PREDICTING NOISE-INDUCED HEARING LOSS (NIHL) AND HEARING DETERIORATION INDEX (HDI) IN MALAYSIAN INDUSTRIAL WORKERS USING GDAM ALGORITHM

M. Z. Rehman[1], Nazri Mohd. Nawi[2], M. I. Ghazali[3]

[1]Faculty of Computer Science and Information Technology (FSKTM), Universiti Tun Hussein Onn Malaysia (UTHM), 86400 Batu Pahat, Johor.

[2,3]Faculty of Mechanical and Manufacturing Engineering (FKMP), Universiti Tun Hussein Onn Malaysia (UTHM), 86400 Batu Pahat, Johor.

Email: [1]zrehman862060@gmail.com, [2]nazri@uthm.edu.my, [3]imran@uthm.edu.my

ABSTRACT

Noise is a form of a pollutant that is terrorizing the occupational health experts for many decades due to its adverse side-effects on the workers in the industry. Noise-Induced Hearing Loss (NIHL) handicap is one out of many health hazards caused due to excessive exposure to high frequency noise emitted from the machines. A number of studies have been carried-out to find the significant factors involved in causing NIHL in industrial workers using Artificial Neural Networks. Despite providing useful information on hearing loss, these studies have neglected some important factors. Therefore, the current study is using age, work-duration, and maximum and minimum noise exposure as the main factors involved in the hearing loss. Gradient Descent with Adaptive Momentum (GDAM) algorithm is proposed to predict the NIHL in workers. The results show 98.21% average accuracy between the actual and the predicted datasets and the MSE for both ears is 2.10x10-3. Hearing threshold shift found in the selected workers was greater than 25 dB, which means hearing impairment has occurred. Also, Hearing Deterioration Index (HDI) is found to be quite high for different sound pressure levels such as maximum exposure (dB) and average exposure (dB) but is reported normal for minimum exposure (dB) for all workers.

KEYWORDS*: hearing loss, hearing deterioration index, noise, occupational safety, noise-induced hearing loss.*

1.0 INTRODUCTION

We hear different sounds in our daily life. And sometimes we are exposed to the sound without knowing the consequences of the exposure for a long period of time. When we hear noises that are too loud or it becomes painful to hear then a health condition called Noise-Induced Hearing Loss (NIHL) can occur (Stephen, 2002). NIHL is considered as the second most common form of sensori-neural hearing deficit after presbycusis (age related hearing loss) (Rabinowitz, 2000). NIHL is usually found greater in the developing industries of the world. NIHL is a common problem identified among the workers in the textile plants, basic metal industry, chemical industry, beverages and non-metallic mineral product industry. It was revealed in 1990's Audiometric (hearing loss test) survey by Department of Safety and Occupational Health, Malaysia (DOSH) that about 26.9 percent of industrial workers had a hearing threshold of 3000-6000 Hz which was greater than normal and 21.9 percent of workers were already suffering from detectable hearing loss (Leong, 2003).

A healthy Human ear makes it easier to hear and differentiate loud sounds from whispers. Any problem with the hearing ability damages the human's life by reducing the quality of communication (Zaheeruddin & Jain, 2004). NIHL is a sensori-neural deficit that usually begins at the higher frequencies (such as 3000-6000 Hz) and develops gradually as a result of chronic exposure to excessive sound levels. NIHL can be stopped in earlier stages but in later stages hearing loss becomes permanent (Rabinowitz, 2000). Different studies have been done to detect NIHL in humans, but the recent improvements in Neural Networks have paved way for researchers to predict various harmful effects of noise on humans such as human work efficiency in noisy environment, noise induced sleep disturbance, speech interference in noisy environment, noise induced annoyance (Zaheeruddin, 2006) (Zaheeruddin, Jain, & Singh, 2006) (Zaheeruddin & Garima, 2005) (Zaheeruddin & Jain, 2004).

In a recent study on NIHL by Yahya & Ghazali (2006), three variables such as age, work duration and noise exposure were selected and Levenberg-Marquadt (LM) model was used for hearing impairment prediction in industrial workers. In another study, on tympanic membrane perforation, three factors were identified that directly affect human workers (i.e. noise level, frequency and duration of exposure). It also negated the fact that age; an important factor in permanent hearing loss in older people can play the same effect on the young people (Zaheeruddin & Jain, 2004). Both studies on NIHL are in full-agreement that noise levels in excess of 90 decibels can cause permanent hearing loss to hair cells in the inner ear but still some important factors that can be helpful in finding harmful effects of NIHL in human hearing are neglected.

The main problem with NIHL detection is that mostly the input parameters used by audiometric experts detecting NIHL are unclear and not standardized as the data collected is often not precise and the environmental conditions are not suitable for the collection. For the sake of precision, this paper proposes a new algorithm to improve the working performance of Gradient Descent with Adaptive Gain (GDM-AG) model proposed by Nazri (2007) (Nazri, Ransing, & Ransing, 2007) that will change adaptively the momentum coefficient during the training. The proposed algorithm will be implemented using the input parameters (e.g. duration of exposure, age, minimum exposure, and maximum exposure) to predict NIHL and its effects on workers.

