. Neuro-fuzzy Logic (NFL) computing provides solutions for the varied nature of issues that involve output characteristic predictions. The traditional equation-based technique delivers the required modeling systems solutions that offer linear interrelationships. In the last two decades, most of the influential free techniques that have been used for system modeling have included both Artificial Neural Networks (ANN) and fuzzy logic, which are expected to be utilized more in the future [6, 7].

These techniques introduced alternative methods for modeling complex problems and dealing with the nonlinearity of the information of real-world complicated systems. In general, these techniques offer two distinctive senses. In the broad sense (FL_w), the fuzzy logic is close to the fuzzy theory; however, the narrow sense (Fl_n) is described as a logical system. Using fuzzy logic in its wide sense has recently become dominant [8, 9]. The fuzzy setting theory is the answer to the uncertainty and imperfection introduced by complicated systems [10]. The primary work of the fuzzy theory design regarding decision-making and human thinking was presented by [11].

According to Zadeh [12], fuzzy set theory has proven to be a powerful tool for quantitatively representing and dealing with uncertainty in decision-making processes. In addition, it's a great tool for modeling human knowledge with easy and reasonable labels. For problems that experience a varied nature, an expert can improve the fuzzy system by developing If-THEN rules. However, there are some limitations in the application of this approach due to the problem of turning expert linguistic knowledge into available data for a handling system. The fuzzy system lacks the optimized system parameters, which should be introduced to get the best results. A literature analysis reveals that other researchers have employed various optimization approaches in theory and mathematical programming. However, the majority of these studies have yielded insufficient findings.

A neural network is considered a good and suitable technique for different learning capabilities. Experts in this field have developed an appropriate algorithm for learning according to the provided I/O data pairs of the design parameters adjustment through error function minimization. On the other hand, this technique shows a lack of interpretation capabilities and an inability to explain human decisions explicitly. Based on this introduction about the lack of both fuzzy and neural networks, a suitable method that involves both interpretability and learning together in one system is highly required. In other words, a hybrid system of a fuzzy system and a neural network approach can be a good solution.

Furthermore, a study has been conducted that focuses on evaluating student academic performance using a combination of fuzzy techniques and the ANFIS method to address the incompleteness in decision-making by human experts and its ability to generalize and converge rapidly, particularly in online learning [13, 14]. Students' grades from the first and second semester exams were used to evaluate the suggested Adaptive Neuro-fuzzy Inference System using MATLAB. Results showed that Fuzzy inference models provided an efficient way to evaluate students' academic performance quantitatively, with the adaptive neuro-fuzzy approach used to determine the performance level based on training data sets.

One of the main worries in workplace areas is the connection between noise and mental health. Numerous studies have extensively presented the impact of noise on workers exposed to high noise levels. A questionnaire-type study involving 1053 people near the airport of Kadena in Japan was conducted according to the Cornell Medical Index for Health Symptoms Assessment [15]. The subscales of mental health involve mental instability, neurosis, depressiveness, and nervousness. The noise level was described by WECPNL (Weighted Equivalent Continuous Perceived Noise Level) according to the noise exposure level from 75 dB and over 95 dB.

Several significant differences were statistically presented in unadjusted analyses in scores of nervousness, neurosis, and depressiveness subscales between the pooled group that is exposed to 75–95 WECPNL and the non-noise-exposed control group. Several parameters were considered including marital status, sex, age, house type, and residence length. Noise exposure above 95 WECPNL was linked with higher neurosis and depressiveness scores. Clear relationships of the dose-response were not obtained between the noise exposure and scale scores, as presented in five unit steps.

The current study exclusively investigates the current state of noise pollution at the Al-DORA Thermal Power Plant located in Baghdad-Iraq and the effect of exposure duration to various noise levels on the mental performance of workers. Both fuzzy logic toolboxes inherited in MATLAB software using ANFIS were implemented in the current study. Several mental tasks were performed, including design, mathematical model development, and control-related functions. Epochs were used for the training purpose of the model.

2. Method and system modeling

2. 1. Method

The prediction of noise pollution's A-weighted decibels was measured during the summer using a sound level meter three times a day over nine weeks. The questionnaire was administered to 75 operators exposed to an extensive range of noise levels up to 110 dB distributed around noisy steam turbines with different exposure durations.

