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Prediction of Power Tiller Noise Levels Using a Back Propagation Algorithm

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ABSTRACT

The use of neural networks methodology is not as common in the investigation and prediction noise as statistical analysis. The application of artificial neural networks for prediction of power tiller noise is set out in the present paper. The sound pressure signals for noise analysis were obtained in a field experiment using a 13-hp power tiller. During measurement and recording of the sound pressure signals of the power tiller, the engine speeds and gear ratios were varied to cover the most normal range of the power tiller operation in transportation conditions for the asphalt, dirt rural roads, and grassland. Signals recorded in the time domain were converted to the frequency domain with the help of a specially developed Fast Fourier Transform (FFT) program. The narrow band signals were further processed to obtain overall sound pressure levels in A-weighting. Altogether, 48 patterns were generated for training and evaluation of artificial neural networks. Artificial neural networks were designed based on three neurons in the input layer and one neuron in the output layer. The results showed that multi layer perceptron networks with a training algorithm of back propagation were best for accurate prediction of power tiller overall noise. The minimum RMSE and R^2 for the four-layer perceptron network with a sigmoid activation function, Extended Delta-Bar-Delta (Ext. DBD) learning rule with three neurons in the first hidden layer and two neurons in the second hidden layer, were 0.0198 and 0.992, respectively.

Keywords: Back propagation, Noise, Power tiller, Prediction.

INTRODUCTION

Technological progress is the main reason for mechanical power to have replaced human and animal power for performing farm operations. So, at present, tractors and agricultural machineries are an integral part of agricultural mechanization. On the other hand, the introduction of tractors and agricultural machinery into farms has led to some occupational health and safety problems for the operators of these machines and farmers. Excessive noise is one example of this (Sieswerda and Dekker, 1978; Maring, 1979; Talamo, 1987; Suggs, 1987; Brown, 1989; Crocker and Ivanov, 1993; Solecki, 1998, 2000).

Unwanted sound, known as noise, is in fact perturbation in pressure detected by the human ear and is associated with the mechanical vibration of gaseous, liquid or solid media (Crocker and Ivanov, 1993; Crocker, 1998). The most unpleasant effects of noise on humans are: temporary and permanent hearing loss, mental and nervous discomforts, decreased of work efficiency and increased risk of hazards (Irwin and Graf,

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1979; Roth and Field, 1991; Crocker and Ivanov, 1993; Crocker, 1998). Considering the threats of noise on humans, occupational health and safety associations in different countries have established regulations in order to restrict the duration of human noise exposure in noisy environments. The National Institute for Occupational Safety and Health (NIOSH) is an example (NIOSH, 1998). Exposure to a 85 dB(A) noise level for eight-hours in a day or exposure to 88 dB(A) noise level for four-hours a day are regarded as one noise dose (NIOSH, 1998). Research work conducted by Solecki (2000) showed that the average noise dose of farmers over 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), although some countries are conducting noise reduction and control programs to bring noise levels lower than 75 dB(A) (Crocker and Ivanov, 1993).

Studies by Broste *et al*. (1989) and also Dennis and May (1995) showed that the overall noise level at driver's ear position for tractors without a cab or with open windows in was some cases greater than 95 dB(A). Bean (1995) reported that most tractors tested today have overall noise levels exceeding 90 dB(A), while other farm machinery, such as self-propelled combines, corn pickers, hammer mills and driers may produce levels in excess of 100 dB(A). Results from Italian researchers have revealed that the most people who have been tractor drivers for about 20 years had some hearing loss and 34% of them endure major hearing problems (Crocker and Ivanov, 1993). Studies by Solecki (1998, 2000) showed that 56% of tractor drivers under study endured hearing loss about 20 dB (A) less than the control group with the same age. Furthermore, this finding showed this to be more severe for drivers over 30 years old.

Ergonomic evaluation of power tillers showed that the noise and vibration of power tillers play an important role in damage experienced by farmers and extension workers (Kang *et al*., 1988). Furthermore, high noise levels emitted by power tillers were the reason for the suggesting the replacement of the diesel engines of power tillers by electric power sources (Bodria and Fiala, 1995). On the other hand, the limited space for the small engines fitted on the power tillers and other limitations do not allow for equipping them with sound absorbing materials or provide them with the driver's cab (Brown, 1988), though the noise received by farmers and bystanders still present a further dilemma.

There are more than 120,000 power tillers in Iran (Anonymous, 2003). The primary purpose of a power tiller in any field application is to produce the required power output. Besides on-farm application of power tillers in Iran, they are also engaged in transportation of agricultural products and human beings on asphalt and dirt rural roads as well as grasslands. Investigations by Hassan-Beygi *et al*. (2004, 2005), Hassan-Beygi and Ghobadian (2004, 2005) showed that overall noise levels of 13-hp power tiller at the driver's ear position reached 92 dB(A) at 2,200 rpm engine speed and at different gear ratios for asphalt and dirt rural roads and grasslands, which was higher than the standard upper limit of 85 dB(A). Also Hassan-Beygi *et al*. (2004, 2005) have developed regression prediction models for power tiller overall noise levels using statistical analysis. On the other hand, investigations by Hassan-Beygi (2004) showed that noise prediction of agricultural machinery are not common by ANN.