The rest of the paper is organized as follows: the next sections describe the Artificial Neural Network (ANN), Back Propagation Neural Network (BPNN) and the effect of using the momentum coefficient in BPNN. Section-2.1.1, introduces the Gradient Descent with Adaptive Momentum (GDAM) algorithm for GDM-AG Model proposed by Nazri (2007). Results and Discussion of GDAM on NIHL data are discussed in Section-3 and finally the paper is concluded in the Section-4.

2.0 ARTIFICIAL NEURAL NETWORKS (ANNS)

Artificial Neural Networks (ANNs) are analytical techniques modeled on the learning processes of human cognitive system and the neurological functions of the brain. ANNs works by processing information like biological neurons in the brain and consists of small processing units known as Artificial Neurons, which can be trained to perform complex calculations (Deng, Chen, & Pei, 2008).

An Artificial Neuron can be trained to store, recognize, estimate and adapt to new patterns without having the prior information of the function it receives. This ability of learning and adaption has made ANN superior to the conventional methods used in the past. Due to its ability to solve complex time critical problems, it has been widely used in the engineering fields such as biological modeling, financial forecasting, weather forecasting, decision modeling, control systems, manufacturing, health and medicine, ocean and space exploration etc (Zheng, Meng, & Gong, 1992) (Kosko, 1994) (Basheer & Hajmeer, 2000) (Krasnopolsky & Chevallier, 2003) (Coppin, 2004) (Lee T. L., 2008).

Back-Propagation Neural Network (BPNN) is one of the most novel supervised-learning Artificial Neural Network (ANN) model proposed by Rumelhart, Hinton and Williams (Rumelhart, Hinton, & Williams, 1986). The BPNN learns by calculating the errors of the output layer to find the errors in the hidden layers. This qualitative ability makes it highly suitable to be applied on problems in which no relationship is found between the output and the inputs. Due to its high rate of plasticity and learning capabilities, it has been successfully implemented in wide range of applications (Lee, Booth, & Alam, 2005). Despite providing successful solutions BPNN has some limitations. Since, it uses gradient descent learning which requires careful selection of parameters such as network topology, initial weights and biases, learning rate, activation function, and value for the gain in the activation function. An improper use of these parameters can lead to slow network convergence or even network stagnancy. Previous researchers have suggested some modifications to improve the training time of the network. Some of the variations suggested are the use of learning rate and momentum to stop network stagnancy and to speed-up the network convergence to global minima. These two parameters are frequently used in the control of weight adjustments along the steepest descent and for controlling oscillations (Zaweri, Seneviratne, & Althoefer, 2005).

2.1 BPNN with Momentum Coefficient

Momentum coefficient is a modification based on the observation that convergence might be improved if the oscillation in the trajectory is smoothed out, by adding a fraction of the previous weight change (Rumelhart, Hinton, & Williams, 1986) (Fkirin, Badwai, & Mohamed, 2009). So the addition of momentum-coefficient helps to smooth-out the descent path by preventing extreme changes in the gradient due to local anomalies (Sun, Zheng, Miao, & Li, 2007). In this case, it is essential to suppress any oscillations that results from the changes in the error surface (Norhamreeza, Nazri, & Ghazali, 2011).

In earlier studies, static momentum-coefficient was found to be beneficial for the convergence to global minima but in later studies it was revealed that Back-propagation with Fixed Momentum (BPFM) shows acceleration results when the current downhill of the error function and the last change in weights are in similar directions, when the current gradient is in an opposing direction to the previous update, BPFM will cause the weight direction to be updated in the upward direction instead of down the slope as desired, so in that case it is necessary that the momentum-coefficient should be adjusted adaptively instead of keeping it static (Shao & Zheng, 2009) (Nazri, Rehman, & Ghazali, 2011).

In recent years several adaptive modifications of momentum are offered. In 1994, one such modification known as Simple Adaptive Momentum (SAM) (Swanston, Bishop, & Mitchell, 1994) was proposed to enhance the convergence capability of BPNN to global minima. SAM works by changing the momentum-coefficient according to the similarities between the changes in the weights at the current and previous iterations. If the weight change is in the similar 'direction' then the momentum is increased to speed-up convergence otherwise it is decreased. Although SAM was found as a better alternative to Conjugate Gradient Descent and conventional BPNN but it success and failure rate was to be same as conventional BPNN. C. Yu and B. Liu (2002) introduced a more efficient Back Propagation and Acceleration Learning (BPALM) method, to answer the convergence failure problem in a much better way by adding some momentum to the adjustment expression. This can be accomplished by adding a fraction of the previous weight change to the current weight change. This encourages movement in the same direction on successive steps. The addition of momentum-step helps smooth-out the oscillations in the path by suppressing extreme changes in the gradient due to local anomalies. In 2008, R. J. Mitchell suggested adjusting the momentum-coefficient in SAM (Swanston, Bishop, & Mitchell, 1994) by considering all the weights in the Multi-layer Perceptrons (MLP). This technique of global adjustment of weights was found much better than the previously proposed SAM (Swanston, Bishop, & Mitchell, 1994) and helped improve the convergence rate to global minima (Mitchell R. J., 2008).

In 2007, Nazri *et al.* proposed that by varying the gain parameter adaptively for each node can drastically progress the training time of the network. Based on Nazri *et al.* (2007) research, this paper proposes a further improvement on the algorithm that will use adaptive momentum and will keep the gain value fixed for all the trials.

