

# Prediction of a Power Tiller Sound Pressure Levels in Octave Frequency Bands Using Artificial Neural Networks

SEYED REZA HASSAN-BEYGI<sup>1</sup>, BARAT GHOBADIAN<sup>†</sup>, MOHAMMAD-HOSEIN KIANMEHR AND REZA AMIRI CHAYJAN<sup>‡</sup>

*Department of Agricultural Technical Engineering, Abureihan Campus, University of Tehran, Tehran, Iran*

*<sup>†</sup>Department of Mechanics of Agricultural Machinery, Tarbiat Modares University, Tehran, Iran*

*<sup>‡</sup>Department of Farm Machinery Engineering, Bu-Ali Sina University, Hamedan, Iran*

<sup>1</sup>Corresponding author's e-mail: rhbeigi@ut.ac.ir

## ABSTRACT

Prerequisite of power tillers sound control provides information about the overall sound levels and frequency. This study was conducted to explain the application of artificial neural networks for prediction of a 13-hp power tiller sound pressure levels in octave frequency bands. The results showed that four layer perceptron network with training algorithm of back propagation, hyperbolic tangential activation function, Delta training rule with five neurons in first hidden layer and three neurons in second hidden layer was the best for accurate prediction of the power tiller sound. The minimum root mean square error (RMSE) and coefficient of determination ( $R^2$ ) for the multilayer perceptron (MLP) network were 0.0484 and 0.983, respectively. Comparison between measured and predicted octave sound pressure levels of the power tiller showed that the maximum difference was  $\pm 2$  dB.

**Key Words:** Power tiller; Noise; Intelligent prediction; Octave; Artificial neural networks

## INTRODUCTION

Now-a-days, widespread use of agricultural tractors and machineries for field operations in spite of their valuable advantages have caused some occupational health and safety problems for operators of these machines and farmers, the excessive noise is an example (Sieswerda & Dekker, 1978; Maring, 1979; Talamo, 1987; Suggs, 1987; Brown, 1988; Crocker & Ivanov, 1993; Solecki, 1998, 2000).

Un-wanted sound, called noise, is in fact perturbation in pressure detected by human ear. This is associated with the mechanical vibration of gaseous, liquid or solid media (Crocker & Ivanov, 1993; Crocker, 1998). The most displeasing effects of noise on human are: temporary or permanent hearing loss, mental and nervous discomforts, loss of working efficiency and increased risk of hazards (Irwin & Graf, 1979; Roth & Field, 1991; Crocker & Ivanov, 1993; Crocker, 1998). Considering these threats of noise on human, occupational health and safety associations in different countries have established regulations in order to restrict human noise exposure duration in noisy environments. The National Institute for Occupational Safety and Health (NIOSH) is an example (NIOSH, 1998). Exposure to 85 dB (A) noise level for eight-hours in a day or exposure to 88 dB (A) noise level for four-hours in a day are named as one noise dose (NIOSH, 1998). Research works conducted by Solecki (2000) showed that average noise dose of farmers in different months of the year was within 1.8 to 5.7. Therefore, it was recommended that noise

levels should not be more than 80 dB (A), though some countries are conducting noise reduction and control programs to bring noise levels lower than 75 dB (A) (Crocker & Ivanov, 1993).

There are more than 120,000 power tillers in Iran (Anonymous, 2003). Noise and vibration of power tillers have been reported to play an important role in damages experienced by the users (Kang *et al.*, 1988). Furthermore, high noise levels emitted by power tillers were the reason for suggesting the replacement of the diesel engines by electric power sources (Bodria & Fiala, 1995). Hassan-Beygi *et al.* (2004, 05a) showed that overall noise levels of 13-hp power tiller at driver's ear position was as high as 92 dB (A) at 2200 rpm engine speed in different gear ratios for asphalt and dirt rural roads and grasslands. On the other hand, the limited space of the small engines fitted on the power tillers and other limitations do not allow equipping them with sound absorbing materials or provide them with the driver's cab (Brown, 1988) though the noise received by bystanders is still another dilemma. Therefore, sound control and reduction measure or operators protection management is essential to be implemented on these machines. Prerequisite of power tillers sound control and reduction is to know about the overall sound pressure level as well as frequency content of sound emitted from them. In a study, overall noise levels of a 13-hp power tiller was measured and estimated using statistical analysis and artificial neural networks by Hassan-Beygi *et al.* (2004, 05a & b).