An artificial neural network has some special characteristics as follows, which makes it a powerful predictor (Khanna, 1990; Dayhoff, 1990):

a. High processing rate due to parallel processing construction,

b. Learning ability through pattern presentation,

c. Prediction of an unknown pattern at desired precision after learning,

d. Flexibility at undesired errors of input training pattern, and

e. If a part of network connections is damaged, created error is not notable.

In the present paper, back propagation algorithm was used as a tool for accurate prediction of a 13-hp power tiller overall noise level in transportation conditions on asphalt and dirt rural roads as well as grassland.

MATERIALS AND METHODS

Specifications of the Test Power Tiller

The power tiller used for this research study was fitted with a single cylinder, four stroke, naturally aspirated, water-cooled IDI diesel engine, providing 13-hp power at rated engine speed of 2,200 rpm. The travel speed of the power tiller was six stage forward and two stage reverse.

Measuring and Recording Instrumentation

The instruments used in this study, consisted of a sound level meter, a microphone, a tachometer, a lap-top computer and a few other devices. The detailed specifications of the instruments are given in Table 1. The lap-top computer along with the sound recording software (Cool Edit 2000) and Yamaha OPL3-SAX, A/D sound card provided a suitable means of sound recording instrumentation scheme instead of more expensive and complex instrumentation (Hassan-Beygi, 2004).

The Test Site

The test site was prepared and maintained according to ISO (ISO 5131, 1996) and SAE (SAE J1174, 1985) sound measurement standards. 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 measurement. 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. Figure 1a shows the dimensions of the area in which the power tiller noise measurement was carried out. In this figure, R stands for the distance from the obstacles to the measurement zone; L and W are the length and width of the measurement zone, respectively. The minimum values of R, L and W were 15 m, 10 m and 2 m, respectively. Figure 1b shows the instrumentation set up for measuring noise near the operator's ear.

Table 1. Specifications of the instruments.

Name of the instrument	Sensitivity	Range/Capacity	Accuracy/ Resolution	Make and Model
Prepolarized condenser microphone	50 mV Pa^{-1}	20-146 dB	-	B and K 4415 Denmark
Sound level meter	-	24-130 dB	0.1 dB	B and K 2230 Denmark
Digital tachometer	-	0.5 –19999 rpm	1 rpm over 1000 rpm	Lutron D-2236 Taiwan
Digital thermometer	-	-10 – 50°C	0.1°C	Testo Germany
Digital anemometer	-	0 - 15 m s^{-1}	0.01 m s^{-1}	Testo Germany
Lap-top	-	-	-	Toshiba Satellite 2335D, Malaise
Sound card	-	-	16 bits	Yamaha OPL3-SAX
RAM memory	-	64 M bytes	-	NEC Japan
Hard disk	-	8 G bytes	-	NEC Japan

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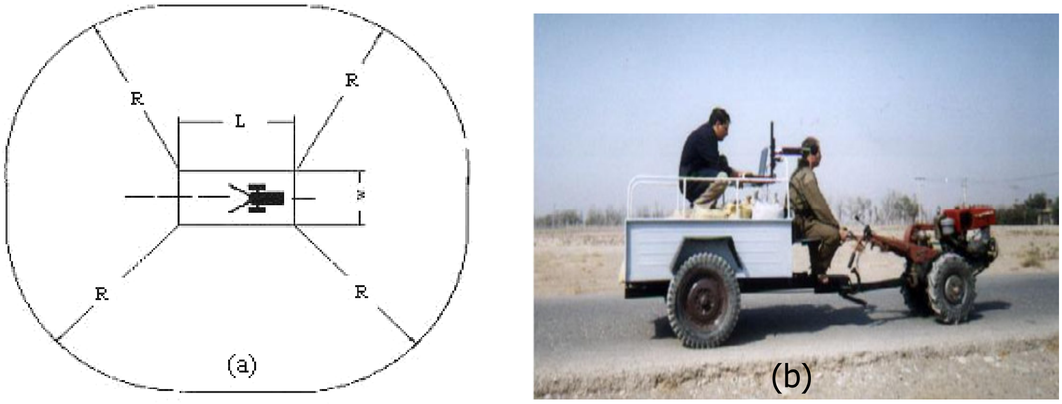

Figure 1. (a) Dimensions of the measurement area and (b) Test site for driver's position.

Data Acquisition and Signal Processing

The selected variables were engine speed, gear ratios and surface types in this study. The range of variables considered to perform the test could cover the normal and safe operating range of the power tiller during operation under transportation conditions for asphalt, dirt rural roads, and grassland. Table 2 shows the test matrix for the power tiller under test. For simulating actual transportation conditions, a 9,000 Newton weight was placed on the trailer to be pulled by the power tiller.