The noise level was measured using the Cirrus sound level meter, which is sensitive to sound pressure over a range of 20 to 20000 Hz. It is used for measuring after calibrating by utilizing a microphone adapter. The sensitivity range of the device is 30–100 dBA for the low sound pressure value within ±3 % of accuracy [16]. The standard distance for placing a sound level meter might vary depending on the industry, rules, and guidelines in a given area.

The noise levels could be measured by placing the sound level meter sufficiently far from any obstacles or reflectors. Ideally, the microphone of the sound level meter should be positioned about 1.3 to 1.5 meters above the ground at which the growing noise was anticipated from different operator's sources. The monitoring processes were accomplished at a 1.5-meter height, typically 1 meter (3.28 feet) from a worker's chest and covering 20 locations for time duration of 30 min for each 15 s as a time interval. It was necessary to explore the noise-induced effect among the workers prior to the actual experiments. Seventy-five workers (operators) were questioned to obtain their performance and exposure time for three intervals of time (2, 5, and 8 hrs.), respectively. The operators in this study performed multiple tasks and mental works for different parameter levels (exposure time and noise levels).

2. 2. System modeling

The process of modeling according to ANFIS is presented as the following three steps:

a) Step 1: identification of the system.

The objective of this step is to identify input and output variables by forming the Takagi-Surgeno fuzzy system model (TSK) [17, 18] due to its simplicity and computational efficiency.

The model uses the rules of «if-then» with fuzzy antecedents and functional consequents, representing a fusion of fuzzy and non-fuzzy models. The model features in its computational efficiency. A set of nonlinear parameters defines it, and consequents are a linear combination of input variables and constant (singletons) terms [19].

b) Step 2: network structure determinations.

The neuro-fuzzy system is a hybrid system that compiles the principles of fuzzy logic with the training methods of neural network theory. The learning process operates only on the local information and causes only local changes in the underlying fuzzy system. The basic neuro-fuzzy system can be seen in **Fig. 1**, which consists of three essential sets of layers: the input variables, the middle represents fuzzy rules, and the third represents output variables. Fuzzy sets are encoded as connection weights within the layers of the network, which provides functionality in processing and training the model [20].

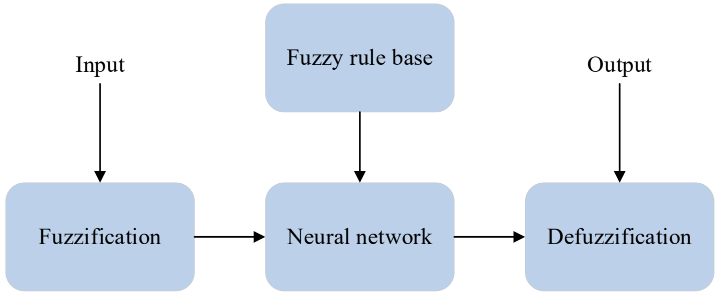

Fig. 1. Basic neuro-fuzzy system

Once the input and output variables are identified, the neuro-fuzzy system is manifested by a network of six layers, as presented in **Fig. 2**. The outputs and inputs of node functions are presented in the subsequent paragraphs:

1. First-Layer-1. Input layer: the inputs variables can be defined as the noise level and exposure time. In general, fuzzy sets are regarded as the input values, with crisp numbers being specific instances of fuzzy sets. The fuzzy sets can be represented either in parametric form or in look-up table form.

2. Second-Layer-2. Fuzzification layer: in this layer the membership functions that go along with each of the input variables are illustrated, denoted as $qA_j(x_j)$ [20, 21]:

$$qA_j\left(x_j\right)=\frac{1}{\left[\left(\frac{x_j-c_j}{a_j}\right)\right]^{b_j}}, \tag{1}$$

where the symbols x_j and A_j denote the number of inputs variables and is their corresponding linguistic labels. The symbols (a_j, b_j, c_j) denote the parameter set.

3. Third-Layer-3. Inference layer: by implementing the multiplicative inference method, the output of each neuron in this layer performs the firing strength (k_i) of each rule.