Hassan-Beygi (2004) showed that there is limited

published information concerning frequency content of power tillers sound levels. In the present paper, artificial neural networks was used as a tool for accurate prediction of a 13-hp power tiller sound pressure levels in octave frequency bands in transportation conditions on asphalt and dirt rural roads as well as grassland.

## MATERIALS AND METHODS

**Power tiller.** A power tiller used in this research work was fitted with a single cylinder, four strokes, naturally aspirated, water-cooled IDI diesel engine, providing 13-hp power at rated engine speed of 2200 rpm. Travel speed of the power tiller was six stage forward and two stage reverse.

**Measuring and recording instrumentation.** Instruments used in this study were: B and K 4415 microphone with flat frequency response in human threshold of hearing range (20 to 20000 Hz), B and K 2230 sound level meters with 20 - 146 dB dynamic range and 0.1 dB accuracy, a Lutron DT-2236 digital tachometer with 1 rpm accuracy, a Testo thermometer with the range of -10 to 50°C and 0.1°C accuracy, a Testo anemometer with the range of 0 to 15 m s<sup>-1</sup> ± 0.01 accuracy, a Toshiba Satellite 2335D laptop computer. The laptop computer along with the sound recording software (Cool Edit, 2000) and Yamaha OPL3-SAX, A/D sound card provided suitable means for sound recording instead of expensive and complex instrumentation (Hassan-Beygi, 2004).

**Test site specifications.** Test site was prepared and maintained according to ISO (ISO 5131, 1996) sound measurement standard. The test area consisted of a flat open space free from obstacles and the effect of signboards, buildings and hillsides for at least 15 m from measurement zone. The suggested wind speed and other climate limitations were kept in mind during measurements. The microphone was mounted 1.7 m above the ground surface and 100 mm away from the driver's right ear in a horizontal position and pointed in the direction of travel. The background noise was at least 30 dB lower than that for the power tiller. Fig. 1a shows the dimensions of the area in which the power tiller noise measurement was carried out. Here R stands for the distance from the obstacles to the measurement zone; L and W are the length and width of measurement zone, respectively. The minimum values of R, L and W were 15, 10 and 2 m, respectively. Fig. 1b shows the instrumentation set up for measurement of noise near the operator's ear.

**Data acquisition and signal processing.** The selected variables were engine speeds, gear ratios and surface types. For simulating actual transportation conditions, 9000 N weight was applied on trailer to be pulled by the power tiller. In each test run, minimum 10 s sound signal was recorded. In initial data analysis in time domain between 1.5 to 3 s, nearly uniform sound signal was selected to minimize variations between signal peaks for increasing the tests accuracy.

The microphone in conjunction with sound level meter was used for measuring sound pressure signal of test power tiller. According to Nyquist criteria for correct A/D conversion of analog signals to digital ones, data sampling rate must be at least two times of maximum frequency (Oppenheim *et al.*, 1995). Considering the human audio frequency range, A/D conversion with 48000 Hz sampling rate was used for converting output analog signals of sound level meter. The digitized sound signals were stored in computer hard disk, using Cool Edit 2000 software. The recorded digital signals in time domain were converted to frequency domain using a developed FFT computer program. The octave sound pressure levels were then derived from the frequency domain signals with the help of a developed sub-routine computer program.

**Artificial neural networks (ANNs).** An ANN consists of neurons, which have been related together with special arrangement. Neurons are in layers and every network consists of some neurons in input layer, one or more neurons in output layer and neurons in one or more hidden layers. The most of algorithms and architectures of artificial neural networks were varied by variation in neuron model, relationship between neurons and weights between them. The learning purpose in artificial neural networks is weights up-dating, so that with presenting set of inputs, desired outputs are obtained. The most common types of artificial neural networks include: feed forward, feed back and competitive (Menhaj, 1998; Jain & Fanelli, 2000). In this study, feed forward type of neural network is used. This type of neural network is mainly used for the estimation of function and classification of patterns. The multilayer perceptron network (MLP) and radial basis function (RBF) networks are the most commonly used feed forward ANNs.