In each test run, a minimum 10 second sound signal was recorded. In initial data analysis in the time domain between 1.5 to 3 seconds, a nearly uniform signal was selected to minimize variations existing between signal peaks in order to increase the test's accuracy.

The microphone used in this study provides flat frequency response throughout the human audible range (20–20,000 Hz). The microphone in conjunction with a sound level meter was used for measuring the sound pressure signal of the test power tiller. According to Nyquist's criteria for correct A/D conversion of analog signals to digital ones, the data sampling rate must be at least two times that of maximum frequency (Oppenheim *et al*., 1995). Considering the human audio frequency range, A/D conversion with a 48,000 Hz sampling rate was used for converting the output analog signals of sound level meter. The digitized sound signals were stored on the computer hard disk, using Cool Edit 2000 software. Part of a typical sound signal in the time domain is shown in Figure 2a. Since the signal obtained in the time domain could not reveal much information, therefore, the recorded digital data in the time domain was converted to the frequency domain, using a developed FFT computer program. Based on this analysis, the narrow band frequency

Table 2. Matrix of the experimentation.

Parameters	Levels of parameters			
	1	2	3	4
Engine speed (rpm)	1300	1650	2000	2200
Gear ratio	2 high	2 low	3 high	3 low
Type of test courses	Asphalt road	Dirt road	Grassland	-

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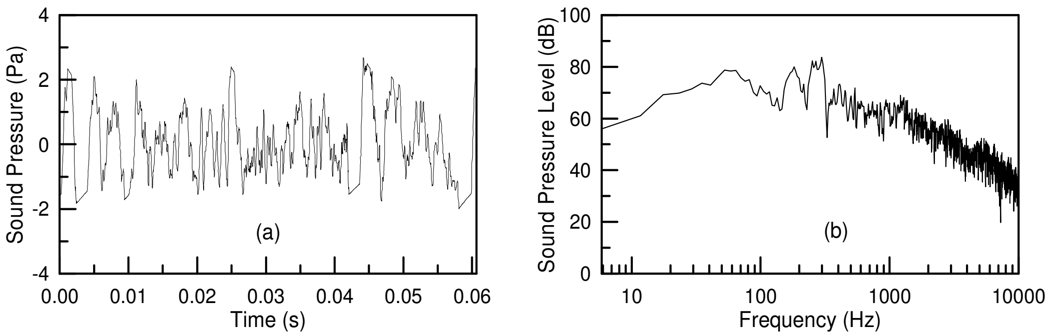

Figure 2. (a) A part of typical sound signal in time domain and (b) The corresponding narrow band frequency domain sound pressure level.

domain sound pressure levels were obtained (Figure 2b). The overall A-weighted sound pressure levels were derived from the narrow band signals in the frequency domain, using a specially developed sub-routine computer program.

Artificial Neural Networks

An artificial neural network consists of neurons, which have been related to each other by special arrangement. Neurons are placed in layers and every network consists of some neurons in the input layer, one or more neurons in the output layer and neurons in one or more hidden layers. Most of the algorithms and architectures of the artificial neural networks were varied by variation in the neuron model and in the relationship between neurons and weights. The purpose of learning in artificial neural networks is updating weights so that, when presenting a set of inputs, the desired outputs are obtained. The most common types of artificial neural networks include: feed forward, feed back and competitive (Menhaj, 1998; Jain and Fanelli, 2000). In this paper, the feed forward neural network was used. The ability of Multilayered Feed forward Neural Networks (MFNN) during non-linear mapping between input and output parameters is the result of the multi layer structure of this network, which is the reason for learning of this type of network to be desirable. This ability can be assured through proper selection in a number of layers and hidden neurons. From a computational point of view, using the minimum number of hidden layers with the minimum number of neurons in them is preferred. Therefore, a structure with the lowest number of hidden layers and neurons was realized to be the optimum one, so that the structure is able to perform computations with desired accuracy. This type of neural network is mainly used for estimating the function and classification of patterns. A Multi Layer Perceptron Network (MLP) is the most common type of feed forward. This network consists of one input layer, one or more hidden layers and one output layer. A Back Propagation (BP) training algorithm is used for training this network. This algorithm increases applications of ANNs because of its strong mathematical base and so it has been use in 80 percent of ANN applications in different scientific disciplines. The synapse connections in a MFNN network with the BP algorithm were propagated in two directions. The signal from the input layers was propagated towards the middle and output layers. Meanwhile the output error signal was propagated from output layer neurons towards previous layers' neurons, so that neurons in each layer received a feedback signal from neurons in the next layer. The training process in the BP algorithm is an iterative process that includes updating of weights between the different layers. During the training process the weights gradually proceed to stability and so the error between target and predicted values is minimized. In the BP algorithm, due to initial weights and learning rate selection, the optimum number of hidden layers and neurons in them cannot be found in advance. Therefore, the optimum number of hidden layers and their neurons are usually determined using a trial and error method. The origin of the BP algorithm is as a gradient descent algorithm in the training of multi-layered neural networks. The feed forward learning process using the BP algorithm is shown in Figure 3 (Menhaj, 1998; Jain and Fanelli, 2000). One of the effective factors in the BP algorithm is the training rule which determines method for up-dating weights. The training rule is a mathematical equation which determines the adjustment of weights during the training phase. During design of a network, an initial training rule was applied for each network layer. The type of training rule depends on the type of network designed. The training rules used in this research work are:

Delta Rule: The output layer error is calculated by the difference between desired and actual output. This error is calculated as a derivation of the transfer function propagated to the previous layer and their calculated sum. The error propagation process continued to the first layer.

Norm-Cum-Delta Rule: This training rule is the other type of Delta rule which attempts to reduce the structure of training process. In this rule, variations of weights are assembled and weights are up-dated at the end of every training cycle. This rule has been normalized because its rate of training is independent of the number of training cycles. The rule automatically regulates training rate as a function of training cycle number.

Delta-Bar-Delta Rule: This rule uses the pervious gradient values to deduce the local curvature of error level. Every connection has a different training rate which is calculated automatically.

Extended Delta-Bar-Delta Rule (Ext. DBD): This rule is an extended version of the Delta-Bar-Delta which is also calculated from the momentum of every connection.

QuickProp Rule: This rule uses a second-order heuristic method for determining orientation and value of the epoch. This rule is used instead of the Delta rule in most of the cases.

MaxProp Rule: This rule is similar to the QuickProp rule but using a different heuristic method.

Design of Artificial Neural Networks

Using three input variables-engine speed, gear ratios and type of surfaces-48 patterns were generated for calculating, training and evaluation of artificial neural networks. The artificial neural network was designed with three neurons in the input layer (engine speeds, gear ratios and surface types) and one neuron in the output layer (Table 2). The topology of the artificial neural network used is shown in Figure 4. The input and output parameters are also shown in Figure 4. The optimum number of neurons in the hidden layer were obtained by using a trial and error method. Generally, networks with more hidden layers, less neurons and fewer width networks, have a better performance compared with networks of less depth and more neurons in one layer, although training in networks of less width is more difficult than for less depth networks (Jain and Fanelli, 2000). Neural Works Professional 11/PLUS software was used for this research work and analysis. To obtain stable topologies, the training process (Figure 3) was repeated eight times for each topology because the software was considered as a different set of initial random values for the weights and bias values (vectors).

For network optimization, an increasing method for selecting the number of neurons and layers was used for network training. New neurons were added to the network gradually, whenever in one stage network a local minimum was involved. This method

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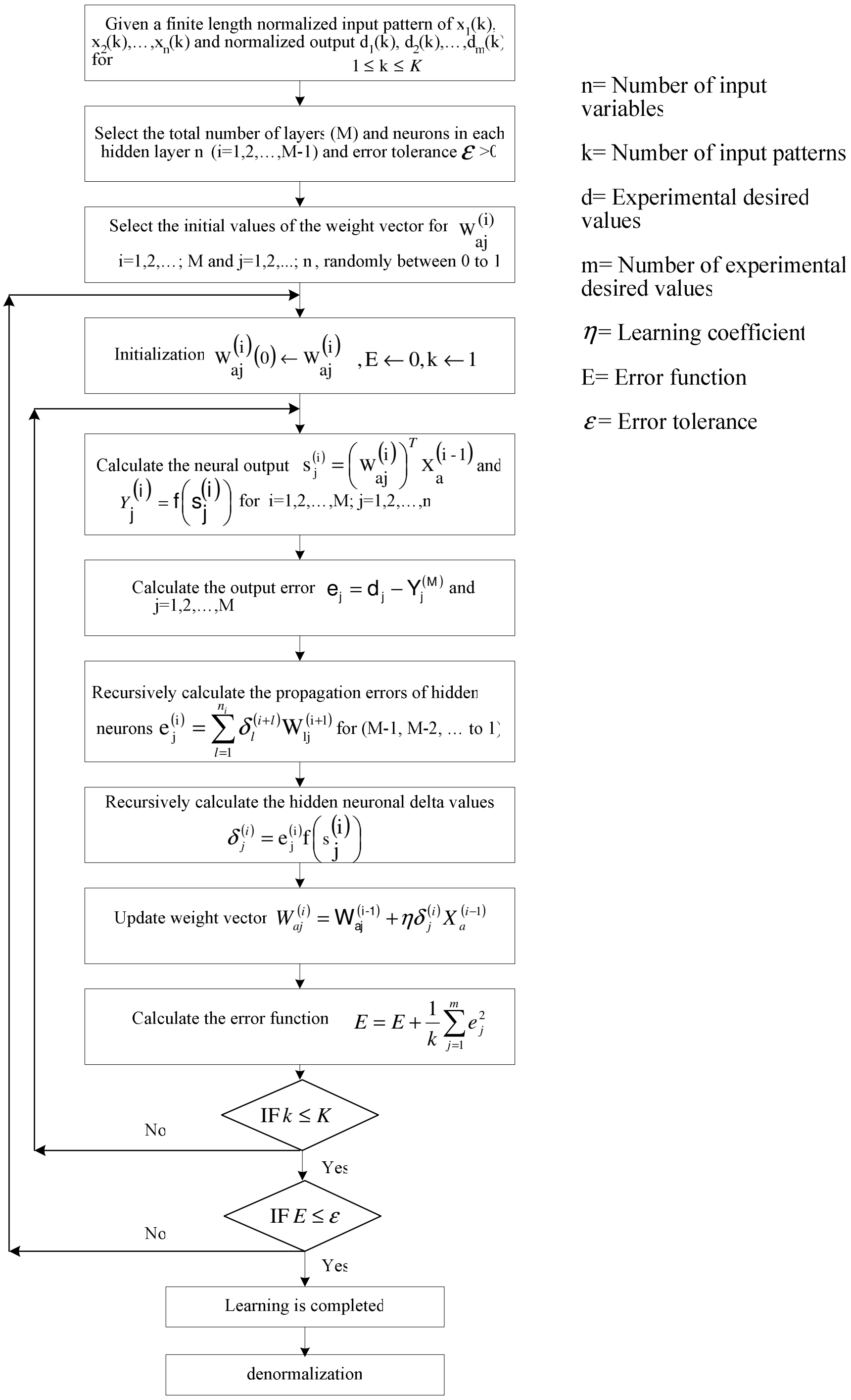