R1: IF noise level is *high* AND the exposure time is *long*, THEN, the reduction in work efficiency is approximately 96 %:

$$\kappa_i = q_{high}\left(\text{No is pollution level}\right)\times q_{long}\left(\text{Exposure time}\right). \tag{2}$$

4. Fourth-Layer-4. Normalization layer: the output of the *i*-th node of the inference layer is normalized as:

$$\bar{\kappa}_i=\frac{\kappa_i}{\kappa_1+\kappa_2+....+\kappa_N}, \tag{3}$$

where $i = 1,2,\ldots, N$, and N is the rules total numbers.

5. Fifth-Layer-5. Output layer: this layer generates the consequent of each rule depending on the normalized firing strength and is given by:

$$O_i=\overline{w}_i f_i, \tag{4}$$

where k_i is the normalized firing strength from layer 3, and if the function (f_i) is a linear function of the input variables, it is referred to as the first-order Sugeno fuzzy model. Conversely, if the function (f_i) is a constant, as is the case in our current model, it is known as the zero-order Sugeno fuzzy model.

6. Sixth-Layer-6. Defuzzification layer: this layer computes the weighted average of output signals of the output layer and is given by:

$$O=\sum_i\left(\overline{w}_i f_i\right). \tag{5}$$

To refine the parameters of the ANFIS model mentioned above, 80 % of the data sets are used for training. During the forward pass, the functional signals propagate forward until the error measure is computed at the output layer.

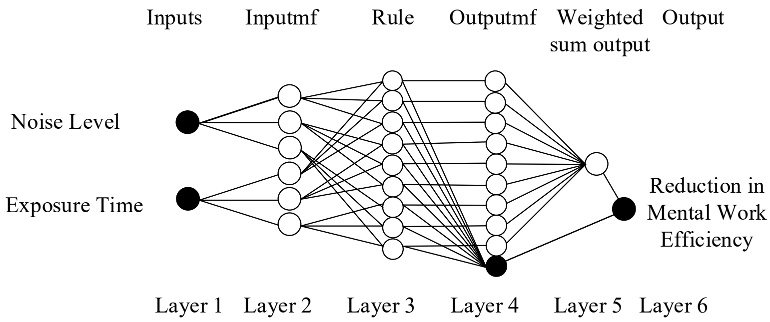

Fig. 2. System structure of the proposed ANFIS model

c) Step 3: parameter tuning and learning algorithm.

The ANFIS model is used to fine-tune the membership function parameters by using either a hybrid learning rule (MATLAB fuzzy logic tool) or by the algorithm of backpropagation learning [22–24]. It uses an external signal of a reference as a teacher then generates a specific signal (error) by the comparison between the response and the reference signals. According to the signal of error, the network modifies and changes the system's performance. The gradient descent method is used to update system parameters. The input/output data pairs are often called learning patterns or training data. These pairs are clamped onto the network, and the functions are spread to the output. The system parameters are updated according to gradient descent technique by implementing the input-output data pairs, is known as learning patterns or training data, which are fed into the network to produce outputs.

2. 3. Implementation

The ANFIS model is the most frequently used approach. This approach was used to execute the presented model [23, 25–27]. Firstly, the system is implemented using a Sugeno-fuzzy interference system, a type of fuzzy logic system. The Sugeno model is used because it ensures the continuity of the output surface and it is compatible with different optimization and adaptive techniques. This system allows two inputs and one output [19]. One significant advantage of the network is its ability to learn knowledge from data to adapt and update all adjustable parameters of the model. Nevertheless, this network commonly lacks disclosure regarding the methods used to accomplish the final results.

Fuzzy inference systems are based on these rules, which have an antecedent (IF portion) and a consequent (THEN part). Thus, by utilizing IF-THEN rules in fuzzy systems, it becomes possible to interpret the outcomes generated by the model. This increases the system's adaptability as these rules can easily be expanded or changed to take into account new data or shifting circumstances [7]:

$$\text{IF A is } x \text{ and B is } y \text{ THEN Z} = F(x,y), \tag{6}$$

where the letter Z represents a polynomial or a constant and the letters (A and B) denote the fuzzy sets. The input variables are set as the exposure time and level of noise. The reduction in the efficiency of the mental work is chosen as the output variable. The inputs are characterized by fuzzy sets (or linguistic-based variables). Next, the T-norm product is used to aggregate the functions of the memberships and to form the rules of IF-THEN, which have antecedent parts besides the constant consequent. The rules of IF-THEN are 9; some of them are:

– R1: IF the level of noise is low AND the time of exposure is short, THEN the reduction in the efficiency of the mental work is approximately equal to 4 %;

– R6: IF the level of noise is medium AND the time of exposure is long, THEN the reduction in the efficiency of the mental work is approximately equal to 25 %;

– R8: IF the level of noise is high AND the time of exposure is medium, THEN the reduction in the efficiency of the mental work is approximately equal to 50 %;

– R9: IF the level of noise is high AND the time of exposure is long, THEN the reduction in the efficiency of the mental work is approximately equal to 75 %.