A MLP network consists of one input layer, one or more hidden layers and one output layer. Back Propagation (BP) training algorithm usually used for this network training. One the effective factors in BP algorithm is training rule, which determines method of weights up-dating. The training rule is mathematical equation, which determines increase or decrease of weights during training process. The training stages in this algorithm including (Dayhoff, 1990; Khanna, 1990): (A). Allocation of randomize weight matrix to each of connections, (B). Selection of input vector and corresponding output vector, (C). Output calculation of neuron in each layer and as a result output calculation of neurons in output layer, (D). Up-dating of weights using error propagation of network to previous layers, which are differences between target and calculated output and (E). Evaluation of trained network performance using some defined indexes such as root mean square error (RMSE) and finally return to part of C or stop of train.

Structure of the RBF network is similar to the MLP network, but network computations are done by neurons in hidden layer. In these networks, there is only one hidden layer so problems of layer severalty may be eliminated, but

single hidden layer structure of these networks may be decreased flexibility of them (Broomhead & Lowe, 1988; Jain & Fanelli, 2000).

**Designing of the ANNs.** Using four input variables of engine speeds (1300, 1650, 2000 & 2200 rpm), octave center band frequencies (125, 250, 500, 1000, 2000, 4000 & 8000 Hz), gear ratios (2 high, 2 low, 3 high & 3 low) and surface types (asphalt & dirt rural roads & grassland) number of 336 patterns were generated for calculating, training and evaluation of artificial neural networks. An ANN was designed with four neurons in input layer (engine speeds, octave center band frequencies, gear ratios & surface types) and one neuron in output layer (sound pressure levels in octave frequency bands). Fig. 2 shows typical neural network topology, also input and output experimental parameters are shown in this figure. Due to initial weights and learning rate selection, optimum numbers of neurons in hidden layer or layers like number of hidden layers were not recognized; therefore, the optimum number of hidden layers and their neurons were determined using trial and error method. Neural Works Professional II/PLUS software was used for analysis.

To obtain suitable prediction in this research work, multilayer perceptron (MLP) and radial basis function (RBF) networks were used for training of ANNs. Training process by these networks is iterative process that includes up-dating of weights between the different layers. During training process the weights gradually proceed to stability. So, it would be minimized error between target and predicted values. In this research, different activation functions such as sinusoidal, sigmoid, linear and hyperbolic tangential (Equ. 1 to 4, respectively) were evaluated to find minimum error between actual and predicted values (Dayhoff, 1990; Khanna, 1990).

$$Y_j = \sin(X_j) \quad (1)$$

$$Y_j = \frac{1}{1 + \exp(-X_j)} \quad (2)$$

$$Y_j = X_j \quad (3)$$

$$Y_j = \tanh(X_j) \quad (4)$$

Where,

$X_j$  i.e., sum of weighted inputs every  $j$ -th layer neuron, which is calculated from:

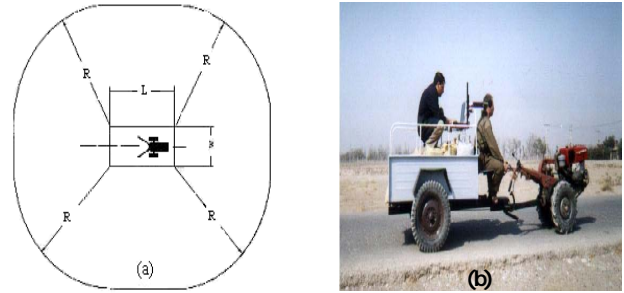
$$X_j = \sum_{i=1}^m W_{ij} \times Y_i + b_j \quad (5)$$

Where,

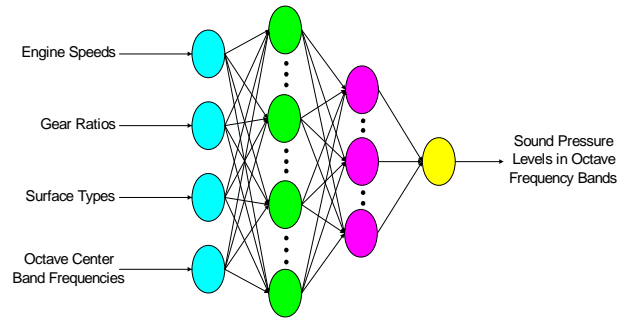
$m$  = number of output layer neurons of MLP and RBF networks,

$W_{ij}$  = weight of connections between layer  $i$  and  $j$  of MLP networks or weight of connected to  $j$ -th layer for RBF

**Fig. 1(a). Dimensions of the measurement area and (b) Test site for driver's position**



**Fig. 2. Topology of artificial neural network**



networks,

$Y_j$  = output of  $i$ -th neuron of MLP networks or function of input vector for RBF networks,

$b_j$  = bias value of  $j$ -th layer neuron of MLP and RBF networks.