2.1.1 Gradient Descent with Adaptive Momentum Algorithm(GDAM)

In-order to increase the accuracy in the convergence rate and to make weight adjustments efficient on the current working algorithm proposed by Nazri *et al.,* (2007) a new Gradient Descent Adaptive Momentum Algorithm (GDAM) is proposed in this section.

In this paper, the modified Gradient Descent Adaptive Momentum (GDAM) algorithm is using batch mode of training for the entire training process. During the batch mode training all weights and biases and momentum are updated for the entire training set which is given to the network. The proposed algorithm, Gradient Descent Adaptive Momentum Algorithm (GDAM) adaptively changes the momentum while it keeps the gain value and learning rate fixed for the entire training. Mean Square Error (MSE) is calculated after each epoch and compared with the target error. The training continues until the target error is achieved or maximum epoch is reached.

For each epoch,
For each input vector,
Step-1:
Calculate the weights and biases using the previous momentum value.
Step-2:
Use the weights and biases to calculate new momentum value.
End input vector
IF Gradient is increasing, increase momentum
ELSE decrease momentum
End IF
Repeat the above steps until the network reaches the desired value.

$$E = \frac{1}{2}\sum_{k=1}^{n}(t_k - O_k)^2 \tag{1}$$

Adaptive Momentum is used to avoid oscillations in the network while searching the global minimum on the error surface. It smooth's-out the descent path and helps the network in avoiding getting stuck in the local minima due to extreme changes in the gradient (Nazri, Rehman & Ghazali, 2011) . Adaptive Momentum generates a value for the weight updates in a network. Here, the weight updates are limited to [0,1] as Log-sigmoid activation function is used to find the output on the jth node;

$$O_j = \frac{1}{1 + e^{-a_{net,j}}} \tag{2}$$

where,

$$a_{net,j} = \left[\sum_{i=1}^{l} w_{ij} O_i\right] + \theta_j \tag{3}$$

Weights and biases are calculated in the same way, the weight update expression for the links connecting to the output nodes with a bias is;

$$\Delta w_{jk} = (t_k - O_k) O_k (1 - O_k) \alpha_k O_j \tag{4}$$

Similarly, bias update expression for the output nodes will be;

$$\Delta \theta_k = (t_k - O_k) O_k (1 - O_k) \alpha_k \tag{5}$$

Where, α is the momentum coefficient and is a positive number in the interval [0,1]. For adjusting the momentum coefficient adaptively, gradient path/trajectory is selected. When the gradient (g_s), is increasing (i.e. uphill), increase the momentum coefficient else decrease the momentum coefficient. So, here all the momentum adjustment is done with respect to an increase or a decrease in gradient. The momentum on each training at epoch ($s + 1$) is calculated as follows:

$$\alpha_{s+1} = \begin{cases} \alpha_{s-p}, if\ g_s < 0 \\ \alpha_{s+p}, if\ g_s > 0 \end{cases} \tag{6}$$

where;

$0.2 < p < 0.9$

Here in the equation (6), 'p' represents the highest and the lowest value in the sigmoid interval, for example; in the interval p = [0.2, 0.9], 0.2 is the lowest and 0.9 is the highest value used to update momentum. After calculating the Momentum Coefficient in each epoch, the weight update expression for the input node links becomes:

$$\Delta w_{ij} = \left[\sum_{k} \alpha_k w_{jk} (t_k - O_k) O_k (1 - O_k)\right] \alpha_j O_j \left(1 - O_j\right) O_i \tag{7}$$

The bias update expression for hidden nodes will be like this;

$$\Delta\theta_j = \left[\sum_k \alpha_k w_{jk}(t_k - O_k)O_k(1 - O_k)\right]\alpha_j O_j(1 - O_j) \tag{8}$$

After calculating biases, hidden and output layer weight, the net weight becomes;

$$w_{net} = w_{ij} + w_{jk} + \Delta\theta_j + \Delta\theta_k \tag{9}$$

Finally, the network weights are calculated after being updated with momentum coefficient, which was used to dampen the oscillations the in the trajectory by adding previous weight change to the current weight in the trajectory (Shao & Zheng, 2009), the net weight becomes;

$$w_{net+1} = w_{net} + w_{net_{l-1}} \quad l = 0,1,2,\ldots \tag{10}$$

3. RESULTS AND DISCUSSIONS

The main focus of this research is to predict NIHL in human industrial workers with more accuracy and Hearing Deterioration will be accurately calculated among the selected workers. Before discussing the simulation test results there are certain things that need be explained such as tools and technologies, network topologies, testing methodology and dataset used during the experimentation process. The discussion is as follows:

3.1 Preliminary Study

The Workstation used for the experimentation comes ready with a 2.33GHz Core-2 Duo processor, 1-GB of RAM and Microsoft XP (Service Pack 3) Operating System. Gradient Descent with Adaptive Momentum (GDAM) algorithm which is an improved version of the proposed algorithm by Nazri (2007) is used to carry-out simulations on MATLAB 7.10.0 software.