Figure 3. Feed forward network learning process.

has better practical potential for finding the correct size of a network. Advantages of this method are:

a. Network entanglements were increased gradually with increasing neuron numbers,
b. Optimum size of network was often obtained with this arrangement, and

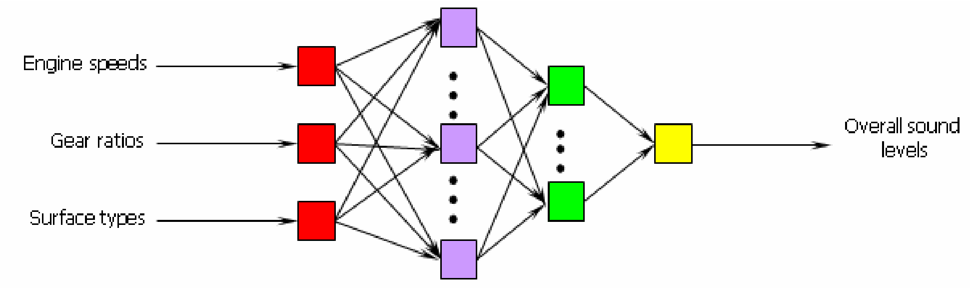

Figure 4. Topology of the artificial neural network**.**

c. Monitoring and evaluation of local minimums were performed during training.

Different activation functions were evaluated to find the optimum state that were:

$Y_j = Sin(X_j)$ Sinusoidal function (1

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

$Y_j = X_j$ Linear function (3

$Y_j = \tanh(X_j)$ Hyperbolic tangential function (4

where, X_j i.e. is the 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,

W_{ij}= Weight between layer i and j,

Y_j= Output of i-th neuron, and

b_j= Bias value of j-th layer neuron.

Input and output data were normalized using Equation (6):

$$X_n = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \quad (6$$

where:

X_n= Normalized value,

X_i= Actual value,

X_{min}= Minimum of actual value, and

X_{max}= Maximum of actual value.

At first, the data was divided randomly into two parts, so that 37 data for training and 11 data were selected for network testing. For finding the difference between the measured and predicted data that is the real error, the output of the output layer was denormalized.

RESULTS AND DISCUSSION

The information on variation of the power tiller sound pressure levels with different engine speeds, gear ratios and surface types are summarized in Figure 5. The vertical and horizontal axes of this figure are the overall A-weighted sound levels and engine speed, respectively. Variations of the sound levels on asphalt, dirt and lawn covered roads are presented in each part of this figure. Parts a, b, c and d of this figure are related to 2^{nd} high, 2^{nd} low, 3^{rd} high and 3^{rd} low gear ratios, respectively. As shown in different parts of this figure, with an increase in engine speed from 1,200 rpm to 2,200 rpm, a maximum of 7 dB(A) increase in overall sound pressure levels could be observed on different surface types. Research work conducted by Suggs (1987) and Meyer *et al*. (1993) also showed the increase of sound levels of agricultural equipments with an increase in engine speed. It can be seen from Figure 5 that variations in the sound levels with respect to surface types at different levels of engine speeds and gear ratios are within ±1 dB (A). Also, the variations of the sound levels with respect to gear ratio at different engine speeds and surface types are with in ±1 dB (A).