Several learning rules were used for training process, such as: Delta Rule, Norm-Cum-Delta, Ext DBD, Quick Prop, Max Prop and Delta-Bar-Delta.

At first, the data randomly was divided in to two parts, so that 233 data for training and 100 data for testing of network were selected. To find a network with proper topology using training algorithms root mean square of error criterion was used.

To increase the precision and velocity of ANN process, all data were normalized by the following relationship:

$$X_n = \frac{X_i(B_U - B_L) + X_{\max}B_L - X_{\min}B_U}{X_{\max} - X_{\min}} \quad (6)$$

Where,

$X_n$  = normalized value,

$X_i$  = actual value,

$X_{\min}$  = minimum of actual value,

$X_{\max}$  = maximum of actual value,

$B_L$  = lower boundaries,

$B_U$  = upper boundaries.

## RESULTS AND DISCUSSION

Occupational health and safety problems for machine

operators and farmers are matters of concern due to excessive noise, which need to be minimized (Crocker & Ivanov, 1993; Solecki, 1998, 2000). Different combinations of networks, activation functions and training rules were evaluated for prediction of the power tiller sound pressure levels in octave bands (Hassan-Beygi *et al.*, 2005a & b). The RMSE criterion was calculated for each network. The results of evaluations are shown in (Table I & II) for MLP and RBF networks, respectively. The results of evaluations of the MLP networks with different topologies revealed that four layers perceptron network with training algorithm of back propagation, hyperbolic tangential activation function, Delta training rule with five neurons in first hidden layer and three neurons in second hidden layer was found to be the best for accurate prediction of the power tiller sound. (Table I). Minimum RMSE of training and coefficient of determination for the MLP network were 0.0484 and 0.983, respectively. Also, evaluations of the RBF networks with different topologies showed that RBF network with linear activation function, Delta training rule with four neurons in hidden layer was the best ones for prediction of the power tiller sound (Table II). Minimum RMSE of training and coefficient of determination for the RBF network were 0.0542 and 0.923, respectively. Comparing the results of MLP and RBF networks showed that the MLP network is more suitable than the RBF network for accurate prediction of the power tiller sound pressure levels in octave frequency bands.

The best four layers perceptron network was optimized. Number of desirable cycles, learning coefficient and momentum coefficient were selected from proper network and desired values for activation functions, learning rules, number of hidden layers and neurons. The suitable value for momentum coefficient was 0.35, learning coefficient for first layer was 0.25, for second hidden layer was 0.25 and for output layer was 0.15.

Comparison between measured and predicted power tiller sound pressure levels in octave frequency bands revealed that the maximum difference between measured and predicted values is  $\pm 2$  dB (Fig. 3). Training condition of optimized network is shown in Fig. 4. To avoid network over training, coefficient of determination was calculated in different training cycles (Fig. 5), where 20000 cycles were determined and found to be the best.

**CONCLUSION**

The result of present research can be useful in selection of proper methods for the power tiller noise control and reduction and design of effective ear protection device for operators.

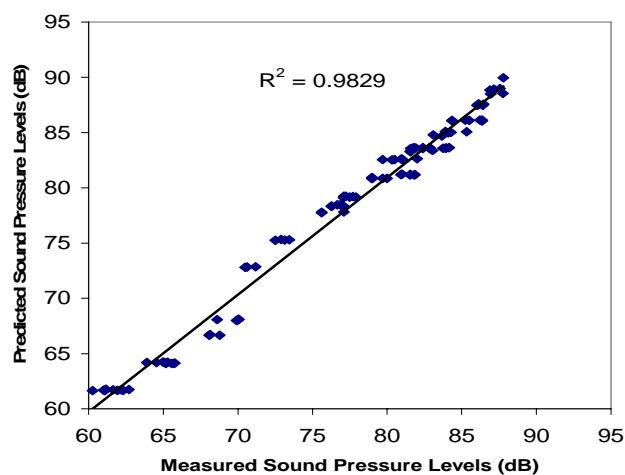
**Table I. Some of the best topologies of MLP network for octave sound prediction**