3.1.1 NIHL dataset and Simulation Results

The Noise-Induced Hearing Loss (NIHL) dataset which consists of audiology study is obtained from Tenaga National Berhad (TNB), the Electric Power Supply Company of Malaysia. The dataset consisting of 1119 instances contains audiometric test information on each employee working from 1998 to 2003 in TNB, Terengganu State facilities. For performing simulations, the dataset is divided into 900 subsets and 219 subsets for training and testing respectively. Three layer back-propagation neural networks are used for testing of the models. The output is separated into two models i.e. left hearing loss and right hearing loss in order to reduce the complexity. Global Learning rate of 0.4 is selected for the entire tests and gain is kept fixed to 0.3. While log-sigmoid activation function is used as the transfer function from input layer to hidden layer and from hidden layer to the output layer. In this paper, the momentum term is varied adaptively between the range of [0, 1] randomly. For each problem, each trial is limited to 5000 epochs. A total of 30 trials are run for each momentum value to validate the best possible results. The network results are stored in the result file for each trial. Mean Square Error (MSE) and Correlation Coefficient(R) is used to verify the accuracy in the results.

Table 1, shows the maximum accuracy, maximum CPU cycles, Mean Square error and best obtained value for Correlation Coefficient (R). The results demonstrated that the good performance in the training and testing sets indicates that the network is able to predict efficiently on the unseen data.

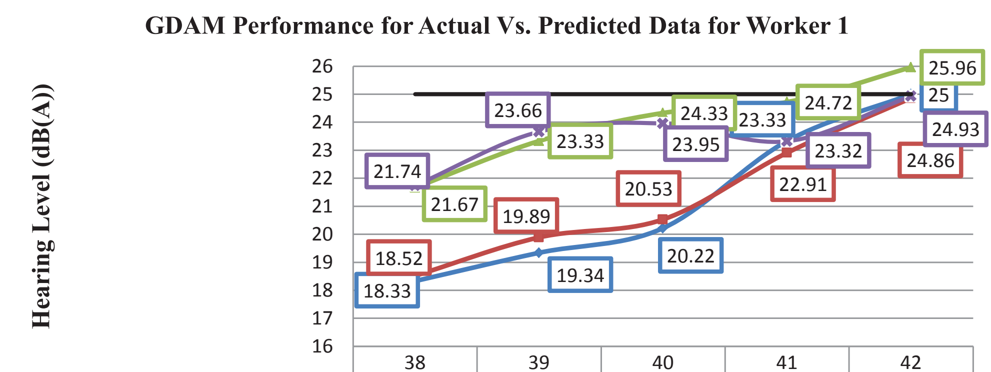
Table 1 Accuracy (%), Mean Square Error (MSE) and Correlation Coefficient (R) values for Hearing Loss Prediction in TNB Workers

NIHL Prediction for Both Ears	
Max CPU Cycles	902.5
Max Epochs	4367.5
Max Accuracy	98.21
MSE	$2.10\text{x } 10^{-03}$
Correlation Coefficient (R)	0.87

3.1.2 The Prediction Accuracy of GDAM

To ensure the capability of the proposed Gradient Descent with Adaptive Momentum (GDAM) Neural Network model, the prediction data and actual data were compared to see the performance of the prediction. To evaluate the prediction performance of GDAM, the Correlation Coefficient (R) value is used. Four (4) workers belonging to middle-age groups are randomly selected here. The selected workers are Worker-1, Worker-2, Worker-3, and Worker-4.

Referring to the Figure 1, the audiometric tests on the Worker 1 started at 38 years old and ended at age 42 years old. The actual data and prediction data comparison gave out the correlating values of 1.00 and 0.91 for Right and Left hearing. Figure 1 also illustrates GDAM prediction performance on worker 13. Worker 13 is working in TNB for the last 15 years and is showing a threshold shift of 25dB on both ears. According to the current noise standards, this person is considered already deaf.

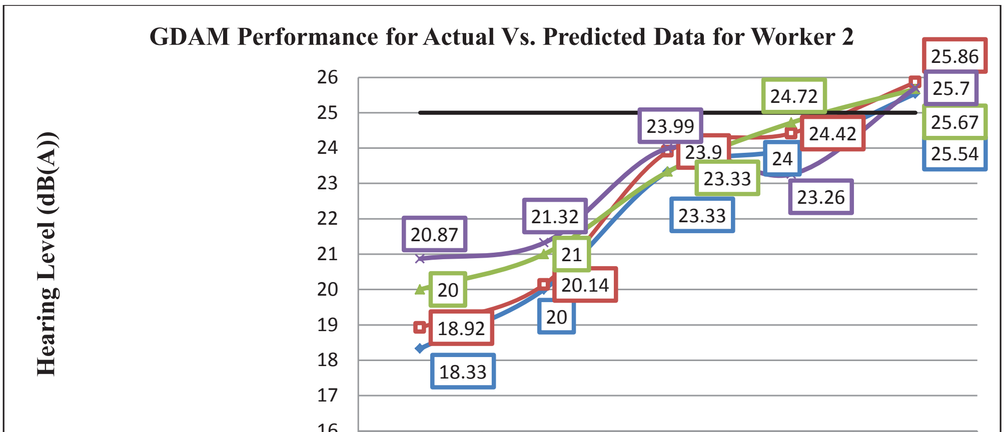


	38	39	40	41	42
Right Hearing Actual Level	18.33	19.34	20.22	23.33	25
Right Hearing Prediction Level	18.52	19.89	20.53	22.91	24.86
Left Hearing Actual Level	21.67	23.33	24.33	24.72	25.96
Left Hearing Prediction Level	21.74	23.66	23.95	23.32	24.93
25dB Loss	25	25	25	25	25