The scatter distribution of data for training is shown in Figure 6. As shown in this figure, the distribution of training data was covered

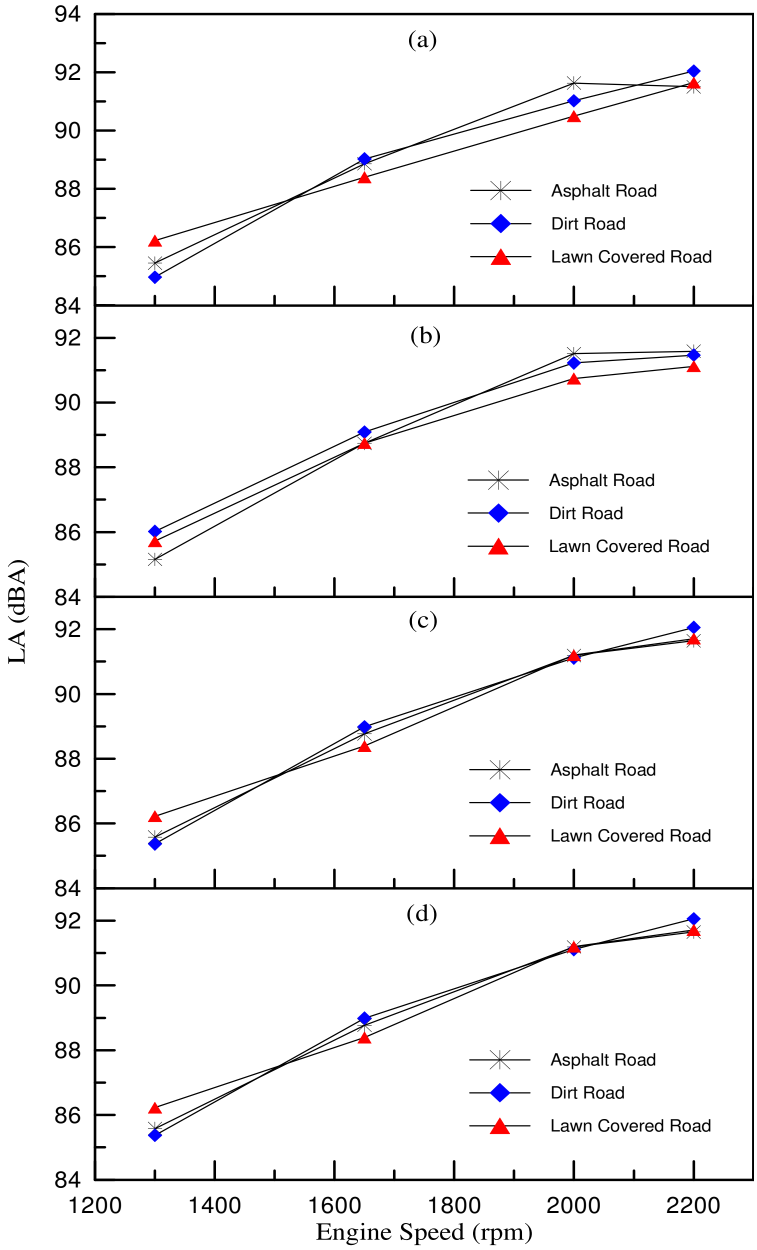

Figure 5. Variations of the A-weighted overall sound pressure levels of the power tiller with respect to engine speeds: (a) 2nd high; (b) 2nd low, (c) 3rd high and (d) 3rd low gear ratios.

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throughout the range of the measured overall sound levels of the power tiller.

The MLP networks with a back propagation error algorithm, activation functions and training rules were evaluated for prediction of the power tiller overall sound levels. The RMSE criterion was calculated for each network. The average results of these evaluations are shown in Table 3.

The results of training of the three layer perceptron networks with different topologies showed that a network with a hyperbolic tan-

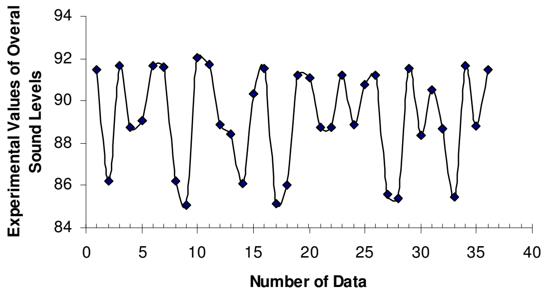

Figure 6. The scatter of training data.

gential activation function, delta training rule and four neurons in the hidden layer was found to give the best results among the three-layer networks. The minimum RMSE and R^2 for the network were 0.0251 and 0.9513, respectively. The four- layer perceptron networks with different topologies were also evaluated to obtain a probable better prediction accuracy. The training of the four-layer networks showed that a network with sigmoid activation function, Ext DBD training rule with three neurons in first hidden layer and two neurons in the second hidden layer had a minimum RMSE 0.0203 and R^2 0.992. This was the best result among the other three- and four- layer topologies for the same initial conditions.