Activation function	Training rule	First hidden layer neurons	Second hidden layer neurons	Training error (RMSE)	R <sup>2</sup>
TanH	Delta	4	-	0.0511	0.9513
Sigmoid	Delta	3	-	0.0551	0.9428
Sin	Delta	5	-	0.0597	0.9328
TanH	Norm-Cum-Norm	3	-	0.1347	0.8928
Sigmoid	Norm-Cum-Norm	5	-	0.0509	0.8921
Sin	Norm-Cum-Norm	3	-	0.1074	0.8952
TanH	ExtDBD	5	-	0.1097	0.9252
Sigmoid	ExtDBD	3	-	0.0574	0.9228
Sin	ExtDBD	3	-	0.0786	0.9309
Sigmoid	Quick Prop	4	-	0.0395	0.9175
TanH	Delta-Bar-Delta	4	-	0.0595	0.9075
TanH	Delta	5	3	0.0484	0.9829
Sigmoid	Delta	5	5	0.0538	0.9442
Sin	Delta	5	5	0.0514	0.9538
TanH	Norm-Cum-Norm	6	3	0.0918	0.9353
TanH	ExtDBD	6	6	0.0833	0.9456
Sigmoid	ExtDBD	6	3	0.0533	0.9256
TanH	Quick Prop	5	4	0.1533	0.9356
Sin	Delta-Bar-Delta	5	4	0.1433	0.8356

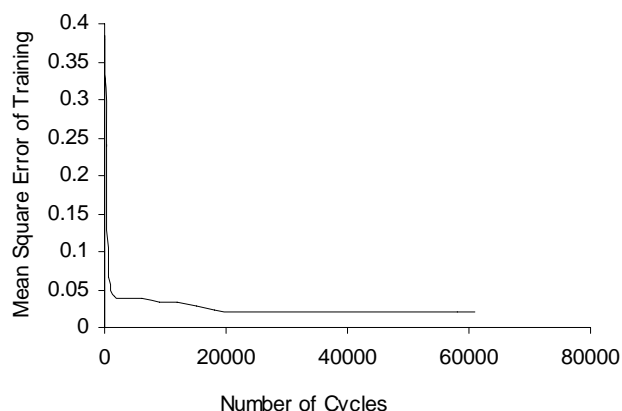
**Table II. Some of the best topologies of RBF network for octave sound prediction**

Activation function	Training rule	Hidden layer neurons	Training error (RMSE)	R <sup>2</sup>
Linear	Delta	4	0.0542	0.9234
TanH	Delta	6	0.0535	0.9034
Sigmoid	Delta	5	0.0582	0.8897
Sin	Delta	3	0.0535	0.9119
Linear	Norm-Cum-Norm	6	0.0755	0.8314
Sin	Norm-Cum-Norm	5	0.0785	0.8624
Linear	ExtDBD	6	0.0997	0.7514
TanH	ExtDBD	3	0.1014	0.7354
Sin	ExtDBD	3	0.1009	0.7586

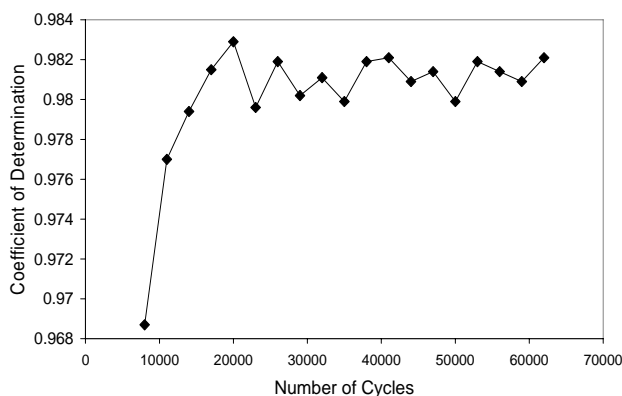
**Fig. 3. The predicted values by MLP network versus actual test data**



**Fig. 4. Training conditions of optimum designed network**



**Fig. 5. Coefficient of determination between predicted and test values in different training cycles**



## REFERENCES

Anonymous, 2003. *Ministry of Jihad-e-Keshavarsi, Center of Development of Mechanization*. Agricultural Census, Tehran, Iran

Bodria, L. and M. Fiala, 1995. Design and testing of an electric-powered walking tractor. *J. Agric. Eng. Res.*, 60: 62–70

Broomhead, D.S. and D. Lowe, 1988. Multivariate functional interpolation and adaptive networks. *Complex Systems*, 2: 321–55