3. Results and discussion

The ANFIS was used to optimize the model parameters. Firstly, 18 fitness parameters are introduced; 9 are premise parameters, and the other 9 are consequent parameters. These parameters are essential for model adaptation. The premise parameters shape membership functions, which define input space fuzzy sets. They evaluate how the input variables are categorized into words like «high, medium, and low». By adjusting these parameters, the model's ability to capture nuances of the input data can be improved by modifying these parameters.

A hybrid learning rule was used for training the model according to the pairs of the I/O data. The data pairs were determined from the Al-DORA power plant by completing a questionnaire prepared for this purpose. Then, 60 data sets of the total number of the examined data set (75) were mainly used for model learning purposes. The model's training was accomplished at 50 epochs for 0.01 as step size, where Epoch represents the number of iterations. With 0 % error tolerance, the other 15 sets were used for model validation and testing purposes.

The trapezoidal-shaped membership was used as the function for characterizing the chosen sets. These shaped functions are significant for describing the selected sets, since they offer a distinct depiction of the extent to which each category (low, medium and high) belongs to different noise levels. This characterization function was preferred over other forms functions, as it includes step or triangle functions.

Fig. 3 shows the trapezoidal-shaped membership for the noise level. According to the graph, there seems to be a discernible pattern or trend in the fluctuation of membership degree in relation to noise levels. The **Fig. 3** depicts three distinct lines creating a triangular layout labeled 'Low', 'Medium', and 'High' with each vertex. The points at 75, 60, and 45 noise levels are linked by lines, indicating that higher noise levels correspond to higher membership degrees. This suggests that as the noise level increases, the degree of membership also increases. Moreover, the outcomes of the noise levels exhibit a symmetrical trend concerning the midpoint of the x-axis, revealing a continuous interaction between the noise level and the degree of membership in the three noise level groups.

Furthermore, **Fig. 4** depicts variation in membership level over time and highlights a distinct relationship between the two variables. It shows the trapezoidal-shaped membership for the exposure time. The same trend can be observed; as the degree of membership increases, the exposure time also increases. Thus, a consistent relationship between the degree of membership across the three categories and exposure time can symmetrically be obtained about the *x*-axis's midpoint.