Figure 1 Noise-Induced Hearing Loss (NIHL) Prediction on Right and Left Ears for Worker 1

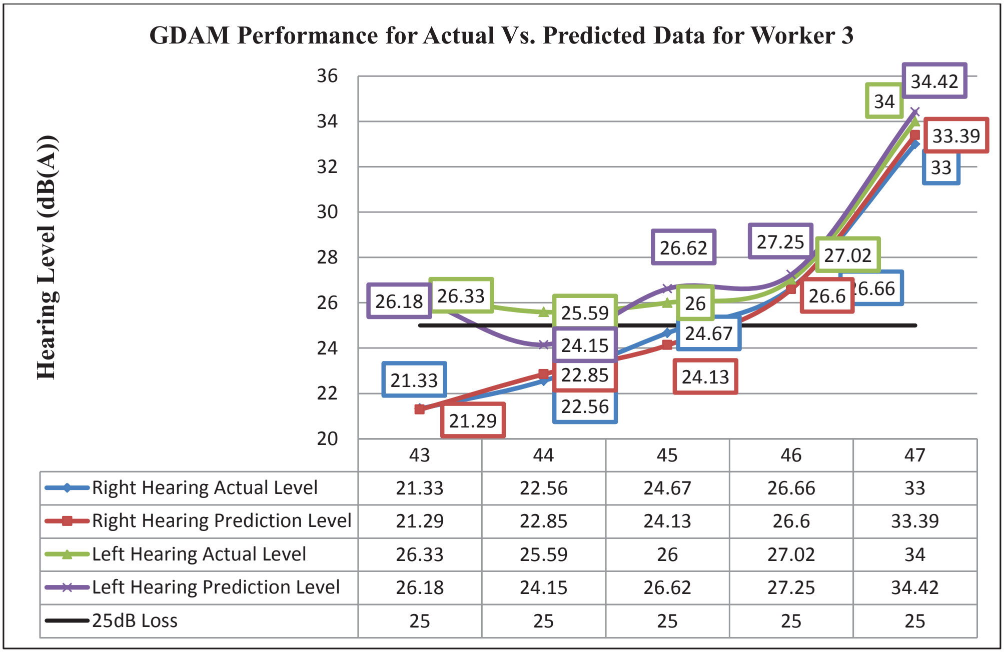
Worker 2 belongs to the middle-aged group and working in TNB for the last 15 years. During the working hours, worker 2 is exposed to maximum noise levels of 105.7 decibels. Audiometric results states that worker 2 show similar results like worker 1 and has developed a hearing threshold shift of more than 25 decibels as shown in the Figure 2. The lines depicted in Figure 2 present the critical hearing loss on both ears of the worker 2. As expected, the company already has a handicapped individual in need of immediate medical attention and guidance for future safety.

Worker 3 is exposed to the 118 decibels of noise during the time period of 18 years. The audiometric tests information starts at age 43 and stops when the user is 47 years of age. The correlation coefficient (R) values for both ears are quite close to 1 which indicates a health trend between the actual and prediction data using GDAM algorithm. Although, there is one clear indication in the data which states that the hearing of both ears is continuously deteriorating with the passage of time. Figure 3, shows the hearing threshold shift of 33dB and 34 dB on both ears in Worker 3, which is quite higher than the 25 decibels threshold limit set by government authorities and calls for immediate attention to stop the further hearing deterioration.



	40	41	42	43	44
Right Hearing Actual Level	18.33	20	23.33	24	25.54
Right Hearing Prediction Level	18.92	20.14	23.9	24.42	25.86
Left Hearing Actual Level	20	21	23.33	24.72	25.67
Left Hearing Prediction Level	20.87	21.32	23.99	23.26	25.7
25dB Loss	25	25	25	25	25

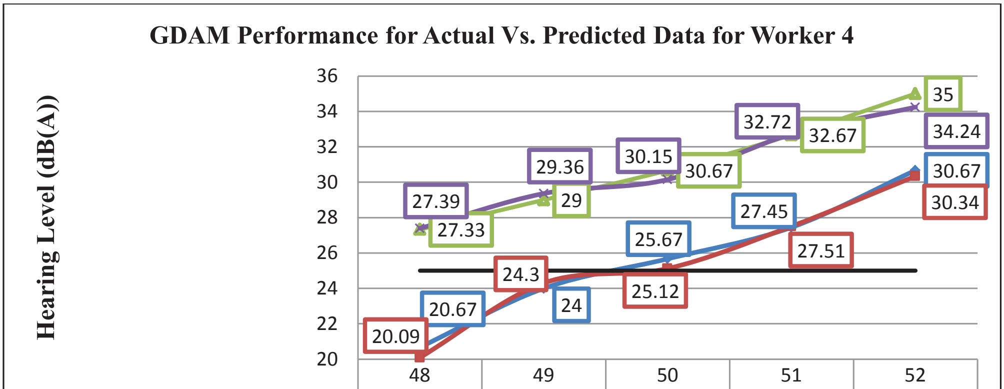
Figure 2 Noise-Induced Hearing Loss (NIHL) Prediction on Right and Left Ears for Worker 2



	43	44	45	46	47
Right Hearing Actual Level	21.33	22.56	24.67	26.66	33
Right Hearing Prediction Level	21.29	22.85	24.13	26.6	33.39
Left Hearing Actual Level	26.33	25.59	26	27.02	34
Left Hearing Prediction Level	26.18	24.15	26.62	27.25	34.42
25dB Loss	25	25	25	25	25

Figure 3 Noise-Induced Hearing Loss (NIHL) Prediction on Right and Left Ears for Worker 3

Figure 4 represents the data related to Worker 4 who is exposed to 110 decibels of sound pressure during a time period of 5 years which starts at the age of 48 and end at the age of 52. The audiometric test results and the prediction data trend are shown in the Figure 4. Worker 4 shows significant hearing loss on both ears but still the person is working in the same noisy environment. This person can recover by means of artificial hearing aids. The correlation coefficient (R) values in this case are 1.00 for Right hearing and 0.90 for left hearing respectively.