Brown, R.H., 1988. *Handbook of Engineering in Agriculture*, Vol. 2: 1<sup>st</sup> ed. Prentice – Hall, Inc, London, UK

Crocker, M.J., 1998. *Handbook of Acoustics*, 1<sup>st</sup> ed. John Wiley and Sons, New York, USA

Crocker, M.J. and I.N. Ivanov, 1993. *Noise and Vibration Control in Vehicles*, 1<sup>st</sup> ed. Interpublish Ltd., St. Petersburg, Russia

Dayhoff, J.E., 1990. *Neural Networks Principles*, 1<sup>st</sup> ed. Prentice-Hall International, USA

Hassan-Beygi, S.R., 2004. Investigating and analyzing of power tiller noise (in Persian). *Ph.D. Thesis*, Tarbiat Modares University, Tehran, Iran

Hassan-Beygi, S.R., B. Ghobadian and N. Kamalian, 2004. Prediction model of a power tiller noise level at rural dirt road (in Persian). *J. Agric. Sci.*, 10: 47–58

Hassan-Beygi, S.R., B. Ghobadian, P. Nasiri and N. Kamalian, 2005a. Investigation, analysis and presentation of prediction models of a power tiller noise pulling a trailer at rural asphalt road (in Persian). *J. Sci. Tech. Agric. Natural Resource*, 8: 225–40

Hassan-Beygi, S.R., B. Ghobadian, R. Amiri-Chayjan and M.H. Kianmehr, 2005b. Intelligent prediction of a power tiller noise levels using artificial neural networks. *Proceedings of International Congress on Information Technology in Agriculture, Food and Environment (ITAFE'05)*, October 12-14, Adana, Turkey

Irwin, J.D. and E.R. Graf, 1979. *Industrial Noise and Vibration Control*, 1<sup>st</sup> ed. Prentice-Hall, Inc., London, UK

ISO 5131, 1996. *Acoustics: Tractors and Machinery for Agriculture and Forestry Measurement of Noise at Operator's Position*. International Organization for Standardization, Geneva, Switzerland

Jain, L.C. and A.M. Fanelli, 2000. *Recent Advances in Artificial Neural Networks: Design and Applications*, 1<sup>st</sup> ed. CRC Press, USA

Kang, C.I.I., N.J. Park, I.S. Oh and Y.B. Lee, 1988. Study on the handling of power tiller in view of ergonomics. *Research Reports of the Rural Development Administration Agricultural Engineering and Farm Management*, 30: 67–71

Khanna, T., 1990. *Foundations of Neural Networks*, 1<sup>st</sup> ed. Addison-Wesley Publishing Company, USA

Maring, J., 1979. *Tractor Noise, Field Measurements of Noise at Ear Level*, P: 15. Research Report of Wageningen University, Wageningen, The Netherlands

Menhaj, M.B., 1998. *Fundamental of Artificial Neural Networks*, 1<sup>st</sup> ed. Amir Kabir University Publishing. (in Persian), Tehran, Iran

NIOSH., 1998. *Criteria for a Recommended Standard, Occupational Noise Exposure, Revised Criteria*. National Institute for Occupational Safety and Health, U.S. Department of Health and Human Services, Publication No. 98–126, Washington D.C., USA

Oppenheim, A.V., A. Willsky and H. Nawab, 1995. *Signals and Systems*, 2<sup>nd</sup> ed. John Wiley and Sons, New York, USA

Roth, O.L. and L.H. Field, 1991. *Introduction to Agricultural Engineering*, 2<sup>nd</sup> ed. Van Nostrand Reinhold, New York, USA

Sieswerda, V. and J.C. Dekker, 1978. Deafness caused by tractor noise. *Landbouwmecanisatia*, 29: 1001–3

Solecki, L., 1998. Occupational hearing loss among selected farm tractor operators employed on large multi-production farm in Poland. *Int. J. Occup. Med. Env. Health*, 11: 69–80

Solecki, L., 2000. Duration of exposure to noise among farmers as an important factor of occupational risk. *Agric. Env. Med.*, 7: 89–93

Suggs, C.W., 1987. *Noise Characteristics of Field Equipment*, ASAE Paper No. 87-1598. St. Joseph, Mich, ASAE

Talamo, J.D.C., 1987. Noise problems in the agricultural industry. *Proceedings of the Institute of Acoustics*, 9: 399–402

(Received 22 December 2006; Accepted 25 April 2007)