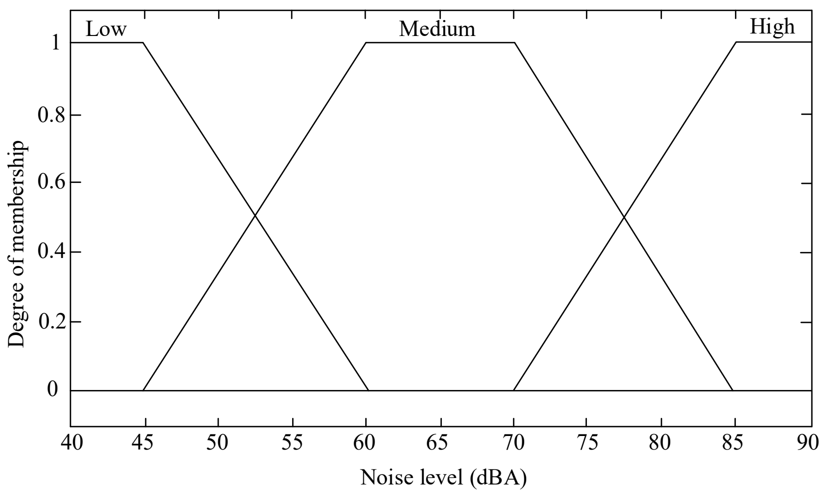

Fig. 3. Membership functions of the noise level in dBA

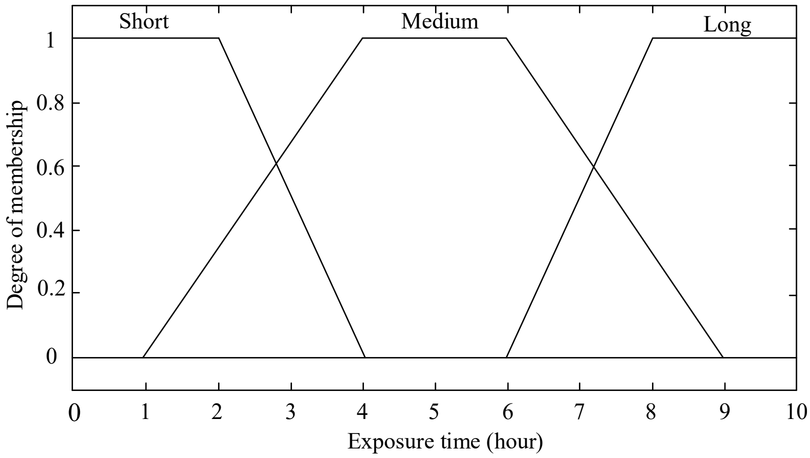

Fig. 4. Membership functions of exposure time in hours

Additionally, 50 epochs were used for the training purpose of the model; however, the learning process was finished in the first 38 epochs, at which the RMS value of the error relaxed to almost 0 % in the 38^{th} Epoch. **Fig. 5** shows the RMS after the system training. It was observed that the membership function shape was somehow modified. The variation in the form of the membership function implies that the system has successfully adjusted to the training data and enhanced its comprehension of the input-output connections. The model's early convergence at 38 epochs indicates the rapid comprehension of the structural patterns and the model's efficiency and resilience. Moreover, after further examination of the training process, it was found that after the 38^{th} epoch, the model became steady, and no noticeable enhancements in accuracy or reduction in error could be obtained. This is evidence of the effectiveness of the model in capturing the essential features with rapid convergence and low RMS error.

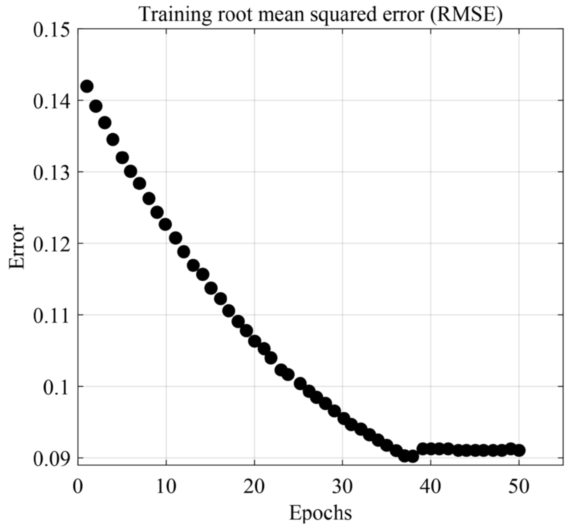

Fig. 5. Training root mean squared error (RMSE)

The main reason for that modification is the clear agreement between the pairs of the input/output data and the knowledge provided by the available experts. **Fig. 6** shows the effect of the noise level on the efficiency of the mental work as a parameter for different exposure periods. It can be seen that for all exposure periods, the reduction in the efficiency of the mental work at noise level up to 65 dBA is almost insignificant, considering an effect of 25 % reduction in mental work efficiency as negligible.

In addition, it is observed that the efficiency of mental work is not affected (6 %, 8 %, and 23 %) at the noise level of 65 dBA for «short, medium, and long» exposure, respectively. At a noise level of 70 dBA, mental work efficiency is not affected for short (13 %) and medium (19 %) exposure time while reduced slightly (37 %) for long exposure time. However, the efficiency reduction in mental work is almost (26 %), (42 %), and (62 %) for «short, medium, and long» exposure time, respectively, at noise level of 85 dBA and above.

At noise level 85 dBA, the mental work efficiency reduced slightly (29 %), moderately (48 %), and highly (68 %) for short, medium, and long exposure time, respectively. The reduction in mental work efficiency was shown clearly at noise level 90 dBA; it reduced slightly (30 %), moderately (50 %), and highly (70 %), for short, medium, and long exposure time, respectively.