	48	49	50	51	52
Right Hearing Actual Level	20.67	24	25.67	27.45	30.67
Right Hearing Prediction Level	20.09	24.3	25.12	27.51	30.34
Left Hearing Actual Level	27.33	29	30.67	32.67	35
Left Hearing Prediction Level	27.39	29.36	30.15	32.72	34.24
25dB Loss	25	25	25	25	25

Figure 4 Noise-Induced Hearing Loss (NIHL) Prediction on Right and Left Ears for Worker 4

3.1.3 Hearing Deterioration Index (HDI)

There are scientific correlations between the noise levels, exposure, and hearing damage risk. Extensive work undertaken in Dresden, Germany (Kraak *et. al.*, 1977, 1981) shows the percentage risk of developing a hearing handicap and the median loss incurred with exposure as (Leong, 2003)(Bies & Hansen, 2003):

I. function of mean sound pressure level in the workplace (dBA) and exposure (years).
II. function of hearing deterioration index, HDI. The formula is shown below:

$$\mathrm{HDI} = 10\log_{10}\left[\int_0^t 10^{L/20}\, dt\right] \qquad (11)$$

where;

L is the mean exposure level (dBA), and
t is the time exposure.

It is evident that the hearing deteriorates very rapidly during the first 10 years and progressively more so as the exposure level rises above 80 dBA. This implies that to avoid hearing impairment in 80 percent of the population, the strategy that should be implemented is to avoid acquiring a HDI greater than 59 during a lifetime. This index is consistent with a noise level of 85 dBA exposure over a lifetime. At 90 dBA, there is a 20 percent risk of developing a hearing impairment after 30 years exposure as shown in the figure 5.

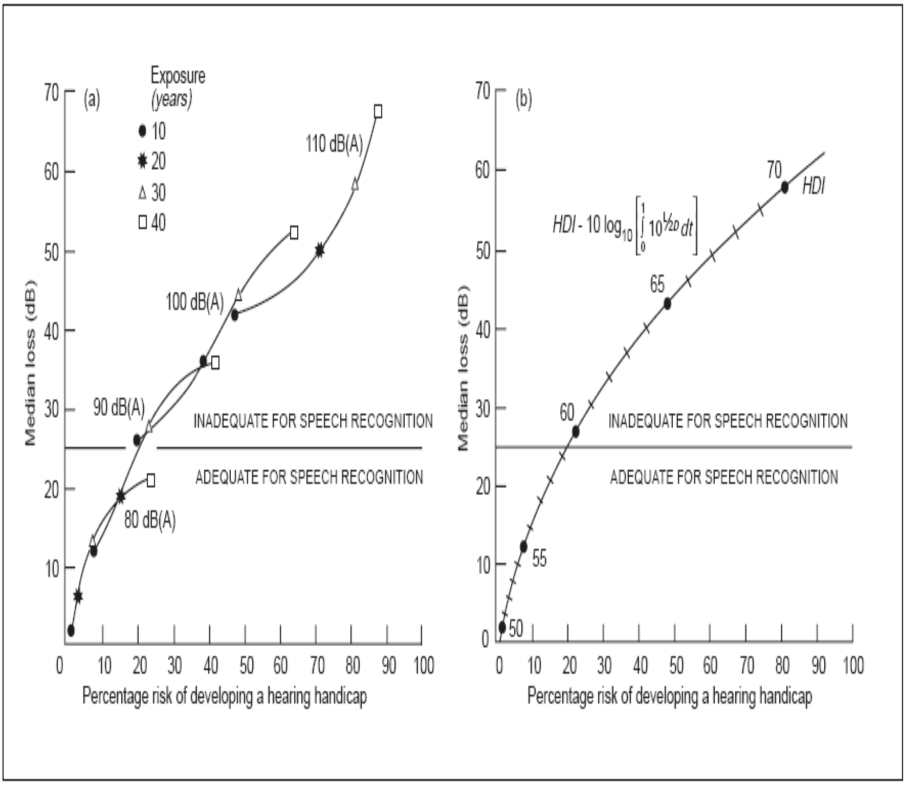


Figure 5 Hearing Damage as a function of Exposure (Bies & Hansen, 2003)

We can easily see from the Table 2 that all of our workers who have been working in the factory for 15 years or more are showing significant Hearing Deterioration Indexes (HDI's) for average sound pressure levels. For average sound pressure levels, the workers are exceeding the HDI of 59 and same is the case with the Maximum sound Pressure levels.

Although, it shows less HDI but still the hearing losses are quite significant here. All the workers are showing normal HDI for Minimum sound pressure levels, but it is an ideal case and is only possible during the start of operation timings of boilers and turbines.