Comparing the results for three-layer and four-layer perceptron networks revealed that, usually, the four-layer networks are more suitable than the three-layer networks for predicting power tiller sound levels.

For optimizing the best four-layer networks and to overcome over-training, different values of learning and momentum coefficients were investigated according to software rec-

Table 3. The best values obtained from training of MLP network with the BP algorithm and with different topologies.

Activation function	Training rule	Number of neurons in first hidden layer	Number of neurons in second hidden layer	RMSE of Training	R^2
Sigmoid	Delta	4	-	0.0301	0.9428
Sin	Delta	6	-	0.0327	0.9328
Sigmoid	Norm-cum-norm	5	-	0.0354	0.8921
Sigmoid	ExtDBD	7	-	0.0374	0.9228
TanH	Delta	4	-	0.0251	0.9513
Sin	ExtDBD	5	-	0.0326	0.9309
Sigmoid	Quick prop	4	-	0.0395	0.9175
TanH	Deta-bar-delta	6	-	0.0415	0.9075
Sigmoid	ExtDBD	4	3	0.0172	0.9818
Sigmoid	ExtDBD	6	5	0.0183	0.9893
TanH	ExtDBD	6	5	0.0183	0.9446
Sigmoid	ExtDBD	3	2	0.0198	0.9920
Sigmoid	ExtDBD	4	4	0.0184	0.9880
Sigmoid	Delta	4	4	0.0218	0.9893
Sigmoid	Delta	5	4	0.032	0.9718
Sigmoid	Delta	7	4	0.0233	0.9918
TanH	Delta	7	5	0.0366	0.9725
TanH	Delta	5	5	0.0288	0.9753
TanH	Delta	5	3	0.0350	0.9854
TanH	Delta	6	6	0.0307	0.9671

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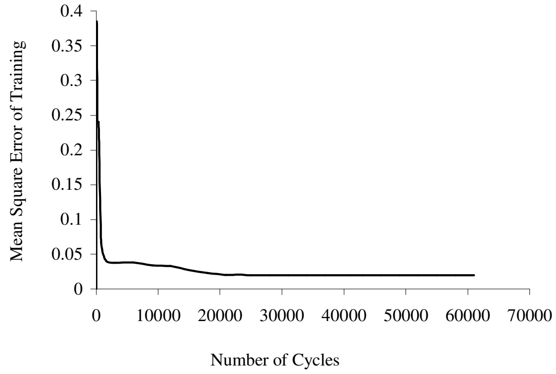

Figure 7. Training conditions of optimum designed network.

ommendations. Thus, the suitable value for momentum coefficient was found to be 0.4, while the learning coefficient for the first layer was 0.3, for the second hidden layer it was 0.25 and for the output layer was 0.15. The training conditions for the optimized network are shown in Figure 7. It can be seen from this figure that RMSE of training of the optimized network decreased with increasing training cycles up to 20,000 cycles. After this cycle, the RMSE of training was stabilized.

To avoid network over-training, the coefficient of determination was calculated in different training cycles (Figure 8). Figure 8 shows that the coefficient of determination was increased before 20,000 cycles, which is the reason for reduction in the RMSE of training. The coefficient of determination was not considerably changed after 20,000 cycles. Therefore, the 20,000 cycles was accepted to be the best one.

The measured test data set and corresponding ones predicted by the trained ANN as well as the difference between measured and predicted sound levels are shown in Table 4. It is obvious from this table that the difference between measured and predicted values is less than ±0.43 dB (A). To compare the accuracy of the trained network with the regression model in predicting the overall sound pressure levels of the power tiller, sound levels predicted by the trained ANN and by a developed regression model (Hassan-Beygi, 2004) were compared with the measured values for the total data set (Figures 9a and b, respectively). The proximity of each point to the 45^{o} line throughout the range of the measured overall sound pressure

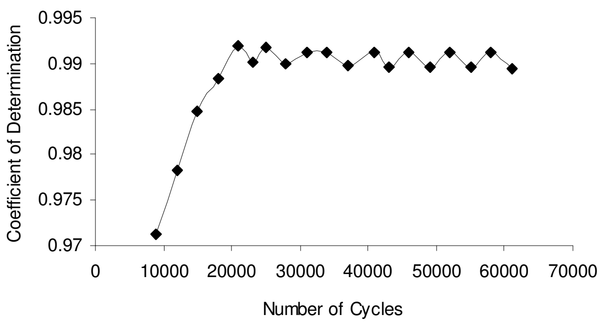

Figure 8. Coefficient of determination between predicted and test values in different training cycles.