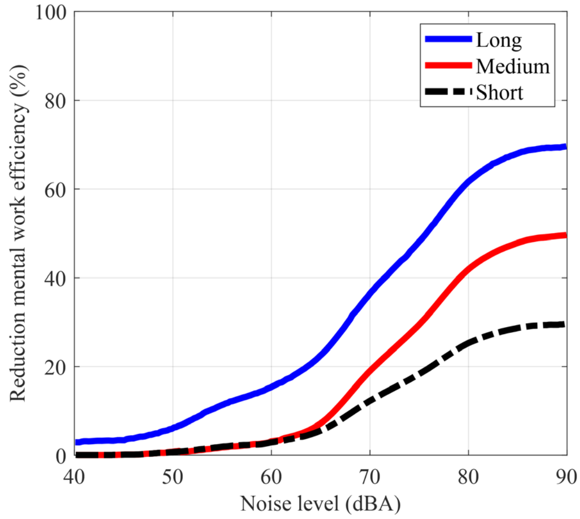

Fig. 6. Relationship between the noise level and mental work efficiency at varied exposure time, black line 'short', red line 'medium', and blue line 'long'

The recommended Safe Exposure Limited (REL) criteria for all worker exposures to noise that has been indicated by The National Institute for Occupational Safety and Health (NIOSH) preferred to be around the value of «85 dBA» for eight hours and should not exceed the limit of «115 dBA» for safety noise effect on hearing loss regardless of the duration of noise exposure.

The current study validates the model by relying on the recommended (REL) criteria that revealed no reduction in worker efficiency if they exposed to max allowable noise level value «85 dBA» through 8 hrs. interval. Whilst, exposed to «105–115 dBA» led to the maximum reduction in efficiency for the same interval. When comparing the most commend methods, the ANFIS method is similar to the Inference System (FIS) and Fuzzy Logic System (FLS) techniques, but numerous important distinctions exist.

ANFIS, FIS, and FLS represent complex systems using fuzzy inputs. However, the former handles output differently. Defuzzification gives FIS crisp results, whereas ANFIS employs fuzzy outputs. FLS defuzzifies for crisp output. A combination of the reasoning capabilities of fuzzy logic systems with the learning capabilities of neural networks are in ANFIS. The system can autonomously modify its parameters through a learning process, enabling it to conform to evolving data patterns. Some fuzzy logic systems may also lack the same amount of learning capacity.

This study is limited to two input variables, exposure time and level of noise, and one output, which is the efficiency of mental work. The ANFIS requires a significant amount of training data to learn the underlying patterns and relationships in the data accurately. In addition, the model is limited to trapezoidal-shaped membership functions, which provide more flexibility between the output of noise levels. However, using this function could be more complex than other functions like triangular or step functions, which need more resources and parameters to set up.

Future work can take into account the implementation of the frequency range, type of noise, and the age of the workers with other input parameters for more efficient study.

4. Conclusions

In this work, a neuro-fuzzy model has been evolved as a main objective of this study in order to prophesy the employee's work efficiency while exposed to various levels of noise at Al-DORA Power Plant in Baghdad city. The results presented as a function of noise level and exposure time which showed that the efficiency of mental work for different exposure periods depends on the noise level. In addition, it confirmed that the medium noise level influences workers or operators exposed to a medium exposure time. In contrast, the operators exposed for longer can be affected even at a smaller noise level. In addition, the present work found that mental work is affected by lower ranges of noise levels than non-cognitive work. Moreover, the results revealed that using ANFIS for training purposes is computationally effective, as the desired values of the RMSE are achieved by using a small number of epochs. In addition, minor variations are noticed in the membership function shape after model training because of the agreement between the I/O data pairs and the knowledge provided by the experts.

This research could offer essential advantages by identifying the optimal acoustic conditions for various mental tasks to improve the performance and productivity of the employees. By establishing a clear relationship between noise levels, exposure time, and mental work efficiency, organizations can implement certain strategies to optimize their acoustic environments. For instance, organizations can use sound-absorbing materials, create quiet zones, or implement flexible work schedules to limit prolonged exposure to higher noise levels.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

Financing

The study was performed without financial support.

Data availability

Manuscript has no associated data.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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