Table 2 Hearing deterioration Index for Workers Exposed to Different Sound Pressure Levels

Worker(s)	Age	T	HDI (Avg. Exp.)	HDI (Min. Exp.)	HDI (Max. Exp.)
Worker 1	38	15	79.88	53.46	64.11
Worker 2	40	15	80.73	54.41	64.41
Worker 3	43	18	85.9	56.20	71.95
Worker 4	48	19	83.68	56.14	67.88

A comparison of HDI in workers, when they are exposed to different levels of sound pressure in a working environment of TNB is shown in the figure 6.

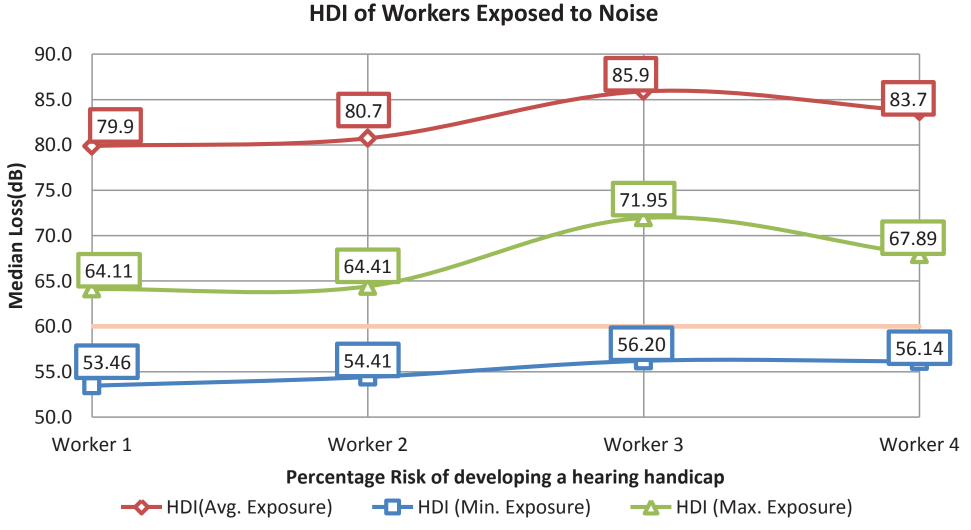


Figure 6 HDI of Workers exposed to different Noise Pressure Levels

4.0 CONCLUSIONS

Noise is a form of pollutant that is causing serious health problems to the workers inside the industry for many years. Continuous exposure to high pressure noise emitting from the machines can cause NIHL. In the developed countries noise is considered a serious threat to the health of blue collared employees. But in developing countries, noise is still not taken as seriously as it should be taken. In the recent years, many studies on NIHL are conducted in the developing countries. Following these studies, legislations are made but not taken seriously by the authorities in the industry and government agencies simply ignore to enforce these laws. The current research is carried out to detect NIHL in human industrial workers by using a proposed Gradient Descent with Adaptive Momentum (GDAM) algorithm to predict NIHL in workers using age, work-duration, and maximum noise exposure and minimum noise exposure. Overall, GDAM has shown outstanding results in-terms of predication accuracy on NIHL dataset collected from TNB. Mean Square Error (MSE) calculated for both ears is 2.10×10^{-3} while 98.21% average accuracy was achieved for the NIHL prediction. In the results it was found that Hearing threshold shift in all the workers was greater than 25 dB, which means hearing impairment has already occurred. Also, Hearing Deterioration Index (HDI) is found to be quite high for different sound pressure levels such as maximum exposure (dB) and average exposure (dB) levels but is reported normal for minimum exposure (dB) levels for all workers.

5.0 ACKNOWLEDGMENT

The Authors would like to thank Universiti Tun Hussein Onn Malaysia (UTHM) for supporting this research under the Fundamental Research Grant Scheme (FRGS), Vote No. 0737.

6.0 REFERENCES

B. Coppin. 2004. Artificial Intelligence Illuminated. Jones and Bartlet illuminated Series, USA.

B. Kosko. 1994. Neural Network and Fuzzy Systems (1st Edition). Prentice Hall of India.

C. Yu, and B. D. Liu. 2002. A Backpropagation algorithm with adaptive learning rate and momentum coefficient. IJCNN, pp. 1218 - 1223. Honolulu.

D. A. Bies, and H. C. Hansen. 2003. Engineering Noise Control: Theory and Practice (3rd Edition). Spon Press, London, UK.

D. E. Rumelhart, G. E. Hinton, and R. J. Williams. 1986. Learning Internal Representations by error propagation. Parallel Distributed Processing: Explorations in the Microstructure of Cognition.

D. J. Swanston, J. M. Bishop, and R. J. Mitchell. 1994. Simple adaptive momentum: New algorithm for training multilayer Perceptrons. IEEE Journal of Electronic Letters, Volume 30 (18), pp. 1498-1500.

Factories and Machinery Act 1967 (ACT 139) and Regulation and Rules (As at 30th August 2011) (2011). Factories and Machinery (Noise Exposure) Regulations, 1989. PU (A) 106/89.