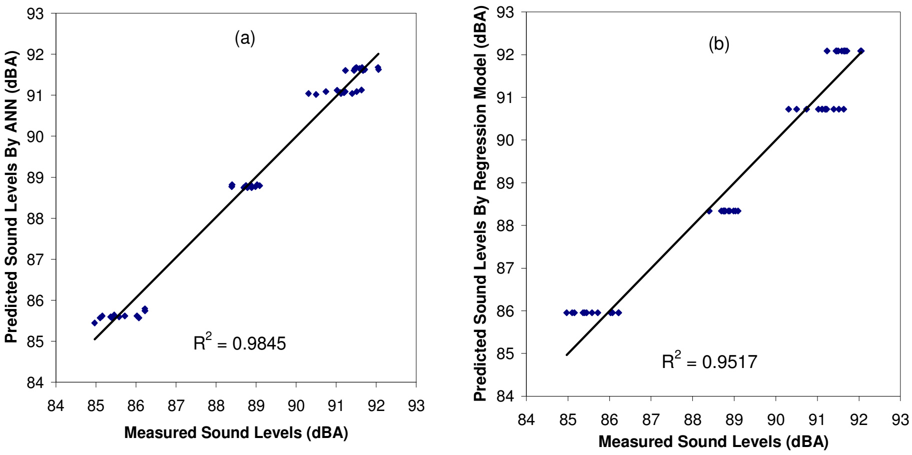

Figure 9. Overall sound pressure levels predicted by the ANN model (a) and by the regression model (Hassan-Beygi, 2004) (b) versus measured values, for the total data set.

Table 4. Real Errors in prediction of actual values by the artificial neural network.

Test values	Predicted values	Real error
85.72	86.06	0.35
85.40	85.67	0.27
89.03	88.82	-0.21
88.98	88.93	-0.05
91.02	91.09	0.07
91.22	91.13	-0.09
91.11	91.09	-0.02
91.40	90.96	-0.43
92.04	91.75	-0.29
91.64	91.53	-0.11
91.67	91.53	-0.14

levels indicates that the ANN model (Figure 9a) is more accurate than the developed regression model (Figure 9b). It can be seen from the figures that the coefficient of determination as well as the maximum difference between measured and predicted values by the trained ANN are 0.985 and ±0.5 dB(A), respectively. The coefficient of determination and maximum difference between measured and estimated values with the regression model are 0.952 and ±1 dB(A), respectively, as well. It can be seen from Table 4 and Figure 9 that ANN is a powerful tool for predicting the power tiller overall sound pressure levels. It could be safely concluded that ANN may be a better substitute of regression analysis as far as sound pressure level analysis is concerned.

CONCLUSIONS

The conclusions drawn from this research works are as follows:

1. The ANN network successfully learned the relationship between the independent parameters and dependent parameter as output.
2. The trained ANN has been shown to be an accurate tool for predicting overall sound pressure levels of the power tiller so that the coefficient of determination and

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maximum difference between measured and predicted values were 0.985 and ±0.5 dB, respectively.

3. The results of the present research can be useful in selecting appropriate methods for power tiller noise control and reduction and also the design of effective ear protection device for operators.

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پیش‌بینی تراز صدای تراکتور دوچرخ با استفاده از الگوریتم پس انتشار خطا

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چکیده

کاربرد شبکه‌های عصبی مصنوعی در مطالعات سروصدا به اندازه تحلیلهای آماری مرسوم نیست. هدف اصلی این مقاله کاربرد شبکه‌های عصبی مصنوعی برای پیش‌بینی سروصدای تراکتور دوچرخ می‌باشد. تحلیل سروصدای تراکتور دوچرخ ۱۳ اسب بخار با استفاده از سیگنالهای فشار صدای اندازه‌گیری شده در یک کار میدانی انجام شد. در حین اندازه‌گیری و ثبت سیگنالهای فشار صدای تراکتور دوچرخ، متغیرهای سرعت دورانی موتور و نسبت دنده طوری تغییر داده شدند تا معمول‌ترین حالتهای کارکرد تراکتور دوچرخ در شرایط حمل و نقل در سطوح آسفالت، خاکی و زمین دارای پوشش گیاهی را در بر بگیرد. سیگنالهای ثبت شده در حوزه زمان با کمک برنامه تبدیل فوریه سریع نوشته شده به حوزه فرکانس تبدیل شدند. سیگنالهای باند باریک برای به دست آوردن تراز فشار صدای کلی در مقیاس وزنی A پردازش شدند. ۴۸ الگو برای آموزش و ارزیابی شبکه‌های عصبی مصنوعی تولید شد. شبکه‌های عصبی مصنوعی بر اساس سه نرون در لایه ورودی و یک نرون در لایه خروجی طراحی شدند. نتایج نشان داد که شبکه پرسپترون چند لایه با الگوریتم آموزش پس انتشار خطا دارای بهترین دقت پیش‌بینی تراز صدای کلی تراکتور دوچرخ می‌باشد. حداقل RMSE و R^2 برای شبکه پرسپترون چهار لایه با تابع آستانه سیگموئید، قاعده یادگیری Ext DBD با سه نرون در لایه پنهان اول و دو نرون در لایه پنهان دوم بترتیب ۰/۰۱۹۸ و ۰/۹۹۲ بود.

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