F. Stephen. 2002. Continuous Noise-Induced Hearing Loss. Austin State University Press. Austin, USA.

H. Shao, and H. Zheng. 2009. A New BP Algorithm with Adaptive Momentum for FNNs Training. GCIS-2009, pp. 16-20. Xiamen.

H. Yan, Y. Jiang, J. Zheng, C. Ping, and Q. Li. 2006. A Multilayer Perceptron-Based Medical Decision Support System for Heart Disease Diagnosis. Expert Systems with Applications, Volume 30 (2), pp. 272-281.

H. Zheng, W. Meng, and B. Gong. 1992. Neural Network and its Application on Machine fault Diagnosis. ICSYSE 1992, pp. 576-579.

I. A. Basheer, and M. Hajmeer. 2000. Artificial Neural Networks: fundamentals, computing, design and application. J. of Microbiological Methods,Volume 43 (1), pp. 03-31.

K. Lee, D. Booth, and P. A. Alam. 2005. Comparison of Supervised and Unsupervised Neural Networks in Predicting Bankruptcy of Korean Firms. Expert Systems with Applications, Volume 29 (1), pp. 1-16.

M. A. Fkirin, S. M. Badwai, and S. A. Mohamed. 2009. Change Detection Using Neural Network in Toshka Area. NSRC-2009, pp. 1-10. Cairo.

M. N. Yahya, and M. I. Ghazali. 2005. Hearing Impairment Prediction on Malaysia Industrial Workers by using Neural Network. 8th International Conference on Quality in Research. Bali, Indonesia.

M. S. Leong. 2003. Noise and Vibration Problems: How they affect us and the Industry in the Malaysian Context. Skudai, Johor: University Teknologi Malaysia (UTM) Press, Malaysia.

M. N. Nazri, M. R. Ransing, and R. S. Ransing. 2007. An improved Conjugate Gradient based learning algorithm for back propagation neural networks. Int. J. of Computational Intelligence, Volume 4 (1), pp. 46-55.

M. N. Nazri. 2007. Computational Issues in Process Optimization using historical data. Ph.D Eng. Thesis, Swansea University, Swansea, United kingdom.

M. N. Nazri, M. Z. Rehman, and M. I. Ghazali. 2011. Noise-Induced Hearing Loss Prediction in Malaysian Industrial Workers using Gradient Descent with Adaptive Momentum Algorithm. Journal: International Review on Computers and Software (IRECOS). Volume 6 (5).

A. Norhamreeza, M. N. Nazri, and R. Ghazali. 2011. The effect of Adaptive Gain and Adaptive Momentum in improving training time of Gradient Descent Back Propagation Algorithm on Classification Problems. ICASEIT 2011, pp. 178-184. Bangi.

P. M. Rabinowitz. 2000. Noise-Induced Hearing Loss. Journal of American Family Physician, Volume 61 (9), pp. 2759-2760.

R. J. Mitchell. 2008. On Simple Adaptive Momentum. CIS-2008, pp. 01-06.

T. L. Lee. 2008. Back-propagation neural network for the prediction of the short-term storm surge in Taichung harbor, Taiwan. Engineering Applications of artificial Intelligence, Volume 21 (1), pp. 63-72.

V. M. Krasnopolsky, and F. Chevallier. 2003. Some Neural Network applications in environmental sciences. Part II: advancing computational efficiency of environmental numerical models. Journal of Neural Networks, Volume 16 (3), pp. 335-348.

W. J. Deng, W. C. Chen, and W. Pei. 2008. Back-propagation neural network based importance-performance for determining critical service attributes. Journal of Expert Systems and Applications, Volume 34 (2), pp. 1-26.

Y. H. Zaweri, L. D. Seneviratne, and K. Althoefer. 2005. Stability Analysis of a Three-term Back-propagation Algorithm. Neural Networks, Volume 18 (10), pp. 1341-1347.

Y. J. Sun, S. Zheng, C. X. Miao, and J. M. Li. 2007. Improved BP Neural Network for Transformer Fault Diagnosis. Journal of China University of Mining and Technology, Volume 17 (1), 138-142.

Zaheeruddin, G. V. Singh, and V. K. Jain. 2003. Fuzzy Modeling of Human Work Efficiency in Noisy Environment. Proceedings of the IEEE Int. conf. on fuzzy systems (FUZZ-2003), pp. 120-124. St. Louis, USA.

Zaheeruddin, and V. K. Jain. 2004. An Intelligent System for Noise-induced Hearing Loss. Proceedings of International Conference on Intelligent Sensing and Information Processing (ICISIP – 2004), pp. 378-384. Chennai, India.

Zaheeruddin, and Garima. 2005. Application of Artificial Neural Networks for the Prediction of Human Work Efficiency in Noisy Environment. CIMCA 2005, pp. 842-846. Vienna, Australia.

Zaheeruddin, and V. K. Jain. 2006. A Fuzzy Expert System for noise-induced sleep disturbance. J. of Expert Systems with Applications , Volume 30 (4), pp. 761-771.

Zaheeruddin, and V. K. Jain. 2005. Fuzzy Modeling of speech interference in noisy environment. ICISIP 2005, pp. 409-414.

Zaheeruddin, V. K. Jain, and G. V. Singh. 2006. A Fuzzy Model for Noise-Induced Annoyance. IEEE Transaction on System, Man and Cybernatics, Volume 36 (4), pp. 697-705.

Zaheeruddin 2006. Modelling of Noise-Induced Annoyance: A Neuro-fuzzy Approach. ICIT 2006, pp. 2686-2691. Mumbai, India.